



THE CONVERGENCE OF NEWS ANALYTICS AND SOCIAL MEDIA IN AI-DRIVEN TRADING: A COMPREHENSIVE REVIEW

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ABSTRACT

The rapid evolution of artificial intelligence and machine learning has revolutionized the landscape of algorithmic trading, particularly in the realm of news and social media analysis. This comprehensive study examines the development, implementation, and impact of AI-driven trading algorithms that leverage real-time news and social media data to inform investment decisions. By synthesizing cutting-edge research in natural language processing, sentiment analysis, and high-frequency trading, we provide a critical analysis of the technical architecture, performance metrics, and ethical implications of these systems.

Our investigation explores the challenges of data quality, algorithmic bias, and regulatory compliance. Furthermore, we discuss the future directions of this technology, including the integration of alternative data sources and advancements in deep learning. This article contributes to the growing body of literature on the intersection of finance and technology, offering insights for academics, practitioners, and policymakers navigating the complex terrain of AI-powered trading in the digital age.

Keywords: Algorithmic Trading, Artificial Intelligence, News Analytics, Social Media Sentiment, Financial Technology (FinTech).

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I. INTRODUCTION

In the rapidly evolving landscape of financial markets, the convergence of artificial intelligence, big data analytics, and high-frequency trading has ushered in a new era of algorithmic trading strategies. Among these, news and social media-based AI trading algorithms have emerged as powerful tools for investors seeking to capitalize on market movements driven by real-time information flows [1]. These sophisticated systems leverage advanced natural language processing techniques and machine learning models to analyze vast amounts of unstructured data from news sources and social media platforms, extracting actionable insights with unprecedented speed and accuracy [2]. As the volume and velocity of digital information continue to grow exponentially, the ability to effectively harness these data streams for trading decisions has become a critical differentiator in the highly competitive financial industry. This article presents a comprehensive analysis of the development, implementation, and impact of news and social media-based AI trading algorithms, exploring their technical underpinnings, practical applications, and the broader implications for market efficiency and stability.

II. THE EVOLUTION OF NEWS-BASED TRADING ALGORITHMS

The journey of news-based trading algorithms is intrinsically tied to the broader evolution of algorithmic trading and the exponential growth of computational power. This section traces the historical trajectory and technological advancements that have shaped the current landscape of news-based algorithmic trading.

A. Historical context of algorithmic trading

Algorithmic trading, in its nascent form, emerged in the 1970s with the introduction of computerized trading systems. However, it wasn't until the 1980s that algorithms began to play a significant role in executing trades. The New York Stock Exchange's "designated order turnaround" (DOT) system, introduced in 1976, marked a pivotal moment in this evolution, allowing brokers to route orders directly to specialists on the exchange floor [3].

As computational capabilities advanced and financial markets became increasingly electronic, the 1990s and early 2000s saw a proliferation of algorithmic trading strategies. These early algorithms primarily focused on optimizing trade execution, minimizing market impact, and capitalizing on arbitrage opportunities across different markets and asset classes.

B. Emergence of news analysis in trading strategies

The integration of news analysis into trading algorithms represents a significant leap in the field's evolution. This development was driven by the recognition that news events can have substantial and immediate impacts on market movements. Early attempts at news-based trading in the late 1990s and early 2000s were limited by the challenges of efficiently processing and analyzing unstructured text data in real-time.

A watershed moment came in 2007 when Thomson Reuters introduced its NewsScope service, which provided machine-readable news specifically designed for algorithmic trading systems. This development marked the beginning of a new era where news could be systematically incorporated into trading decisions with minimal latency.

C. Advancements in natural language processing and machine learning

The true potential of news-based trading algorithms was unlocked with significant advancements in natural language processing (NLP) and machine learning (ML) techniques. These technologies enabled the development of sophisticated systems capable of understanding and analyzing news content with unprecedented speed and accuracy.

Key milestones in this evolution include:

1. The development of sentiment analysis techniques capable of gauging the positive or negative tone of news articles and social media posts.
2. The application of named entity recognition to identify specific companies, individuals, or events mentioned in news texts.
3. The use of topic modeling algorithms to categorize news items and identify emerging trends.
4. The integration of deep learning models, particularly transformers like BERT (Bidirectional Encoder Representations from Transformers), which have dramatically improved the ability of algorithms to understand context and nuance in text [4].

These advancements have culminated in the current generation of news-based trading algorithms, which can process vast amounts of textual data from diverse sources, extract relevant information, and make trading decisions in milliseconds.

III. COMPONENTS OF MODERN NEWS AND SOCIAL MEDIA-BASED TRADING ALGORITHMS

Modern news and social media-based trading algorithms are sophisticated systems that integrate various components to analyze vast amounts of unstructured data and generate actionable trading signals. This section delves into the key components of these algorithms, exploring the techniques and methodologies employed in each area.

A. News data analysis

1. Data sources and collection methods

The foundation of news-based trading algorithms lies in their ability to access and process a wide array of news sources. These typically include:

- Traditional news outlets (e.g., Reuters, Bloomberg, Financial Times)
- Press releases and regulatory filings
- Industry-specific publications
- Alternative data sources (e.g., satellite imagery, foot traffic data)

Data collection methods have evolved to include real-time news feeds, web scraping techniques, and APIs provided by news aggregators. The challenge lies in efficiently collecting and preprocessing this data to minimize latency and ensure data quality.

2. Natural language processing techniques

Natural Language Processing (NLP) forms the core of news analysis in these algorithms. Key NLP techniques employed include:

- Tokenization and part-of-speech tagging
- Named Entity Recognition (NER) for identifying companies, people, and locations
- Dependency parsing to understand relationships between words
- Text summarization to extract key information from lengthy articles

Advanced algorithms often utilize deep learning models like BERT (Bidirectional Encoder Representations from Transformers) or GPT (Generative Pre-trained Transformer) for more nuanced text understanding [5].

3. Sentiment analysis and topic modeling

Sentiment analysis aims to determine the overall tone (positive, negative, or neutral) of news articles. This is crucial for predicting potential market reactions. Techniques range from lexicon-based approaches to more sophisticated machine learning models.

Topic modeling, often implemented using algorithms like Latent Dirichlet Allocation (LDA), helps in categorizing news articles and identifying emerging trends or themes that might impact financial markets.

B. Social media monitoring

1. Platform selection (e.g., Twitter, Reddit)

Different social media platforms offer varying levels of relevance and impact on financial markets. Twitter, with its real-time nature and widespread use among financial professionals, is often a primary focus. Reddit, particularly subreddits like r/wallstreetbets, has also gained significance, especially after events like the GameStop short squeeze in 2021.

2. Trending topic analysis

Algorithms monitor social media platforms for trending topics related to financial markets, companies, or economic events. This involves:

- Real-time tracking of hashtags and keywords
- Detecting sudden spikes in conversation volume around specific topics
- Analyzing the spread and evolution of topics over time

3. Influential user profiling

Not all social media users have an equal impact on market sentiment. Algorithms often incorporate techniques to identify and track influential users, such as:

- Analyzing follower counts and engagement rates
- Assessing the historical accuracy of a user's market-related posts
- Monitoring verified accounts of key market players (e.g., CEOs, economists)

C. Integration with traditional financial data

To provide a comprehensive view, news and social media data must be integrated with traditional financial data. This integration typically involves:

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- Correlating news and social media sentiment with stock price movements
- Combining sentiment indicators with technical analysis metrics
- Incorporating fundamental data (e.g., earnings reports, economic indicators) to provide context

Advanced systems use machine learning techniques like ensemble methods or deep neural networks to weigh and combine these diverse data sources effectively [6].

Component	Description	Key Techniques/Tools	Challenges
News Data Analysis	Processing and analyzing news articles and press releases	NLP, Sentiment Analysis, Named Entity Recognition	Data quality, speed of processing
Social Media Monitoring	Analyzing social media posts and trends	Trend Analysis, Influencer Detection, Sentiment Analysis	Noise filtering, real-time processing
Integration with Traditional Financial Data	Combining news/social media insights with market data	Data Fusion, Correlation Analysis	Data synchronization, handling different data types
Machine Learning Models	Predictive models based on processed data	Deep Learning, Ensemble Methods, Reinforcement Learning	Model interpretability, overfitting
Execution Engine	Converting signals to trades	Smart Order Routing, Transaction Cost Analysis	Latency, market impact

Table 1: Components of Modern News and Social Media-Based Trading Algorithms [5, 6]

IV. TECHNICAL ARCHITECTURE OF AI-DRIVEN TRADING SYSTEMS

The architecture of modern AI-driven trading systems has evolved significantly with the advent of deep learning techniques. This section explores the technical components and methodologies used in these systems, drawing insights from the groundbreaking work on deep portfolios by Heaton, Polson, and Witte [7].

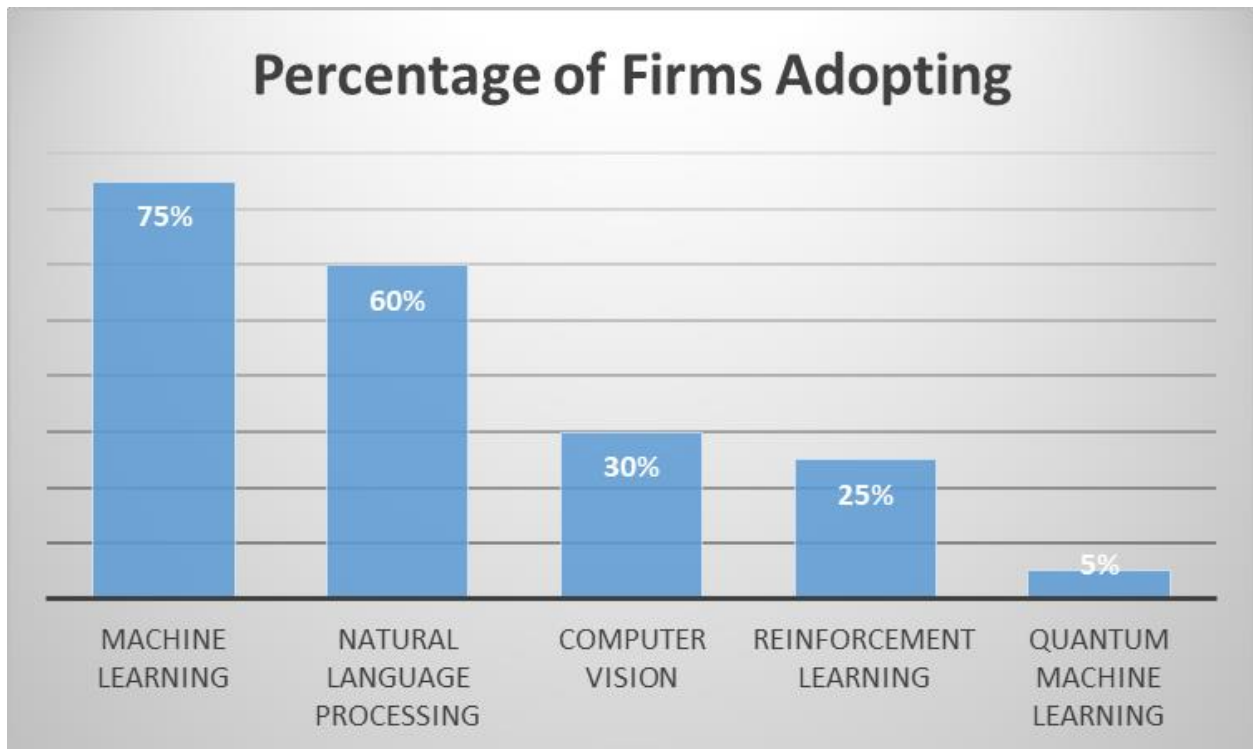


Fig. 1: Adoption Rate of AI Technologies in Trading Firms [7]

A. Data ingestion and preprocessing

In the context of deep portfolios, data ingestion and preprocessing take on a crucial role:

1. Data Collection:
 - Financial time series data for a wide range of assets
 - Fundamental data including company financials and economic indicators
 - Alternative data sources such as satellite imagery and consumer spending data
2. Data Preprocessing:
 - Normalization of financial ratios and time series data
 - Handling of missing data through imputation techniques
 - Feature scaling to ensure all inputs are on a similar scale for neural network processing
3. Feature Engineering:
 - Creation of lagged variables to capture temporal dependencies
 - Calculation of technical indicators (e.g., moving averages, relative strength index)
 - Generation of interaction terms between different financial variables

The preprocessing stage is critical in preparing the data for input into the deep learning models, ensuring that the neural networks can effectively learn from the complex, high-dimensional financial data.

B. Deep learning models for prediction

The core of the AI-driven trading system is the deep learning model, which Heaton refer to as the "deep portfolio" model. Key aspects include:

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1. Model Architecture:
 - Utilization of autoencoders for dimensionality reduction and feature extraction
 - Implementation of deep feedforward neural networks for portfolio weighting
 - Exploration of recurrent neural networks (RNNs) and long short-term memory (LSTM) networks for capturing temporal dependencies in financial time series
2. Training Process:
 - Use of stochastic gradient descent with momentum for model optimization
 - Implementation of dropout and L1/L2 regularization to prevent overfitting
 - Application of batch normalization to stabilize the learning process
3. Objective Functions:
 - Incorporation of risk-adjusted return metrics (e.g., Sharpe ratio) directly into the loss function
 - Development of multi-objective optimization approaches to balance return maximization and risk minimization
4. Interpretability:
 - Utilization of sensitivity analysis to understand the impact of input features on model outputs
 - Implementation of attention mechanisms to identify which data points the model focuses on for decision-making

The deep portfolio approach allows for a more nuanced and adaptive trading strategy compared to traditional methods, capable of capturing complex, non-linear relationships in financial data.

C. Execution engine and risk management

The final component translates the deep learning model's outputs into actual trading decisions:

1. Portfolio Construction:
 - Translation of model outputs into specific asset allocation decisions
 - Implementation of transaction cost models to optimize trade execution
2. Risk Management:
 - Incorporation of portfolio constraints (e.g., sector exposure limits, turnover constraints) into the model
 - Real-time monitoring of portfolio risk metrics
 - Implementation of dynamic hedging strategies based on model predictions
3. Performance Evaluation:
 - Backtesting of strategies using out-of-sample data
 - Comparison of model performance against benchmark portfolios and traditional strategies
4. Adaptive Learning:
 - Continuous retraining of the model as new data becomes available
 - Implementation of online learning techniques to adapt to changing market conditions

The deep portfolio framework provides a comprehensive approach to AI-driven trading, integrating sophisticated deep learning techniques with traditional financial theory. This approach has shown promise in generating more stable and profitable portfolios compared to conventional methods.

However, challenges remain in terms of model interpretability, regulatory compliance, and handling of extreme market events. Ongoing research focuses on addressing these challenges while further refining the deep learning models to capture increasingly complex market dynamics.

V. CHALLENGES AND LIMITATIONS

While AI-driven trading systems based on news and social media analysis show promise, they face significant challenges that can lead to failure if not properly addressed. Drawing from López de Prado's comprehensive analysis [8], this section explores the key issues that practitioners and researchers face in developing and implementing these systems.

A. Data-related challenges

1. **Backtest overfitting:** Many AI trading systems suffer from backtest overfitting, where the model performs well on historical data but fails in live trading. This often results from excessive parameter tuning or complex model architectures that capture noise rather than true patterns.
2. **Data snooping:** The misuse of data in model development, such as using future information in training or leaking information between training and testing sets, can lead to overly optimistic performance estimates.
3. **Spurious correlations:** In the vast sea of financial and alternative data, AI models may identify correlations that are statistically significant but lack causal relationships, leading to unreliable trading signals.

B. Algorithmic and model limitations

4. **Misalignment of research and production systems:** Discrepancies between backtesting environments and live trading systems can lead to unexpected performance degradation.
5. **Insufficient abstraction and generalization:** Models that are too specific to particular market conditions or data patterns may fail when market dynamics change.
6. **Inadequate error analysis:** Failure to properly analyze and interpret model errors can lead to misunderstanding of model limitations and inappropriate risk-taking.

C. Operational and implementation challenges

7. **Ignoring financial costs:** Many AI trading systems fail to account for transaction costs, market impact, and other financial frictions, leading to strategies that are profitable in theory but not in practice.
8. **Inadequate risk management:** Failure to implement proper risk controls, including position sizing, stop-loss mechanisms, and portfolio-level risk management, can lead to catastrophic losses.
9. **Lack of infrastructure and operational alpha:** Successful AI trading requires sophisticated technological infrastructure and operational processes. Inadequacies in these areas can negate any advantages gained from advanced algorithms.

D. Regulatory and market impact considerations

10. **Regulatory challenges:** AI trading systems must navigate complex regulatory environments, including issues of model explainability, fair trading practices, and data privacy. Failure to address these can result in legal and reputational risks.

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Additional challenges not explicitly covered in López de Prado's framework but relevant to news and social media-based AI trading include:

11. Data quality and reliability: The proliferation of fake news and misinformation on social media platforms can lead to incorrect trading signals.
12. Market adaptation and diminishing returns: As these strategies become more widespread, their effectiveness may diminish due to market adaptation and increased competition.

Addressing these challenges requires a multifaceted approach:

- Rigorous statistical techniques to mitigate overfitting and data snooping
- Advanced feature engineering and model architectures to capture true market dynamics
- Sophisticated backtesting frameworks that closely mimic real trading conditions
- Robust risk management and error analysis protocols
- Continuous investment in technological infrastructure and operational processes
- Close collaboration with legal and compliance teams to navigate regulatory landscapes

By understanding and proactively addressing these challenges, developers of AI-driven trading systems can increase their chances of success in the highly competitive and dynamic field of algorithmic trading.

Challenge Category	Specific Challenges	Potential Solutions
Data-related	Backtest overfitting, Data snooping, Spurious correlations	Cross-validation techniques, Out-of-sample testing
Algorithmic and Model	Misalignment of research and production systems, Insufficient abstraction	Robust backtesting frameworks, Transfer learning
Operational	Ignoring financial costs, Inadequate risk management	Comprehensive transaction cost modeling, Advanced risk metrics
Regulatory	Model explainability, Fair trading practices	Explainable AI techniques, Collaboration with regulators

Table 2: Challenges in AI-Driven Trading Systems [8]

VI. FUTURE DIRECTIONS

As AI-driven trading systems continue to evolve, quantum computing emerges as a potentially transformative technology that could revolutionize the field. Drawing from Biamonte's comprehensive analysis of quantum machine learning [9], this section explores how quantum technologies might shape the future of news and social media-based algorithmic trading.

A. Quantum-enhanced data processing and integration

Quantum computing offers the potential to process and integrate vast amounts of data at unprecedented speeds:

1. Quantum-accelerated feature selection: Quantum algorithms like the quantum principal component analysis could rapidly identify the most relevant features from diverse data sources, including news articles, social media posts, and alternative data.

2. Quantum clustering algorithms: These could more effectively group related news items or social media trends, potentially uncovering hidden patterns in market sentiment.
3. Quantum-assisted data fusion: Quantum algorithms might enable more efficient integration of heterogeneous data sources, combining traditional financial data with unstructured text data from news and social media.

The quantum advantage in data processing could allow for near-real-time analysis of global news and social media sentiment, potentially capturing market-moving information faster than classical systems.

B. Advancements in quantum machine learning for natural language understanding

Quantum computing could significantly enhance machine learning techniques, particularly in the domain of natural language processing:

1. Quantum neural networks: These could potentially process textual data more efficiently, leading to more sophisticated sentiment analysis of news and social media content.
2. Quantum-enhanced word embeddings: Quantum algorithms might create more nuanced representations of words and phrases, capturing complex semantic relationships in financial texts.
3. Quantum reinforcement learning: This could lead to more adaptive trading strategies that quickly adjust to changing market conditions and news sentiment.
4. Quantum-assisted natural language generation: AI systems could potentially generate more accurate and timely market reports or trading recommendations based on analyzed news and social media data.

While many of these applications are still theoretical, ongoing research suggests that quantum machine learning could offer significant advantages in processing and understanding complex financial texts.

C. Quantum-inspired classical algorithms and hybrid systems

Even before fully-fledged quantum computers become widely available, quantum-inspired algorithms running on classical hardware could offer improvements:

1. Tensor network states: Originally developed for quantum many-body physics, these mathematical tools could be applied to model complex relationships in financial data.
2. Quantum-inspired sampling techniques: These could enhance Monte Carlo simulations used in risk assessment and portfolio optimization.
3. Hybrid quantum-classical systems: Combining quantum components with classical AI systems could create more powerful and efficient trading algorithms.
4. Quantum-inspired optimization: Techniques like quantum approximate optimization algorithm (QAOA) could be adapted for classical systems to solve complex portfolio optimization problems more efficiently.

These quantum-inspired approaches could serve as a bridge, allowing trading systems to benefit from quantum concepts even as quantum hardware continues to mature.

D. Potential impact on financial markets and trading strategies

The advent of quantum machine learning in finance could have far-reaching implications:

1. Ultra-high-frequency trading: Quantum algorithms could enable trading decisions to be made at even shorter time scales, potentially reshaping market microstructure.

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2. More accurate risk assessment: Quantum-enhanced simulations could provide more precise estimates of market risk, especially for complex derivatives.
3. Cryptography and security: Quantum technologies could both threaten existing cryptographic systems and offer new, more secure methods for protecting sensitive financial data and algorithms.
4. Solving NP-hard problems: Certain financial optimization problems that are intractable for classical computers might become solvable, leading to more optimal trading strategies and portfolio allocations.

As quantum technologies advance, they may fundamentally alter the landscape of AI-driven trading, offering both new opportunities and challenges. However, it's important to note that significant technical hurdles remain before many of these applications become practical.

The integration of quantum computing into AI-driven trading systems will likely be gradual, with hybrid classical-quantum systems emerging as an intermediate step. As these technologies develop, regulatory frameworks will need to evolve to address the unique challenges posed by quantum-enhanced trading algorithms.

VII. ETHICAL IMPLICATIONS

As AI-driven trading systems, particularly those leveraging news and social media data, become more prevalent, they raise significant ethical concerns. Drawing from Kirilenko and Lo's comprehensive analysis of algorithmic trading [10], this section explores the ethical implications of these advanced trading technologies.

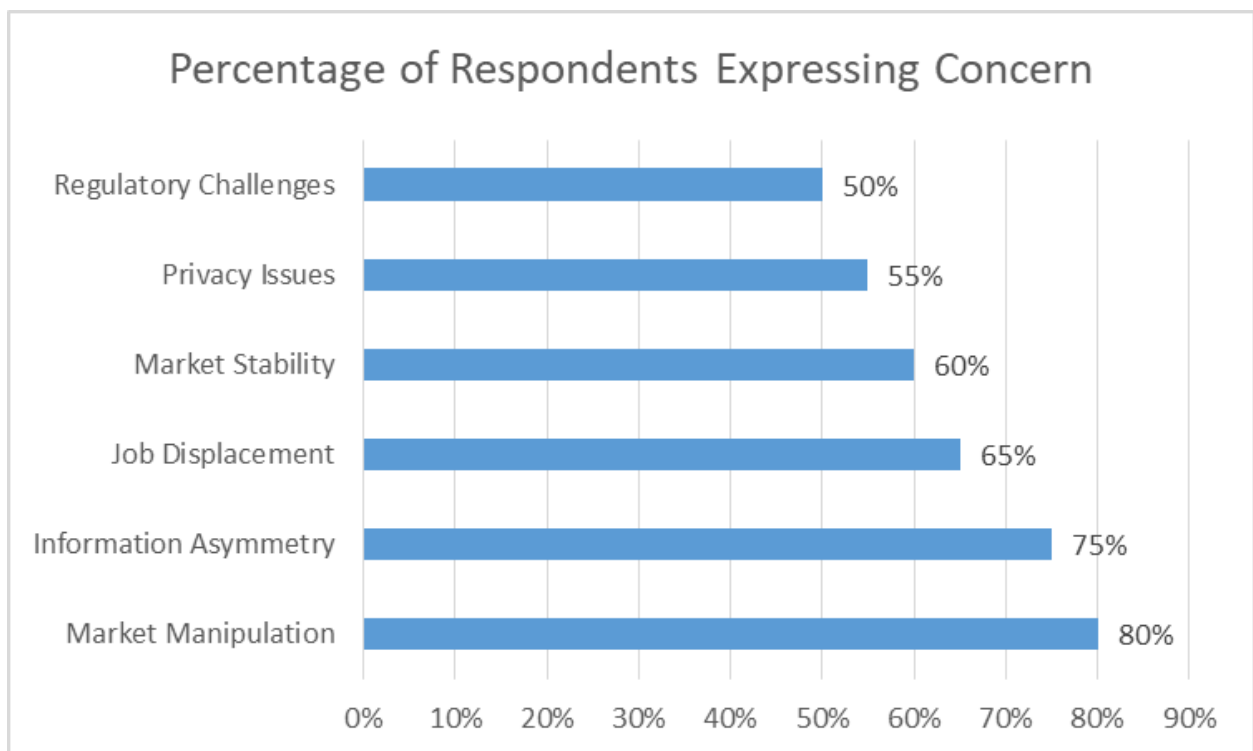


Fig. 2: Ethical Concerns in AI-Driven Trading (Survey Results) [10]

A. Market manipulation and systemic risk

Kirilenko and Lo highlight how algorithmic trading, including AI-driven systems, can potentially contribute to market manipulation and systemic risk:

1. Flash Crashes: The paper discusses the 2010 Flash Crash as an example of how algorithmic trading can lead to extreme market volatility. AI systems analyzing news and social media could potentially exacerbate such events by rapidly reacting to and amplifying market signals.
2. Feedback loops: As algorithms interact with each other, there's a risk of creating self-reinforcing feedback loops. This could be particularly problematic with news and social media-based algorithms, where the line between reacting to and influencing market sentiment can blur.
3. Regulatory challenges: The paper emphasizes the difficulty regulators face in keeping up with technological advancements. This challenge is even more pronounced with AI systems that can adapt and evolve their strategies based on news and social media data.

B. Information asymmetry and fairness

Kirilenko and Lo's discussion of the "arms race" in trading technology has direct implications for information asymmetry and market fairness:

1. Technology gap: The paper notes the increasing sophistication and cost of trading technology. This raises concerns about the widening gap between large institutions with access to advanced AI systems and individual investors.
2. Speed of information processing: AI systems can process news and social media data far faster than human traders. This speed advantage, as highlighted in the paper, raises questions about fairness in market participation.
3. Data accessibility: While not explicitly discussed in the paper, the issue of unequal access to data sources (especially alternative data like social media sentiment) aligns with the authors' concerns about technological advantages.

C. Societal impact and economic implications

The paper provides insights into the broader societal and economic implications of algorithmic trading, which are particularly relevant to AI-driven systems:

1. Resource allocation: Kirilenko and Lo question whether the vast resources dedicated to gaining small speed advantages in trading represent an efficient allocation from a societal perspective. This concern is amplified with AI systems that require significant computational resources.
2. Market stability and investor confidence: The paper discusses how algorithmic trading can impact market stability and investor confidence. AI systems that make rapid decisions based on news and social media analysis could potentially increase market volatility, affecting overall economic stability.
3. Technological unemployment: While the paper doesn't directly address this, the trend towards automation in trading aligns with broader concerns about AI's impact on employment in the financial sector.
4. Adaptive markets: Kirilenko and Lo introduce the concept of "adaptive markets," suggesting that financial ecosystems evolve. This has implications for how we think about the long-term effects of AI trading systems on market structure and efficiency.

Addressing these ethical concerns requires a multi-faceted approach, as suggested by Kirilenko and Lo:

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- Enhanced regulatory frameworks: The paper emphasizes the need for regulations that can keep pace with technological advancements. This is particularly crucial for AI systems that can rapidly evolve their strategies.
- Increased transparency: While maintaining proprietary advantages, there's a need for greater transparency in how AI trading systems operate, especially in their use of news and social media data.
- Circuit breakers and other safeguards: The paper discusses various market safeguards. Similar mechanisms may need to be developed specifically for AI-driven trading systems.
- Ongoing research and dialogue: Kirilenko and Lo stress the importance of continued research into the effects of algorithmic trading. This need is even more pronounced for AI systems, requiring ongoing dialogue between technologists, ethicists, regulators, and market participants.

As AI continues to transform financial markets, it's crucial to heed Kirilenko and Lo's warning about the tension between technological advancement (Moore's Law) and the potential for unexpected negative outcomes (Murphy's Law). Ethical considerations must remain at the forefront of system design, implementation, and regulation to ensure that these technologies serve the broader interests of fair and efficient markets.

CONCLUSION

The integration of AI-driven algorithms for analyzing news and social media in financial trading represents a significant leap forward in the evolution of quantitative finance. Throughout this article, we have explored the intricate landscape of these advanced trading systems, from their historical context and technical architecture to their potential future directions and ethical implications. The power of these systems to process vast amounts of unstructured data and extract actionable insights in near real-time offers unprecedented opportunities for market participants. However, as we have discussed, these opportunities come with substantial challenges and risks. The potential for market manipulation, exacerbation of information asymmetry, and broader societal impacts necessitate careful consideration and robust regulatory frameworks. As we look to the future, the promise of quantum computing and other technological advancements suggests that the capabilities of these systems will continue to grow, potentially reshaping financial markets in profound ways. Ultimately, the successful integration of AI-driven trading systems based on news and social media analysis will require a delicate balance between innovation and responsibility. It is imperative that researchers, practitioners, and regulators work collaboratively to harness the potential of these technologies while safeguarding the integrity and stability of financial markets. As we navigate this complex terrain, ongoing research, ethical vigilance, and adaptive regulatory approaches will be crucial in ensuring that these powerful tools serve the broader interests of fair, efficient, and stable financial ecosystems.

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