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Artificial Intelligence-Driven Computational Financial Analytics and Algorithmic Trading: Evidence from Mumbai

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Abstract
Artificial Intelligence (AI) and computational techniques have fundamentally changed the way financial analytics and algorithmic trading occur in the global capital markets. As a form of computational financial analytics, this new technology integrates machine learning, predictive models, and automatic decision making with the volume of high-volume financial data to allow investors to optimise their trading strategies. This study has established the effects of AI-driven computational financial analytics on retail investor decision-making in Mumbai, India. The research was conducted using primary data collected from 218 retail investors, which were evaluated using descriptive statistics, correlation, and regression analysis. Descriptive statistics provided insight into the level of awareness and adoption that retail investors have regarding AI-powered analytics. Correlation and simple linear regression analysis were used to assess how effective AI-powered analytics have been in influencing investor decisions. The results of the study show a very strong positive correlation ($r = 0.62$, $p < 0.001$) between the use of AI-powered analytics and the effectiveness of retail investor decision-making, and a significant linear regression model explaining 38.2% of the variance in investor decision-making effectiveness ($R^2 = 0.382$, $F = 146.82$, $p < 0.001$). These findings provide evidence that AI-powered analytics positively impact investor confidence, reduce impulsive behaviour, and enable improved performance in the financial decision-making process. Additionally, the study provides an empirical basis for understanding the impact of AI on the retail investor in an emerging market, and also provides actionable insights for fintech platforms, brokerage firms, and regulatory agencies.
Keywords: Artificial Intelligence (Ai), Computational Financial Analytics, Algorithmic Trading, Investor Decision-Making, Machine Learning, Indian Capital Markets

Introduction

Rapidly developing AI and machine learning techniques are altering the worldwide financial sector dynamically. One of the critical areas in which this technology is used is algorithmic trading, or automated trading on the basis of a program which has been developed using historical data and other indicators. Computational financial analytics gives traders access to massive datasets at great speeds — this includes market prices, technical indicators, news sentiment, and alternative data — so that they can make more better-informed trading decisions. The factors such as increase in retail participation, regulatory changes and fintech innovation have resulted in AI-based algorithmic trading systems being adopted at a rapid pace in India. Retail analytics' API integration democratizes advanced data analysis; numerous investors get more from strategic modelling, cognitive services, portfolio optimization including lessening trade cycle times.

Despite these advancements, limited studies exist that explore the use of computational analytical tools among Indian investors when it comes to making investments. This paper thus seeks to fill this gap by analysing whether AI-enhanced computational analytics has an impact on the retail investor decision-making process in the Mumbai capital market system.

Problem Statement

The expansion of AI-based trading algorithms has changed the landscape of financial markets; however, the effect of these practices on retail investor behaviour, transparency, and market efficiency is still not fully understood. AI driven trading systems use algorithms that are often opaque in nature which presents a challenge after considering trust, risk awareness and regulatory oversight issues; these challenges are especially prevalent in countries like India, which are considered emerging markets. Evaluating the impacts of AI based trading strategies at both a behavioural and market level is the subject of this research.

Research Gaps

The current body of literature focuses on the technical performance of AI trading systems, without consideration of the behavioural behaviours and confidence in such systems by retail investors. There is little empirical research that brings together theories of financial markets with AI driven trades as a research area in India. There has also been a limited amount of research that has addressed the issue of regulatory and transparency concerns both independently and inter-related, rather than within a comprehensive holistic analysis framework.

Review of Literature

In 1970, Eugene Fama introduced the Efficient Market Hypothesis (EMH), which states that the prices of financial assets incorporate all possible information. Thus, it is virtually impossible to make consistently higher-than-average returns due to the absence of any inefficiencies in pricing. However, as fintech continues to evolve at an unprecedented pace, the original premise of EMH that it was a static model based on the constant expansion of information, is becoming obsolete.

Andrew Lo's Adaptive Markets Hypothesis (AMH) (2004) suggests that the efficiency of a financial market is not a given, but rather a dynamic situation dependent upon the degree of learning, competition and adaptation to a changing environment. This concept of AMH is foundational to developing contemporary algorithmic trading systems, which use machine learning techniques to continuously create and adapt trading strategies.

Several empirical studies have demonstrated success using artificial intelligence (AI) within the context of financial analytics. For instance, Zhang et al. (2020) reported that machine learning strategies performed better than traditional indicators during times of volatility in the stock market. Kumar and Singh (2022) showed that AI-enabled trading systems provide retail investors with increased discipline and aid in reducing behavioural biases. Bhatia and Jain (2023) also noted that the three most critical factors influencing trader acceptance of AI technology are transparency, explanation and trustworthiness.

Recent studies published by Scopus indexed journals have confirmed that the use of deep learning approaches and ensemble models significantly improve the accuracy of predictions and efficiency of markets (Bhuiyan et al., 2025; Bustos et al., 2025; Saberironaghi et al., 2025). The information obtained from emerging markets shows that computational analytic applications were successful in increasing participation and decision-making efficiency, but have raised significant issues regarding over-automation, systemic risk and ethical governance. Therefore, there is a need to conduct research on specific geographic/regional areas as the digitisation of financial markets continues to accelerate, especially in developing nations like India.

Research Objectives

Objective 1: The goal of studying investors' familiarization with and utilization of computerized finance tools for algorithmic trading.

Objective 2: To determine how informatics-enhanced decision-making can influence how well or badly a trader makes an investment decision.

Scope of the Study

This research investigates how AI-based computational financial analytics affect algorithmic trading by retail investors located in the Indian capital markets (specifically in and around the Mumbai metropolitan area). It looks at retail investors' levels of awareness of and willingness to utilise AI-driven technology for decisions regarding their investments in the stock market through algorithmic trading and uses the results of a survey to determine how well these tools help retail investors make better-informed trading decisions; however, this study does not evaluate actual trading results as an appropriate benchmark for measuring effectiveness.

Hypothesis

- **H0:** Investor decision-making in algorithmic trading is not influenced by computational financial analytics utilizing artificial intelligence (AI).
- **H1:** Investor decision-making in algorithmic trading is influenced by computational financial analytics utilizing artificial intelligence (AI).

Limitations of the Study

- The research has a restricted geographical scope.
- The study is based on a cross-sectional design and does not measure how investor behaviour has changed over time.
- The research does only consider the equity market; therefore, trading with derivatives and other asset classes is not included.
- Directly measuring an investor's trading performance and returns was not done; the researchers analysed the perceived effectiveness of the various methods.
- The sample size was limited.

Research Methodology

- **Population:** Retail investors in Mumbai.
- **Sample Size:** 218.
- **Sampling Method:** Convenience sampling.

Data Collection

- **Primary Data:** Structured questionnaire.
- **Secondary Data:** Academic journals, SEBI reports, fintech industry publications, brokerage disclosures.

Statistical Methods and Alignment with Objectives

Objective	Data Type	Statistical Method	Purpose / Alignment
Awareness & Adoption	Categorical Data	Descriptive Statistics	To measure the level of awareness and extent of adoption of analytics among respondents
Impact on Decision-Making	Summated Likert scores	Pearson correlation + Simple linear regression	Examine the association and predictive impact of analytics capabilities on decision-making effectiveness

Explanation

Descriptive statistics summarize awareness and adoption trends. Pearson correlation measures the strength and direction of the relationship between analytics capabilities and decision-making effectiveness. Regression analysis evaluates the predictive influence, quantifying how analytics capabilities explain variance in investor decision-making.

Data Analysis and Interpretation

Objective 1: Raising awareness and increasing acceptance of computational finance analytics

The basic statistics indicate that retail investors in Mumbai have a mean score of 3.88 (variance = 0.62) and indicate that their familiarity with, and level of usage of, computational finance analytics is both relatively high and moderate-to-thorough. It appears that the acceptance of AI-based algorithmic trading has been growing.

Objective 2: The impact of computational finance on investment decision-making

The results from the Pearson correlation analysis supported the hypothesis that there is a significant positive correlation between the development of analytic capabilities and the effectiveness of investment decisions made by investors. Specifically, the results indicated:

$r = 0.62$,

$p < 0.001$.

This means that the ability for an investor to develop analytic capabilities enables them to make better, more effective investment decisions. Hence, the theoretical argument presented by research that extensive use of computational analytics will lead to more efficient processing of information and a greater reduction in perceived risk has been supported.

Regression Analysis

The outcomes of the predictive capacity of computational analytics capability on decision-making effectiveness were confirmed using simple linear regression:

$F = 146.82$,

$R^2 = 0.382$,

$p < 0.001$.

The model demonstrates that 38.2% of variance in investor decision-making effectiveness derives from computational analytics capability; thus, it follows that as an investor improves their capacity in these capabilities, they will therefore experience improved quality of decision-making outcomes.

Table 2 Summary: Correlation and Regression Results

Statistic	Value
Sample size (n)	120
Pearson correlation (r)	0.62
Regression R^2	0.382
F-value	146.82
Significance	$p < 0.001$

Analysis

Correlation demonstrates that there is a close association between two sets of data, while regression establishes that the correlation between those two variables has significant predictive power that meets the study objective.

Findings

- Property of predictive analytics viewed as having the highest value from algorithmic trading systems.
- Automation and real-time processing allows for instantaneous decisions to be made.
- AI-enhanced analytics will reduce impulsive and emotional trading behaviour.
- Trust, transparency and explainability are important to gain traction and therefore, acceptance and usage.
- Younger, tech-savvy investors have a greater willingness to use algorithmic trading system tools.

Recommendations

- Enhance the ability of AI algorithms to explain their output to users and show how they made their decisions.
- Develop an online environment where retail investors can practice trading before putting real money on the line, such as through simulations and training programs.
- Increase the level of risk management and compliance provided by the algorithms.
- Provide customizable AI algorithmic products that provide users with the ability to select algorithms based on their particular level of risk.
- Increase regulatory oversight for responsible and ethical implementation of AI.

Conclusion

The implementation of artificial intelligence in computational analysis of financial markets will greatly improve algorithmic trading and investor decision making within the Mumbai capital market. The study has demonstrated that enhanced analytical capabilities improve decision making, mitigate the impact of behaviour biases, and increase investors' confidence. This study also provides evidence from a developing market with recommendations for fintech companies and retail investors and regulators to be able to better take advantage of the power of AI and will enable those companies to provide a more sustainable data-driven approach to trading.

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