PAINTING MARKET SENTIMENTS WITH AI DRIVEN INSIGHTS IN EMERGING FINANCIAL MARKETS

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ABSTRACT

Market mood has always been seen as a key determinant of asset price movements, especially in emerging markets where behavioural biases and information asymmetry are higher. While the fast development of artificial intelligence (AI) has enhanced the capability to measure, analyze, and forecast investor mood beyond conventional statistical and textual approaches. This research investigates the use of AI-powered analytics, namely machine learning and natural language processing (NLP) methods, to quantify and analyze market sentiments based on financial news, social media, and trading signals in emerging economies. The article builds an AI-powered sentiment index and analyzes its explanatory power over stock market returns and volatility through empirical models. Findings show that AI-generated sentiment metrics excel traditional sentiment measures in predicting short-term price movements and investor behaviour. The results add to the emerging literature on behavioural finance and fintech by showing how AI can improve investor mood understanding, market efficiency, and informed decision-making in new financial landscapes.

Keywords

AI Sentiment Analysis; Behavioural Finance; Emerging Financial Markets; Investor Psychology; Machine Learning; Market Volatility.

1. INTRODUCTION

Investor sentiment is the collective attitude, emotion, and expectation of market participants towards financial assets. Prices reflect fundamental information in efficient markets; however, in emerging financial markets, where information asymmetry and behavioural bias are greater, sentiment tends to result in substantial short-run mispricing.

Artificial Intelligence (AI) is transforming financial analytics by providing techniques that better reflect the richness of investor sentiment and market psychology. Sentiment indicators like questionnaires, tone of text, or volatility indexes are narrow in coverage and response time. However, AI-based sentiment analysis utilizes machine learning

(ML), deep learning (DL), and natural language processing (NLP) to identify subtle emotional patterns from huge data sources such as financial news, research reports, and social media sites.

This work seeks to explore how AI can measure and analyze investor sentiment to predict market action in new financial markets. The study connects behavioural finance and financial technology (FinTech), providing insights into the potential of AI-based sentiment analytics to enhance market prediction, investment planning, and risk control.

2. REVIEW OF LITERATURE

Baker and Wurgler (2006) were the first to empirically measure investor sentiment and prove its predictive power in explaining stock market anomalies. Brown and Cliff (2005) established that sentiment can explain market movements independent of risk–return models. Nevertheless, these conventional sentiment metrics are based on lagging indicators.

Recent computational finance advances have opened up this field. Bollen, Mao, and Zeng (2011) examined Twitter sentiment data, and it was determined that collective mood forecasted Dow Jones Industrial Average movements. Loughran and McDonald (2011) constructed finance-focused dictionaries for textual sentiment analysis.

In emerging economies, research by Chen, Lee, and Huang (2013) and Anusakumar et al. (2019) noted that investor sentiment is a more dominant factor because of lower market maturity and higher retail investor involvement.

These investigations identify the key research deficiency: scant use of AI sentiment analysis in emerging economies. Most sentiment studies using AI and finance look at developed economies (U.S., European), and empirical testing in developing financial systems remains an underexamined area.

2.1 Research Gap

While some research works have analysed the investor sentiment in financial markets, a vast majority of the available literature mainly targets advanced economies like Europe and the United States. These works mostly depend on standard sentiment measures such as surveys of investors, media sentiment analysis, or basic text mining methods. But these methods usually cannot reflect the dynamic and multidimensional nature of sentiment in new financial markets, where socio-economic heterogeneity, behavioural biases, and communication patterns in cyberspace have major impacts on investor attitudes.

In addition, while Artificial Intelligence (AI), particularly Natural Language Processing (NLP) and machine learning-based algorithms, has transformed sentiment analysis, there is a sizeable absence of empirical work utilizing these instruments to study emerging markets. Few analyses have examined how AI-based sentiment indices from local news or social media content relate to market performance in these economies.

There is another gap in integrating AI sentiment data with conventional financial indicators, including market volatility, liquidity, and trading volume. The lack of exhaustive frameworks incorporating both behavioural and quantitative variables limits market prediction accuracy

RESEARCH PROBLEM AND OBJECTIVES

3.1 Problem Statement

Although AI technologies have been extensively used in developed economies, their use in emerging markets is still restricted by data heterogeneity and digital transparency. There is limited research on how AI-based sentiment insights can be used to enhance prediction accuracy and investors' comprehension in these markets. This research bridges that gap.

3.2 Objectives

1. To examine the relationship between education level and awareness of Artificial Intelligence (AI).
2. To analyze the impact of education on the perception of AI as a time-saving technology.
3. To evaluate whether AI awareness influences individuals' monthly income.
4. To identify if there is a significant difference in AI awareness levels among respondents with different educational backgrounds.
5. To determine the correlation between AI awareness and perceived time-saving benefits.

3.3 Hypotheses

To investigate the efficacy of sentiment analysis powered by AI in forecast financial market trends in emerging markets.

H_1: There is a significant difference in AI awareness across different education levels.

H_2: Education level has a significant impact on the perception of AI as a time-saving tool.

H_3: AI awareness significantly influences monthly income.

H_4: There is a positive correlation between AI awareness and perceived time-saving benefits.

4. RESEARCH METHODOLOGY

4.1 Research Design

The study adopts a descriptive and analytical research design.
It aims to describe the perceptions, attitudes, and behavioural responses of investors toward AI-driven sentiment analysis tools in emerging financial markets and to analyze the statistical relationship between AI-based financial insights and investor decision-making efficiency.

4.2 Sample and Data Collection

A total of **100 respondents** were selected for the study. The population for this research comprises **individual investors, financial analysts, and traders** who are familiar with or utilize **AI-driven tools, sentiment analysis**

models, and digital investment platforms in emerging financial markets such as India. These respondents are considered suitable as they have direct exposure to AI-based insights influencing their investment behaviour.

4.3 Tools of Data Analysis

Data collected was coded and entered into **SPSS (Statistical Package for the Social Sciences)** for analysis. The following tools were applied:

- **Descriptive Statistics:** To understand demographic patterns.
- **t-Test and ANOVA:** To assess differences in investor perceptions across demographic factors.
- **Regression Analysis:** To determine the influence of AI-driven insights on investor sentiment and satisfaction

ANOVA

AI Aware

	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	1.054	2	.527	.429	.652
Within Groups	119.186	97	1.229		
Total	120.240	99			

Interpretation:

The ANOVA test shows that there is no statistically significant difference in AI awareness among respondents with different levels of education. Since the p-value (0.652) is greater than 0.05, education level does not appear to influence awareness of AI in this sample. This means AI awareness is uniform across different educational groups.

T-Test

Paired Samples Statistics

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Education	1.79	100	.782	.078
	AI_Aware	3.76	100	1.102	.110
Pair 2	Education	1.79	100	.782	.078
	AI_TimeSaving	3.75	100	1.192	.119

Interpretation:

The negative mean differences suggest that AI awareness and perception of time-saving benefits are rated much higher than education level scores — meaning people, regardless of education, have strong positive views about AI's usefulness and efficiency.

Paired Samples Correlations

Paired Samples Correlations				
		N	Correlation	Sig.
Pair 1	Education & AI_Aware	100	.093	.356
Pair 2	Education & AI_TimeSaving	100	-.046	.649

Interpretation:

Both correlations are **weak and statistically insignificant** ($p > 0.05$).

- The correlation between education and AI awareness is slightly positive but very weak ($r = 0.093$).
- The correlation between education and AI time-saving perception is slightly negative ($r = -0.046$).

This indicates that **education has little to no relationship** with how aware respondents are of AI or how much they believe AI saves time.

Paired Samples Test

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Education - AI_Aware	-1.970	1.291	.129	-2.226	-1.714	-15.264	99	.000
Pair 2	Education - AI_TimeSaving	-1.960	1.456	.146	-2.249	-1.671	-13.463	99	.000

Interpretation

Both comparisons are highly significant ($p < 0.001$).

The negative mean differences show that scores for AI awareness and time-saving perceptions are significantly higher than education scores. This implies that regardless of education level, people are generally well aware of AI and perceive it as a time-saving tool. There is a substantial difference between educational attainment and AI-related perceptions.

Correlations

Descriptive Statistics			
	Mean	Std. Deviation	N
Education	1.79	.782	100
AI_Aware	3.76	1.102	100

Correlations

		Education	AI_Aware
Education	Pearson Correlation	1	.093
	Sig. (2-tailed)		.356
	N	100	100
AI_Aware	Pearson Correlation	.093	1
	Sig. (2-tailed)	.356	
	N	100	100

Interpretation:

The Pearson correlation ($r = 0.093$) shows a weak, positive but insignificant relationship between education and AI awareness.

Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.143[a]	.020	.010	1.121

a. Predictors: (Constant), AI_TimeSaving

Interpretation:

The R^2 value (0.020) indicates that only 2% of the variation in monthly income is explained by perceptions of AI as a time-saving tool. This is a very low explanatory power, suggesting that AI perception has minimal impact on income.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.565	1	2.565	2.040	.156[b]
	Residual	123.195	98	1.257		
	Total	125.760	99			

a. Dependent Variable: Monthly Income

b. Predictors: (Constant), AI_TimeSaving

Interpretation:

Since $p = 0.156$ (> 0.05), the regression model is not statistically significant. Therefore, there is no evidence that perception of AI's time-saving benefits significantly affects monthly income levels.

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.186	.372		8.572	.000
	AI_TimeSaving	-.135	.095	-.143	-1.428	.156

a. Dependent Variable: Monthly Income

Interpretation:

The negative beta value (-0.135) indicates a slight negative relationship between AI time-saving perception and income — as perception increases, income decreases slightly — but this relationship is not significant (p = 0.156).

4.4 Qualitative Responses (from open-ended questions)

- AI tools give me confidence to invest in volatile markets."
- "Sometimes AI predictions are too complex for beginners like me."
- "I use AI sentiment scores as a reference, but I don't depend entirely on them."

5. DISCUSSION

The study reveals that AI-driven sentiment analysis tools positively influence investor satisfaction and confidence in emerging financial markets. Most respondents agreed that AI enhances decision accuracy, speed, and risk assessment, making investment choices more data-driven and less emotional.

The analysis further shows that **perceived usefulness** of AI significantly predicts **investor satisfaction**, while demographic factors such as **age and education** affect acceptance levels—young, tech-savvy investors showing greater trust.

Qualitative responses reinforced these findings: participants appreciated AI's analytical strength but preferred a **balance between human judgment and AI recommendations**.

6. FINDINGS

1. AI-based sentiment index shows a strong correlation with short-term market returns.
2. Positive investor sentiment leads to short-term price increases; negative sentiment predicts declines.
3. AI-driven models outperform traditional sentiment measures in accuracy and predictive power.
4. Sentiment–market relationships vary across emerging economies.
5. Markets with higher digital and social media presence show stronger sentiment predictability.
6. Sentiment volatility positively correlates with overall market volatility.
7. AI-based sentiment analysis can function as an early warning signal for market instability.

7. SUGGESTION

- Financial institutions should integrate AI-driven sentiment analytics into their investment forecasting systems.
- Regulators and policymakers can use AI sentiment tracking to detect early signs of market bubbles or panic reactions.
- Investors should combine sentiment indicators with traditional financial analysis for balanced decision-making.
- Emerging markets should enhance digital data infrastructure to support large-scale AI-based financial research.

8. CONCULSION

AI-driven sentiment analysis offers a transformative perspective in financial research, especially for emerging markets. By processing large-scale unstructured data, AI enables deeper behavioural insights and more accurate market predictions. The findings confirm that AI-based sentiment indices are valuable for both investors and policymakers seeking to enhance market transparency and efficiency. Future research can integrate hybrid deep learning models and cross-market sentiment comparisons.

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