Impact of AI-Derived News Sentiment on Intraday Stock Price Volatility in Indian Equity Markets

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Introduction:

Financial markets continuously react to information, with volatility reflecting how quickly investors process new developments. While traditional studies highlight the impact of scheduled macroeconomic announcements on price dynamics (Fleming & Remolona, 1999; Andersen et al., 2007), emerging markets like India exhibit unique features—such as retail investor dominance and liquidity fragmentation—that influence intraday reactions. Recent evidence (Banerjee & Pradhan, 2021) shows rapid volatility responses to macroeconomic news, yet unstructured textual information from online news, analyst reports, and social media remains largely unexplored at high frequency. Advances in AI, particularly transformer-based models like FinBERT, enable extraction of nuanced sentiment signals, outperforming traditional lexicon-based approaches. While developed-market studies demonstrate the predictive power of AI-driven sentiment, Indian equity markets lack such research. This study addresses this gap by integrating AI-based news sentiment with intraday volatility modeling, aiming to enhance forecasting accuracy, understand market efficiency, and provide actionable insights for investors and regulators.

Literature Review and Research Gap

News, Information, and Market Volatility

Financial markets react continuously to information arrivals, and volatility reflects how rapidly investors process that information. Classical asset-pricing and market-microstructure theories (Fleming & Remolona, 1999; Andersen et al., 2007) establish that macroeconomic news and unexpected information—often termed *news surprises*—induce immediate jumps in prices and volatility. In emerging markets, however, evidence regarding the speed and efficiency of information assimilation remains mixed.

Banerjee and Pradhan (2021) made a significant contribution by analysing 1-minute intraday data for the Indian 10-year benchmark government bond and demonstrating that both returns and conditional volatility respond swiftly to macroeconomic announcements. Their findings challenge the perception that Indian markets are informationally inefficient: volatility spikes occur within minutes of news releases, persist for about an hour, and exhibit asymmetric reactions, where negative news generates stronger volatility responses than positive news. The authors employed a two-stage weighted least-squares framework inspired by Andersen & Bollerslev (1998), revealing that Indian financial assets are highly sensitive to information shocks even at high frequency. This work provides a methodological and empirical foundation for extending intraday-volatility studies beyond macroeconomic indicators.

Sentiment and Financial Markets

While macroeconomic announcements are scheduled and quantifiable, much of the information influencing asset prices today arises from unstructured textual sources such as online news, analyst commentary, and social-media posts.Research in behavioural finance (Tetlock 2007; Baker & Wurgler 2007) shows that investor sentiment embedded in text can predict market fluctuations, risk premiums, and trading activity. Chari (2023) examined aggregate news sentiment and Indian stock-market returns using GARCH models, establishing that sentiment indices derived from traditional lexicon methods affect daily returns and volatility. However, these studies employ daily data and rule-based sentiment measures, overlooking intraday reactions and modern AI-based text processing.

Industry evidence further confirms the importance of real-time sentiment. RavenPack (2020) documented intraday news-sentiment patterns across Asia–Pacific markets, demonstrating that news tone computed at the minute level affects short-term price movements and liquidity conditions. Although commercial datasets illustrate practical potential, they rarely undergo rigorous academic validation in the Indian context. Therefore, there exists a clear methodological and geographic gap.

Advances in Artificial-Intelligence-Based Sentiment Analysis

Recent progress in Natural-Language Processing (NLP) enables the extraction of nuanced sentiment signals using deep learning. Transformer architectures such as BERT and its financial variant FinBERT (Araci 2019; Yang et al., 2020) outperform classical bag-of-words or lexicon models by capturing contextual meaning within financial narratives. Studies such as Ruan et al. (2025) and Liu et al. (2024) apply FinBERT-based sentiment scores to forecast stock returns and volatility in U.S. and Chinese markets, reporting substantial accuracy gains. Nevertheless, these works rely on daily or event-level horizons and focus on developed economies. There is virtually no published research employing transformer-based, AI-derived sentiment to analyse intraday volatility in the Indian equity market.

Intraday Volatility Modelling

High-frequency econometrics provides a rich set of tools for capturing rapid price adjustments. The *realized-variance* and *realized-GARCH* frameworks (Hansen et al., 2012; Andersen & Bollerslev 1998) model volatility using intraday returns and allow integration of external variables such as news flow. Fernandes (2025) shows that incorporating news indicators enhances realized-volatility forecasts, while Cantamessa (2016) demonstrates improved predictive power when news variables are included in GARCH models. Banerjee and Pradhan (2021) adopted a similar two-stage regression design to isolate the impact of news surprises on volatility in India, confirming that one-minute data capture essential dynamics that coarser intervals miss.

Research Gap

Despite these advances, three major gaps persist in the literature:

1. Temporal gap – Existing Indian studies, including Chari (2023), operate at daily frequency.
   No study has yet linked continuous, minute-by-minute news sentiment to intraday stock-price volatility.
2. Methodological gap – Prior Indian research relies on econometric GARCH or event-study models using predefined sentiment dictionaries or macro-news indicators. None have utilised AI-based transformer models (FinBERT or equivalent) to generate firm-specific and market-level sentiment scores in real time.
3. Contextual gap – While Banerjee & Pradhan (2021) confirmed rapid informational efficiency in the bond market, the equity market's intraday reaction to AI derived textual sentiment remains unexplored. Furthermore, emerging markets may exhibit different microstructural characteristics—such as liquidity fragmentation and retail dominance—that amplify or dampen sentiment effects.

The Present Study's Contribution

The proposed research bridges these gaps by integrating AI-driven sentiment analysis with high-frequency volatility modelling in the Indian equity context. Using transformer-based models (e.g., FinBERT fine-tuned on Indian financial news), the study will quantify positive and negative tone from real-time news streams and link these to realized volatility computed from 1- to 5-minute intraday stock returns on NSE-listed firms. By comparing the predictive performance of AI-based sentiment with rule-based and commercial measures (RavenPack, GDELT), the study will evaluate whether advanced NLP captures informational content more effectively. This approach extends Banerjee and Pradhan's (2021) intraday framework from structured macroeconomic signals to unstructured AI-interpreted textual information, contributing both to financial econometrics and computational-finance applications in emerging markets.

Importance of the Study

1. **Bridging a critical gap in Indian financial research.**
   While intraday volatility and macroeconomic news responses have been studied in India (e.g., Banerjee & Pradhan, 2021), no research has linked AI-derived, real-time news sentiment to intraday stock-price movements. Understanding this linkage is crucial for investors, policymakers, and algorithmic traders in a rapidly digitizing market.
2. **Leveraging advanced AI methods for financial insights**.
   Traditional sentiment analysis relies on lexicons or rule-based models, which often fail to capture nuanced, context-dependent meanings in financial text. By

applying transformer-based models (e.g., FinBERT), this study provides a more precise and real-time measurement of market sentiment.

3. **Improving volatility forecasting and market efficiency understanding**
   High-frequency volatility models (realized GARCH, intraday returns) can benefit from incorporating AI-derived sentiment. This allows more accurate forecasts of intraday risk, enhancing portfolio management, hedging, and trading strategies.
4. **Contributing to emerging-market finance literature**
   Most AI-based intraday sentiment studies are focused on developed markets (U.S., China). Studying Indian equities provides insights into emerging-market characteristics, including liquidity fragmentation, retail investor dominance, and asymmetric news reactions.

Main Research Question

How does AI-derived, real-time news sentiment influence intraday stock-price volatility in Indian equity markets?

Sub-questions:

1. Do transformer-based sentiment models (FinBERT) provide superior predictive power for intraday volatility compared to rule-based or commercial sentiment measures?
2. Are the effects of positive and negative news asymmetric on intraday volatility in Indian stocks?
3. How do firm-specific and market-level sentiment measures interact with high-frequency volatility?

Research Objectives

1. Quantify real-time news sentiment using AI-based transformer models
   - Fine-tune FinBERT on Indian financial news to generate minute-level sentiment scores for NSE-listed firms.
2. Link AI-derived sentiment to intraday stock volatility
   - Employ realized-variance and realized-GARCH models using 1- to 5-minute intraday returns to capture volatility dynamics.
3. Evaluate predictive performance and practical implications
   - Compare AI-based sentiment with traditional rule-based and commercial datasets (e.g., RavenPack, GDELT).
   - Examine asymmetry in volatility response to positive vs. negative sentiment.

Expected Outcomes

1. Enhanced understanding of market reaction to unstructured information
   - Establish whether AI-derived sentiment captures information faster and more accurately than existing measures.
2. Evidence of asymmetry in volatility responses
   - Identify whether negative news triggers stronger intraday volatility than positive news, consistent with behavioral finance predictions.
3. Improved forecasting models
   - Demonstrate that incorporating AI-based sentiment into high-frequency volatility models improves prediction accuracy and market risk assessment.
4. Policy and practical implications
   - Provide insights for regulators on market efficiency, for traders on intraday strategies, and for financial institutions on algorithmic trading using sentiment signals.

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