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# A Generative AI Framework for Transforming Stock Market Forecasting, Sentiment Analysis, and Investment Decision-Making

**[1]Dhanya Abraham, [2].Dr.G. Indhumathi**
[1]Research Scholar ,Department of Commerce, Mother Teresa Women's University, Kodaikanal
[2]Associate Professor,Department of Commerce, Mother Teresa Women's University, Kodaikanal.
Email:[1]dhanyajooby@gmail.com ,[2]indhunila2000@gmail.com,

**Abstract**

***The rapid growth of artificial intelligence (AI) and generative artificial intelligence (GenAI) is transforming financial markets by enabling automated information processing, predictive analytics, sentiment analysis, and personalized decision support. The Indian securities market, represented primarily by the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), generates large volumes of structured and unstructured information that can be difficult for retail investors and financial professionals to process efficiently. Conventional forecasting techniques such as ARIMA and standalone recurrent neural networks are often limited in their ability to integrate market prices with news, social-media sentiment, corporate disclosures, and other qualitative information.***

***This paper proposes GenAI-StockPredict, a hybrid framework that combines Large Language Models , financial sentiment analysis, Generative Adversarial Networks and Transformer-based time-series forecasting. Using the proposed experimental design, Nifty 50 market data from 2020–2025 can be combined with financial news and sentiment information to evaluate directional prediction performance against conventional benchmark models. The paper further examines the implications of GenAI for brokerage services, portfolio management, retail investment education, and intelligent business. The study concludes that GenAI has significant potential to augment, rather than replace, human financial expertise. However, hallucination, explainability, data quality, model risk, privacy, market manipulation, and regulatory compliance remain important challenges.***

**Keywords:** ***Generative AI, Stock Market Prediction, Large Language Models, Sentiment Analysis, FinTech***.

## 1. Introduction

Financial markets are among the most information-intensive environments in modern commerce. Stock prices are influenced not only by historical price and trading-volume patterns but also by corporate earnings, macroeconomic conditions, geopolitical events, investor sentiment, regulatory announcements, and rapidly changing public information. The increasing participation of retail investors has further intensified the demand for accessible and timely financial information.

India has experienced substantial growth in equity-market participation, supported by digital trading platforms, mobile applications, simplified account-opening processes, and increasing financial awareness. The NSE and BSE provide extensive market data, while financial news platforms, social-media networks, corporate disclosures, analyst reports, and earnings communications generate large quantities of unstructured information.

Traditional financial forecasting models generally rely on structured numerical data. Models such as Autoregressive Integrated Moving Average (ARIMA) are useful for identifying statistical relationships in historical time series but have limited capacity to understand textual information. Machine-learning approaches can capture nonlinear temporal dependencies but do not inherently understand the semantic content of financial news.

The emergence of Generative AI provides an opportunity to combine these capabilities. Large Language Models can process and summarize large quantities of textual information, while domain-specific models such as FinBERT can estimate financial

sentiment. Transformer architectures can model temporal relationships, and generative models can create synthetic scenarios for stress testing and data augmentation.

Objectives:

1. To examine the role of Generative AI in stock-market forecasting.
2. To develop a hybrid framework integrating market data, financial sentiment, and generated market scenarios.
3. To examine how GenAI can transform brokerage, portfolio-management, research, risk-management, and retail-investment services.

Review of Literature

Efficient Market Hypothesis

Fama's Efficient Market Hypothesis (EMH) argues that security prices incorporate available information. Under the strong interpretation of market efficiency, consistently generating abnormal returns using publicly available information is extremely difficult.

However, subsequent research has identified various market anomalies, behavioral effects, and nonlinear relationships that have motivated the development of machine-learning approaches to financial prediction.

The relevance of EMH to AI-based forecasting is not necessarily that AI can perfectly predict prices. Rather, AI can potentially identify short-lived relationships, sentiment effects, nonlinear patterns, and information-processing advantages that conventional models may not capture.

**Machine Learning and Stock Prediction**

Early financial forecasting models were predominantly statistical. ARIMA and related approaches remain useful benchmarks because of their interpretability and established statistical foundations.

Deep-learning methods subsequently introduced nonlinear prediction capabilities. LSTM networks are particularly relevant because they can model sequential dependencies and retain information across time. Research has demonstrated the usefulness of LSTM architectures for financial time-series prediction, although their performance varies significantly according to market, period, features, and experimental methodology.

A major limitation of price-only models is that financial markets are influenced by information that cannot be represented adequately by OHLCV variables alone.

**Financial Sentiment Analysis**

Financial sentiment analysis attempts to quantify the emotional or informational tone of textual content such as news articles, corporate announcements, analyst reports, and social-media posts.

FinBERT, a BERT-based model adapted for financial language, represents an important development in this area. Domain-specific language models can distinguish financial terminology and contextual meanings more effectively than generic sentiment classifiers.

For example, words such as *liability*, *debt*, *loss*, *downgrade*, and *guidance* have highly specific financial implications. Consequently, incorporating financial sentiment into stock-prediction systems may provide information beyond historical prices.

**Generative AI in Financial Services**

Generative AI extends conventional predictive AI by generating new content, explanations, summaries, scenarios, and decision-support outputs. Large Language Models can process earnings-call transcripts, summarize corporate announcements, compare companies, and generate natural-language investment research.

The use of GenAI in finance nevertheless introduces new risks. A language model may generate plausible but factually incorrect statements, commonly described as hallucinations. In financial applications, such errors can potentially lead to inappropriate investment decisions.

Therefore, GenAI-based financial systems should ideally incorporate retrieval-augmented generation (RAG), source verification, numerical validation, human oversight, and explicit risk controls.

**Research Gap**

Existing studies frequently investigate individual components such as LSTM forecasting or financial sentiment classification. However, comparatively less attention has been given to an integrated framework combining:

- market time-series forecasting;
- financial-news sentiment;
- generative scenario creation;
- LLM-based information synthesis;
- retrieval-augmented investment explanations; and
- business-process transformation.

This study addresses this gap by proposing GenAI-StockPredict as a unified architecture for the Indian market.

## 2.MATERIAL AND METHODS

### Research Design

The study follows a quantitative, experimental, and framework-development approach. The proposed system integrates numerical market information with textual financial information.

### Data Sources

The proposed study uses three principal categories of data.

#### A. Market Data

Daily Nifty 50 data covering the period **January 2020 to December 2025** are considered for the experimental framework. The dataset may contain:

- Opening price
- Closing price
- High price
- Low price
- Trading volume
- Daily returns
- Moving averages
- Volatility indicators

Technical indicators can additionally include Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and rolling volatility.

#### B. Financial News and Social-Media Data

Financial news headlines and articles can be collected from relevant financial-information sources. The proposed dataset includes textual observations, subject to verification and licensing availability.

Each textual observation can be associated with:

- publication date;
- company/index reference;
- headline;
- article text where legally available;
- sentiment score; and
- relevant financial event.

Social-media sentiment may also be incorporated where data-access, platform terms, and research permissions permit.

#### C. Corporate and Fundamental Information

Corporate information can include:

- quarterly financial results;
- earnings-call transcripts;
- management commentary;
- corporate announcements;

- major regulatory disclosures; and
- relevant macroeconomic information.

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## 3.RESULT AND DISCUSSION

The supplied experimental results are summarized below.

| Model | Directional Accuracy | RMSE |
|---|---|---|
| ARIMA | 68.2% | 145.3 |
| LSTM | 74.5% | 112.7 |
| LSTM + FinBERT | 82.1% | 89.4 |
| **GenAI-StockPredict** | **87.3%** | **67.2** |

According to these reported results, the proposed hybrid framework performs better than the individual benchmark models.

The improvement from ARIMA to LSTM indicates the potential benefit of nonlinear sequence modelling. The further improvement obtained by combining LSTM with FinBERT suggests that textual information may provide additional predictive signals beyond historical price information.

The proposed GenAI-StockPredict model demonstrates the highest reported accuracy. This may be attributed to the combination of:

- temporal market patterns;
- financial sentiment;
- contextual information;
- synthetic stress scenarios; and
- LLM-based information integration.

However, accuracy alone should not be interpreted as evidence of profitable investment performance. A rigorous financial evaluation should additionally consider transaction costs, slippage, turnover, drawdown, Sharpe ratio, maximum loss, and out-of-sample performance.

### Business Transformation Through GenAI

The importance of GenAI extends beyond prediction accuracy. Its larger contribution may be its ability to transform financial-business processes.

### Brokerage and Equity Research

Traditional equity research requires analysts to examine large quantities of financial information.

GenAI can automate preliminary tasks such as:

- earnings-call summarization;
- financial-news aggregation;
- company comparison;
- sentiment monitoring;
- report drafting;
- event detection; and
- generation of research summaries.

The analyst can therefore focus more heavily on validation, interpretation, and strategic judgement.

The supplied case results report a reduction in research preparation time from approximately six hours to 45 minutes. This figure should be independently validated through a controlled human-versus-AI workflow study before publication as a definitive empirical finding.

### Portfolio Management

GenAI can assist portfolio managers by combining quantitative and qualitative information.
Potential applications include:

- portfolio monitoring;
- risk alerts;
- sector exposure analysis;
- scenario analysis;
- earnings-event monitoring; and
- rebalancing suggestions.

AI-generated suggestions should remain decision-support tools rather than autonomous investment decisions.

**Retail Investors**

One of the most significant applications is financial-information democratization.
Instead of requiring investors to interpret lengthy financial reports, an AI system can translate complex information into accessible explanations.
For example:
"Explain why this company's share price declined today."
The system can combine:

- price movement;
- corporate announcements;
- news;
- sector performance;
- market sentiment; and
- relevant historical information.

Regional-language interfaces could further increase accessibility for Indian investors.

**Case Illustration: Adani-Hindenburg Event**

The Adani-Hindenburg episode in January 2023 provides an important example of the potential role of sentiment analytics in event-driven markets.
A financial sentiment system could monitor rapidly changing news sentiment and identify unusually negative textual signals.
A conceptual workflow would be:
**News Event → Sentiment Change → Volatility Alert → Risk Analysis → Human Review**
The supplied draft reports that FinBERT identified negative sentiment approximately 18 hours before a subsequent major price decline. This is potentially interesting, but it requires a properly timestamped event study to establish whether the signal genuinely preceded the price movement, whether the information was already publicly available, and whether the signal remained significant after controlling for market and company-specific factors.
Therefore, this finding should be treated as a **case-study hypothesis requiring validation**, rather than a confirmed causal result.

**Ethical and Regulatory Considerations**

The deployment of GenAI in financial markets creates several important ethical challenges.

**Hallucination**

LLMs can generate convincing but incorrect information. In financial applications, fabricated earnings figures, incorrect corporate events, or unsupported investment recommendations could cause substantial losses.
Consequently, financial GenAI systems should use:

- verified data sources;
- RAG;

- citation mechanisms;
- numerical validation;
- confidence scores; and
- human review.

**Investor Protection**

An AI system that provides personalized investment recommendations may fall within financial-advisory and regulatory requirements depending on its functionality and deployment model.

AI deployment should therefore be aligned with applicable **SEBI regulations and investor-protection requirements**.

**Market Manipulation**

Generative systems could potentially be misused to produce large volumes of misleading financial content.

For example, malicious actors could generate artificial positive or negative narratives around a security.

Therefore, market-integrity safeguards are necessary.

**Data Privacy**

Financial applications may process sensitive investor information.

Systems should implement:

- data minimization;
- access controls;
- encryption;
- appropriate retention policies; and
- privacy-preserving practices.

**Explainability**

Investors should not receive a prediction without understanding its major supporting factors.

The proposed framework should therefore provide an explanation such as:

**Prediction: Negative**

**Major factors:**

- negative earnings sentiment;
- increased volatility;
- weakening technical trend;
- adverse sector news.

This improves transparency and supports informed human judgement.

**Limitations**

The proposed study has several limitations.

1. Stock markets are inherently noisy and affected by unexpected events. No AI model can guarantee accurate prediction.

2.The quality of sentiment analysis depends on the quality, timing, and representativeness of textual data.

3. Social-media sentiment may contain bots, coordinated campaigns, duplicate information, and manipulation.

4.Synthetic data generated through GANs may not accurately reproduce extreme real-world market events.

5. LLM outputs may contain hallucinations despite the use of RAG and verification mechanisms.

6.Model performance measured on historical data may not translate into future profitability because of changing market regimes, transaction costs, liquidity constraints, and competition among market participants.

## 4.CONCLUSION

Generative Artificial Intelligence has the potential to fundamentally transform financial commerce by integrating quantitative forecasting with qualitative information processing. Conventional models primarily analyze historical numerical data, whereas

GenAI enables financial systems to interpret news, corporate disclosures, sentiment, and complex textual information alongside market data.

This paper proposed **GenAI-StockPredict**, a three-layer hybrid architecture combining market-data processing, financial sentiment analysis, Transformer-based forecasting, synthetic scenario generation, and LLM-based retrieval-augmented reasoning.

The reported experimental results indicate that the proposed framework can outperform conventional ARIMA, LSTM, and LSTM-FinBERT benchmarks in directional prediction. More importantly, the framework demonstrates potential applications beyond prediction, including automated equity research, portfolio monitoring, risk alerts, financial education, and personalized information delivery.

However, the adoption of GenAI in financial markets must be accompanied by strong safeguards. Prediction accuracy does not automatically imply investment profitability, and AI-generated recommendations should not substitute for appropriate professional judgement, regulatory compliance, or investor responsibility.

The future of financial commerce is therefore unlikely to be purely human or purely artificial. Instead, it is likely to involve **human-AI collaboration**, in which artificial intelligence performs large-scale information processing and scenario analysis while human professionals provide judgement, accountability, and strategic interpretation.

GenAI-StockPredict represents a conceptual step toward this **intelligent-business model**, where financial services become increasingly predictive, personalized, automated, explainable, and inclusive.

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