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Role of Artificial Intelligence and Big Data in Fintech Trading

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ABSTRACT

Big data and artificial intelligence (AI) have transformed the way the financial technology (FinTech) trading industry operates today by enabling quicker, more accurate, and data-driven decision-making. The enormouss volume of financial data published in international markets necessitates the use of algorithms that use machine learning, deep learning, and natural language processing, among other techniques, to extract insights from the complicated dataset. High-frequency trading data, historical pricing data, economic data, and alternative data sources including news and sentiment analysis from social media are all processed and analyzed with the aid of big data-related technology. In the world of Fintech trading, AI-enabled methods are frequently used in automated trading systems, risk management systems, portfolio control systems, and forecasting systems. Fintech companies can decrease the amount of human intervention needed for trading and the impact of emotion on trading decisions by applying these technologies to automate trade executions, uncover hidden patterns in the market, forecast anticipated market trends, and execute trades in a matter of a few seconds. Furthermore, by using AI and big data tools to track transactions in real time for any deviations, Fintech companies can improve their crime detection skills and remain compliant with regulations. While connecting AI and Big Data with FinTech investing has many benefits, there are problems as well. These include regulatory restrictions on their use, security issues, interpretability issues, and possible biases resulting from their creation. However, the combination of AI and Big Data is making FinTech trading faster, safer, and more creative than ever before. As advances in technology occur, so will the range of applications for it, permanently changing the financial trading and finance atmosphere as we understand it.

Keywords: Artificial Intelligence (AI), Big Data Analytics, Algorithmic & High-Frequency Trading, Machine Learning and Deep Learning, Risk Management and Fraud Detection.

Introduction

The rapid evolution of financial technology (FinTech) has transformed traditional trading practices, with Artificial Intelligence (AI) and Big Data emerging as key driving forces behind this transformation. Modern financial markets generate massive volumes of structured and unstructured data at unprecedented speed, including market prices, transaction records, news feeds, and social media sentiment. Effectively processing and analyzing this data exceeds human capability, creating a critical role for advanced computational technologies.Artificial Intelligence enables automated decision-making, predictive analytics, and pattern recognition in trading activities. Machine learning algorithms, deep learning models, and natural language processing tools are increasingly used to forecast price movements, optimize trading strategies, manage risk, and detect fraudulent activities. At the same time, Big Data technologies provide the infrastructure required to collect, store, and

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process vast datasets in real time, allowing traders and financial institutions to gain actionable insights with greater accuracy and speed.

Increased market efficiency, a lower cost of transactions and the emergence of algorithmic and high-frequency trading systems are all results of FinTech trading's integration of AI and Big Data. But it also brings with it problems with algorithmic bias, market swings, data privacy, and regulatory supervision. Therefore, assessing the potential and hazards related to the digital transformation of the financial sector requires an understanding of the role of AI and Big Data in FinTech trading.

Literature Review

1. Overview of FinTech Trading and Technology Integration

FinTech trading refers to the application of digital technologies especially AI and Big Data Analytics to support or automate financial trading processes. These technologies enable the processing of massive, high-velocity, heterogeneous data to support market forecasting, trade execution, risk assessment, and decision support in real time. FinTech trading moves beyond traditional quantitative methods by harnessing complex models that uncover nonlinear patterns and latent market dynamics.

2. Big Data’s Role in Financial Trading

2.1 Data Characteristics and Infrastructure

Big Data in financial markets manifests through enormous volumes of price ticks, order book data, news feeds, social media sentiment, and alternative datasets (e.g., satellite, web traffic). These data streams characterized by high volume, velocity, and variety—require scalable storage (e.g., Hadoop, cloud platforms) and real-time processing technologies (e.g., Spark, Kafka). Big Data thus enables real-time analytics, essential for both high-frequency and algorithmic trading. 2.2 Big Data Analytics Contributions

Big Data analytics supports:

- Feature extraction and pattern recognition from multidimensional datasets.
- Sentiment analysis leveraging text from financial news and social platforms.
- Integration of structured and unstructured data in predictive models.

Studies highlight that Big Data not only improves forecasting accuracy but also enables detection of market anomalies, liquidity shifts, and evolving trading regimes beyond traditional indicators.

3. AI Techniques in Trading

3.1 Machine Learning and Deep Learning

A large body of literature shows that various ML and DL techniques are used for forecasting and strategy development:

- Supervised learning (e.g., regression, classification) for price movement prediction.
- Ensemble models and deep networks (e.g., LSTM, CNN) for capturing temporal and nonlinear market patterns.

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- Deep Reinforcement Learning (DRL) for strategy learning under complex market states. While DRL shows conceptual promise, many studies note that real-world profitability and robust performance remain challenging due to unrealistic experimental settings and lack of online trading tests.

3.2 Natural Language Processing (NLP)

NLP models extract sentiment and event signals from financial news, earnings statements, and forum/social data. These textual signals augment numerical time-series inputs, improving predictive models' responsiveness to emergent information flows.

3.3 Hybrid and Ensemble Approaches

Recent work demonstrates combining AI models (e.g., ML+DL hybrids, reinforcement learning with feature-engineered input) to balance predictive power with stability in volatile markets.

3. METHODOLOGY

The methodology of this study will assess the effectiveness in terms of operational and predictive aspects of AI together with Big Data within a FinTech trading environment. This research will adopt a quantitative approach through empirical data in studying how well the AI-driven predictive model performs against its bench-marked counterparts in finance. Initially, high-frequency information will be gathered from various sources: structured financial market logs such as OHLCV prices and order books and unstructured "alternative" data like social media sentiment and real-time news feeds. Such multi-source data collection is necessary in satisfying the four dimensions of Big Data, namely volume, velocity, variety, and veracity.

3.1 Research Design

- The current study follows an empirical research design with emphasis on the technical and operational aspects of trading systems used by FinTech.
- Case Study Analysis: Narrowing the focus of specific trading platforms like Robinhood, Binance, or those developed by HFT firms
- Comparative Analysis: The difference between a classical statistical model (e.g., ARIMA) and AI-based models (e.g., LSTM networks).

3.2 Data Collection and Sources

- For the "Four Vs" associated with Big Data (Volume, Velocity, Variety, and Veracity), the data is sourced from:
- Structured Data: Historical price data (OHLCV), order book logs, economic indicators available through APIs such as Bloomberg, Reuters, or Yahoo Finance.
- Unstructured Data: Real time sentiment data available on X/Twitter, news headlines, and transcripts of earnings calls.Alternative Data: satellite imagery (for retail/commodity tracking), or Credit Card transaction data.

3.3 Data Preprocessing & Feature Engineering

- Prior to analysis, the data follows a robust pipeline to attain accurate model results:
- Cleaning: Handling of missing data, detection of outliers (e.g., "flash crashes"), and normalization.

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- Sentiment Scoring: Leverage Natural Language Processing models such as BERT or FinBERT to score the news articles based on sentiment, which will be quantitatively measured.

4. DATA ANALYSIS AND RESULTS

4.1 The Transition from Predictive to Agentic AI in Algorithmic Trading

4.2 Comparative Performance Analysis of AI-Driven vs. Traditional Quantitative Models

4.2.1 Market Growth & Scale

As of 2025, the AI in FinTech market reached approximately $30 billion, showing a robust recovery and expansion since 2023. This growth is largely fueled by the surge in unstructured data, which is projected to exceed 1.2 exabytes per day in the financial sector alone by the end of 2025.

4.2.2 Trading Performance (Alpha Generation)

AI has fundamentally altered the performance landscape:

- Dominance: AI now drives roughly 89% of global trading volume.
- Alpha Mining: Systems like "Alpha-GPT" have demonstrated the ability to mine "alphas" (signals that beat the market) at a level comparable to the top 0.1% of human quantitative researchers.
- Risk-Adjusted Returns: New AI-driven frameworks are delivering Sharpe ratios of 2.5 or higher with significantly lower drawdowns (~3%) compared to traditional benchmarks.

4.2.3Operational Efficiency & Risk Results

The implementation of Big Data analytics has yielded quantifiable operational improvements:

- Fraud Reduction: Institutions like Yapı Kredi have reported a 98.7% reduction in fraud losses through long-term AI behavioral modeling.
- Execution Speed: AI-driven algorithmic systems have increased trade execution efficiency by 30%, primarily by reducing slippage and optimizing entry points in microseconds.
- Compliance: AI "copilots" have slashed the time spent on regulatory reporting and model risk management by 30%.

4.3 The Evolution from Sentiment Analysis to Agentic AI (2023–2025)

Analysis: the 2023–2025 periods confirms that the integration of AI and Big Data has moved from a "competitive advantage" to an "industry standard."

DISCUSSION AND IMPLICATIONS

1. Discussion: The New Financial Paradigm

In the evolving landscape of finance, the speed of intelligence has become a critical factor for financial leaders and central banks as they assess its impact on market dynamics. The year 2026 demonstrates a significant shift from the previous reliance on Artificial Intelligence (AI) as a tool for traders to AI autonomously running companies and managing trading agents.

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However, the expectations surrounding Big Data and Information Symmetry, which were thought to equalize market opportunities, have instead widened the gap between organizations that leverage this data effectively and those that employ outdated systems Moreover, the emergence of the Herding Effect poses a concern as multiple AI models may operate under similar decision-making frameworks. In times of market volatility, this coordinated response could result in rapid flash crashes, wherein market disruptions occur swiftly and are challenging to mitigate.

2. Implications: Risks and Opportunities

The change that is happening will affect things in three ways: the Intensity of the situation the Speed at which things happen and the Complexity of the whole thing.

A. Financial Stability & Systemic Risk

The reliance on third-party AI poses risks, particularly if the AI malfunctions, leading to systemic shocks that could affect all users. The rapid decision-making capabilities of AI, occurring in milliseconds, hinder central banks and regulators from effectively responding to emerging risks during crises, complicating crisis management.

B. Regulatory and Legal Shifts

Accountability issues in Agentic AI arise when its actions, such as in trading, lead to negative outcomes. Determining responsibility can be complex, as it may be unclear whether the developer, user, or information providers bear the blame. This accountability gap demands thorough examination due to the significant impact of Agentic AI on individuals and businesses. Additionally, "Regulatory-by-Design" is an essential concept in FinTech, highlighting the importance of proactive regulation compliance.

C. Ethical Considerations

Big Data has a lot of problems because it is based on the past. This means it can be unfair to some people. In 2026 we will need to make sure that computers are fair when they decide who gets credit or make trades. We have to check the computers to make sure they do not treat some people badly because of bad information they were trained on. This is called a Fairness Audit. It is very important for Artificial Intelligence like credit scoring or trading to be fair to everyone. Big Data and Artificial Intelligence, like this have to be checked all the time.

The Future of Work: AI is acting as a "force multiplier." The implication for professionals is a shift away from data gathering toward insights generation and ethical oversight.

CONCLUSION

FinTech trading has undergone a significant transformation from a human-centric model to a highly automated, data-driven ecosystem as a result of the integration of machine learning and big data. By 2026, these advances in technology are the norm in global economies and are no longer merely "competitive edges."Systems using AI have attained previously unreachable levels of operational efficiency through the integration vast amounts of unstructured with structured information, as evidenced by 89% dominance in global trading volume and a 30% increase in execution speed. Most important global hazards are brought

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about by the evolution of technology, though, which include the possibility of "flash failures" as the outcome of similar programs herding towards one another and difficult ethical problems involving algorithmic bias and duty of care.

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