European Economic Letters
ISSN 2323-5233
Vol 15, Issue 4 (2025)
http://eelet.org.uk

Unveiling the Black Box: Explainable AI and the Diffusion of Machine Learning in Algorithmic Trading

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Abstract:
Machine learning (ML) is increasingly integrated into algorithmic trading, offering significant predictive accuracy and real-time adaptability. However, widespread adoption is constrained by critical barriers including model complexity, the "black box" problem of transparency, and regulatory concerns. This paper investigates how emerging paradigms such as Explainable AI (XAI) can resolve these challenges and shape future adoption trends. Employing a qualitative case study methodology guided by the Diffusion of Innovations (DOI) theory, this research analyses the diffusion of these technologies through the dimensions of relative advantage, compatibility, complexity, trialability, and observability. Findings reveal that while existing literature recognizes ML's capacity to enhance decision-making accuracy, limited studies analyse whether transparency-driven ML structures can accelerate systemic adoption. This study presents a framework connecting advanced AI capabilities with the practical requirements of user trust and regulatory compliance. The results highlight the pivotal role of XAI not only in mitigating the "black-box" barrier but also in aligning AI-driven trading strategies with risk management and regulations.

1. Introduction:

Financial markets have long been central to global economic activity, continually growing through technological advancements. Trading strategies involved in making a profit within these financial markets have evolved significantly, transitioning from manual investor knowledge dependent decisions to algorithms with defined rules that used computer systems for rapid and quick decision-making. Today, machine learning spear-heads financial innovation in trading; decision-making is now no longer bound to an algorithm but can now be adaptive, predictive, and dynamic due to machine learning (Borch, 2022). Machine learning (ML) is a branch of artificial intelligence (AI) that allows computers to learn and uncover patterns from historical and real-time datasets without explicit programming. The machine learning market is expected to show a CAGR of 32.20% from 2025-2031 only in India, which clearly shows the huge interest in the (Statista, n.d.-b). Hence, Machine learning is advancing the finance industry at an unparalleled rate; it is being used to predict market trends, develop adaptive trading strategies, analyze sentiment data in news, and many other facets in finance (Borch, 2022; Hansen, 2020). Tran et al. (2023) clearly mentions that 75% of shares traded on United states stock exchanges come from automatic trading systems, with increasing ML adoption.

Machine learning can substantially enhance trading strategies through quick analysis of huge datasets which leads to identifying patterns that would otherwise be invisible (Sahu, 2023). ML can also adapt versatilely to new data from new market conditions to overrule rules that become redundant, giving rise to highly profitable trading strategies (Khoa & Huynh, 2021; Borch, 2022). According to Deloitte Insights (2019), which surveyed over 200 US financial services executives with over 52% respondents using DL, financial services executives are now using some Deep Learning (DL) in developing trading strategies. Noticeably, there has been a surge in the number of traders, likely due to covid, and also from the general 2.80% CAGR of trading volume (Statista, n.d.-a). People who started working from home during covid most likely contributed to this rise in number of traders as they became increasingly aware of investment vehicles in markets. The study (Hajj & Hammoud, 2023) found there is a statistically significant negative correlation between number of professional experience years and inclination to AI and ML adoption, which implies that people with less professional experience are more likely to be open to adopting AI and ML technologies, probably as they have had early exposure to technology. Extrapolating, recent Gen millennial and Gen Z trader influx, traders who are more inclined to adapt to technological advancements like ML compared to their older counterparts, could imply that the idea of ML-based trading strategies being utilized could be more widely accepted and could open a large potential for market-wide adoption. These new generations have had early exposure with technology and hence are more likely to adopt technology dependent trading strategies involving machine learning, amplifying the huge potential usage of machine learning in trading strategies (Hajj & Hammoud, 2023).

These new generations of traders are likely to feel compelled towards complex technology like ML. The use of such ML in asset markets comes in a plethora of forms. Supervised learning techniques like decision trees, random forests, and neural networks are being used to train systems to generate trading signals based on certain labelled inputs (Rouf, 2021; Mirete-Ferrer, 2022). Unsupervised learning like clustering and autoencoders is also utilized for identifying hidden patterns in unlabelled data (Sahu, 2023), and reinforcement learning methods like Q-learning, where trial-and-error leads to generation of optimal trade signals based on past rewards/penalties, are particularly good in optimizing portfolios (Aloud & Alkhamees, 2021). A Further application of ML in trading include NLP for sentiment analysis in financial news that can influence a trading strategy (Mirete-Ferrer et al., 2022). Traditional trading methods in use today in contrast to the use of ML like above include three primary methods of analysis to determine trading buy/sell signals. One is technical analysis which is the use of strategies based on past behaviour of a financial asset's price and volume of trade, functioning on the principle that asset prices reflect all asset related information available. Another is fundamental analysis which accounts for corporate economic news and conditions that could possibly affect asset prices (Cohen, 2022). Lastly, investor sentiment analysis involves reviewing the general market psychology of investors on social media and news to determine what general direction asset prices are going to move (Cohen, 2022).

Returning to ML applications, there are a few drawbacks in trading strategies. Machine learning algorithms are prone to overfitting to noise and specific patterns in historical data that may be low-quality, which is obsolete in new unseen real world data (Hajj & Hammoud, 2023). Also, machine learning algorithms sometimes learn inexplicably or without transparency, leading to trading signals being made without solid reasoning that the user could understand. There are further ethical and regulatory concerns on data privacy, fairness to other traders, and regulatory tax considerations to incorporate in ML-based strategies. Numerous similar ML systems in a market might react similarly to market events too, potentially causing systematic risk from herding and increased market disruptions from false signals (Hansen, 2020).

These drawbacks have led to emergence of certain machine learning trading strategies that attempt to reduce these drawbacks. Mainly, there is a drive towards explainable AI to ensure transparency of machine learning models, especially due to regulatory concerns around "black boxes" (ML algorithms that are incomprehensible for humans, a problem with the transparency issue as mentioned earlier, because we have no knowledge on how these complicated ML algorithms work and why they take a particular decision) especially in DNNs (Sahu et al., 2023). Moreover, multimodal AI that combines news sentiment data, market prices, macroeconomic data, and essentially multiple forms of analysis is heavily promoted due to its extensive capabilities in stock returns, prediction of market trends, and adaptability (Mirete-Ferrer et al., 2022). Quantum computing also shows potential as a resolution of forecasting limitations in large dynamic datasets and for solving optimization problems exponentially faster (Palaniappan et al., 2024).

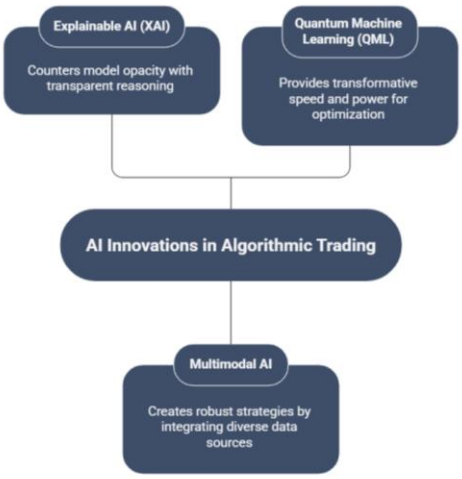

Figure I: The 3 potential emerging paradigms of AI/ML innovation in financial markets

Figure I shows the 3 types of AI/ML innovations in algorithmic trading strategies that will potentially greatly affect future algorithmic trading: XAI, QML, and multimodal AI. As mentioned earlier, XAI reduces ML opacity and hence increases trust while reducing risk inherent in using advanced ML models, and multimodal AI involves using multiple data streams to strengthen predictive accuracy through wide information variety (Mirete-Ferrer et al., 2022; Sahu et al., 2023). QML involves using quantum computing to significantly bolster ML, employing a powerful computational technique to enhance speed in predictions (Palaniappan et al., 2024).

While there is extensive existing research in applying different types of machine learning to financial markets, there is limited research on emerging technologies like XAI and multimodal AI in algorithmic trading. This paper focuses on these innovations in machine-learning based trading strategies and qualitatively discusses their potential adoption through the Diffusion of Innovations (DOI) theory. By examining these innovations and their adoption barriers in trading and financial markets, this paper moves beyond technical models and presents the socio-technical environment of a potential paradigm shift in financial markets. This study investigates XAI and multimodal AI, showing how complexity is reduced while observability and compatibility increases through these innovations. By moving beyond investigations into opaque models such as neural networks, this study highlights transparency and interpretability, facilitating actionable insights for traders and decision-makers to reduce risks, foster trust, and increase regulatory alignment. The research gap that this paper addresses is that while existing literature describes various machine learning applications in finance, there is limited analysis on how emerging trends resolve the core adoption barriers of complexity and the “black box” problem of ML/AI in financial markets.

This paper is organized as follows: Section 1 introduces current ML techniques and trends in trading. Section 2 provides a literature review of these techniques, and Section 3 outlines the research methodology. Section 4 presents the analysis and findings, followed by a discussion in Section 5. Finally, Section 6 concludes the paper.

2. Literature review

ML in trading has revolutionized trading and asset markets. This section reviews existing work in the intersection between trading and ML. In a gist, we observe trends such as reinforcement learning/deep learning models being used, sentiment analysis for financial time series forecasting, explainable AI, and many more ML integrations in financial markets.

2.1. Key forms of Machine Learning used in financial markets

2.1.1. Supervised Learning:

Supervised learning is core to ML when labelled data is used for algorithms to make predictions or classifications (Mirete-Ferrer et al, 2022). It attempts to approximate which inputs lead to which outputs (mapping inputs to outputs); essentially trying to approximate a function $f(x) = y$ in a financial market where the function $f(x)$ represents the prediction/forecast based on the input x of labelled data (Sahu et al, 2023). This type of ML is mainly used in portfolio optimization, financial fraud detection, and stock market prediction due to how accurate it is in output predictions (Lee, 2022). There are mainly two types of supervised learning present in current literature:

1. **Regression method:** these are models employed in supervised learning to forecast continuous outcomes, such as a stock’s future price or returns (Sahu et al, 2023). Some of these types of models are linear regressions, decision regression trees and some other rule-based methods, and XGBoost (Extreme Gradient Boosting). Linear regression is one of the simplest models and is one of the most interpretable machine learning algorithms, and is mainly used for financial fraud detection by performing regression on multiple variables (Ali et al, 2022). Decision regression trees are specific variants of decision trees (constructs hierarchical structure of rules that lead to judgements based on inputs) that are tailored to predict continuous outcomes, and are mainly used when parameters draw connections without linearity (Gurav & Sidnal, 2018; Mirete-Ferrer et al, 2022). They are prone to significant overfitting and are normally used in ensemble models such as random forests and gradient boosting to reduce this overfitting problem and improve performance in predictions (Ayala et al., 2021). XGBoost is an ensemble method that uses weak learners (shallow decision trees that normally have inaccuracy) usually; it uses an initial base weak learner and builds upon it by training the next decision tree to minimize the error of the previous decision tree (Jim et al., 2024). This process of gradient boosting occurs continually creating models that add onto each other, minimizing error and increasing prediction accuracy (Jim et al., 2024).

2. **Classification method:** In supervised learning, classification refers to assigning each input sample to one of a set of discrete categories (Sahu et al, 2023). Some of these types of models include Support Vector Machines (SVMs), random forests, and artificial neural networks (ANNs). SVMs involve classifying items by finding a maximum margin hyperplane (boundary) between categories, and can handle both linear and non-linear classification using kernel functions (Ali et al, 2022; Cohen, 2022). It is mainly used in predicting the direction of general stock market movement (Palaniappan et al, 2024). Random forests work by using an ensemble method of multiple decision trees that work together to aggregate individual tree outputs by majority voting (random forests can also be used in regression methods), which reduces overfitting and increases prediction accuracy rather than compared to an individual decision tree (Mirete-Ferrer et al., 2022). Finally, ANNs are models essentially operating similarly to biological neural networks, where interconnected neurons drive decision-making (Pagliaro, 2025).

2.1.2. Unsupervised Learning:

Unsupervised learning involves finding patterns within data which do not have predetermined labels. These techniques aim to discover hidden structures and patterns without explicit programming. There is no labelling of data so it is difficult to approximate a function f(x) that results in output y, but instead the techniques look for hidden structures within the data that could potentially give rise to generic market direction prediction and anomaly detection (Mirete-Ferrer et al., 2022). Many unsupervised learning techniques are used, but broadly they can be categorized in 2 types:

1. **Clustering:** this method can be used for segmenting (clustering) certain data into groups with similar patterns. K-means clustering and hierarchical clustering are two main techniques. K-means clustering groups data on similarity in behaviour and tries to minimize variance within clusters and is frequently used as a pre-processing technique to reduce number of data points (Pagliaro, 2025). Hierarchical clustering clusters data points with hierarchy, and by either using an agglomerative or divisive method, it creates structure showing the connections between clusters at different hierarchical levels (Pagliaro, 2025). This method is mainly used in asset allocation and portfolio diversification (Mirete-Ferrer et al., 2022).

2. **Anomaly detection:** This type of unsupervised learning, as the terminology implies, aims to identify data points that significantly deviate from the dataset without labelled anomalous examples. These techniques are mostly used for detecting market manipulation and fraudulent transactions. Two common techniques used are isolation forests and autoencoders. Isolation forests are effectively pure anomaly detection – the core function is to identify data points that are significantly different from the majority of the unlabelled data. Autoencoders essentially nonlinearly transform input data and then reconstruct the original data using the transformed data inverse function. The error between the reconstructed data and original data is used to detect anomalies (Passalis et al., 2021).

2.1.4. Reinforcement Learning:

Reinforcement Learning (RL) is an approach for machines to learn how to make decisions over time. An agent learns how to perform actions to maximize future reward or payoff by interacting with an environment (Aloud & Alkhamees, 2021). Some specific techniques utilized in RL include Deep Q networks (DQN) and policy gradient methods. DQNs involve the use of DNNs to approximate the function that estimates future reward for a particular action from enormous financial time-series data and then the DQN aims to optimize the policy by maximizing the expected sum of these future payoffs (Mirete-Ferrer et al., 2022; Park et al., 2020). Policy gradient methods do not employ value-added methods like DQNs and instead involves optimising the policy in terms of its parameters to maximise the long-term reward primarily, which involves parameterising a function that translates a state to an action (Li et al., 2019). Notably, one form of RL application is the use of self-learning trading bots, that generate their own trading policies and decision-making while continually adapting to changing environments in financial markets.

2.1.5 Deep Learning and Neural Networks:

Deep Learning essentially involves leveraging artificial neural networks (ANNs) with multiple hidden layers to automatically learn complex patterns from data (Sahu et al, 2023). One form of deep learning and neural networks are Recurrent Neural Networks (RNN), which involves a variant of ANNs that are designed for time-varying or sequential data, and RNNs have a supposed memory function due to the presence of a interconnect neurons that form loop-like structures (Jim et al, 2024; Mirete-Ferrer et al., 2022). A special type of RNNs are Long Short-Term Memory (LSTM) networks. They are designed to overcome the vanishing gradient problem in RNNs where long-term information that might be relevant to current data that the RNN is processing has been lost, and this done by selectively remembering long-term historical data, which makes LSTMs proficient in financial markets where data relevance changes significantly over time (Song and Choi, 2023; Cohen, 2022). Finally, another variant of RNNs, are the Gated Recurrent Units (GRU) which also address the vanishing gradient problem (lost long-term data problem), but work differently from LSTMs. GRUs work with fewer parameters than LSTMs; GRUs perform the selective remembrance of long-term data with simpler structure by forgetting and remembering data simultaneously which saves computational power and leads to faster training (Jim et al., 2024; Song and Choi, 2023). Both GRUs and LSTMs are used extensively in financial time-series forecasting and are present in many ensemble models; deep learning and neural networks in general have been proven to be useful in multifaceted and extensive ways for time-series forecasting. (Song and Choi, 2023; Cohen, 2022; Lee, 2022). Figure II cdepicts the decision-making process behind choosing a particular RNN architecture, as described earlier on the benefits and drawbacks of each type.

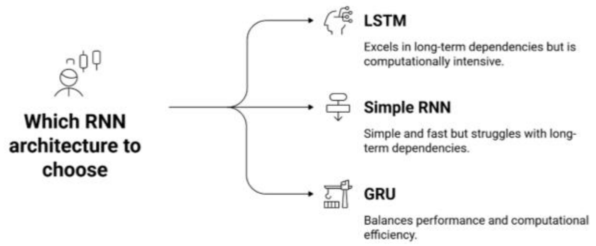

Figure II: RNN architecture overview for trading strategies

2.1.6. Sentiment analysis in trading

The influence of media and news in financial markets is undeniable. This has resulted in the rise of natural language processing (NLP) for sentiment analysis in trading which involves identifying the tone or mood in textual data from relevant news and media in relation to financial markets (Jim et al., 2024). Herd behaviour and other behavioural biases have been proven to take effect through social media and news, which influences stock prices and volatility (Kamal et al., 2022; Cohen, 2022). One specific example of the influence of media sentiment on the stock market is the false message of two bombs exploding near the White House in the US in 2013 on twitter causing a brief decline of USD 136.5 billion of the S&P 500's value (Kamal et al., 2022). These factors have led to trading applications of NLP for sentiment extraction from the media (Kamal et al., 2022). Noise and unreliability do pose a significant concern for sentiment analysis, but overall, this can be used in trading models (Rouf et al., 2021).

2.2. Literature review table of relevant papers

Table I: Key papers and their reviews

Author & Year	Model/methodology	Dataset Used	Key Findings	Limitations
Aloud & Alkhamees, 2021	Directional Change Reinforcement Learning (DCRL)	S&P500, NASDAQ, Dow Jones July 2015-July 2020	QDCRL performs better than DCRL	DCRL model can only trade one asset at a time
Chen and Huang, 2021	Multimodal learning	Financial news 2014-2020, S&P 500	RL and sentiment analysis combination better than individual forms	Overreliance on headlines.

Chen et al., 2020	Light Gradient Boosting Machine (LightGBM) algorithm	China's A-share market 2008-2018	Nonlinear relationships with pricing factors	No short-term analysis, no shorting strategies, low transparency
Chopra & Sharma, 2021	systematic literature review of 148 studies of neural and hybrid-neuro techniques for stock market prediction	Various indices and stock markets	Data pre-processing and complex dimensionality reduction needed	Existing literature is only partially successful
Lee, 2022	GRU-Attention deep neural network with technical indicators (RSI and BIAS)	DJIA index 2000-2017	Achieved 79.2% accuracy in experiments	Conclusions are specific to the RSI and BIAS indicators
Palaniappan et al., 2024	Review on HFT time series forecasting methods: STGPs, ANNs, SVR, decision trees, etc	HFT time series data from the S&P 500	STGP showed superiority, potential of quantum computing	Existing HFT forecasting methods are still unreliable

2.3. Challenges and limitations in ML based trading strategies

The inherent nature of financial data, which is noisy and volatile, makes it difficult for models to distinguish valuable signals from random market fluctuations. This core challenge significantly reduces a model's ability to generalize, identify stable patterns, and accurately predict price movements (Chopra & Sharma, 2021). Overfitting occurs when a model learns this random noise in its training data instead of the underlying patterns. This results in a model that is complex and fails to generalize, which leads to poor predictive performance on new unseen data (Hansen, 2020). The use of ML includes some ethical and regulatory challenges too. Key ethical concerns include algorithmic bias in the market, accountability for opaque "black box" models, and unequal market access due to resource disparity of computational power and data access (El Hajj & Hammoud, 2023, Pagliaro 2025). Regulators struggle to keep pace with rapid technological advances and enforce transparency. Furthermore, widespread AI use introduces systemic risks, as automated systems acting on similar strategies can cause market-amplifying "herding" behaviour or trigger flash crashes by reacting to false signals (El Hajj & Hammoud, 2023).

2.4. Emerging future trends in machine learning

2.4.1. Ensemble and hybrid models

- **Ensemble and Hybrid approaches:** A trend in the development of ensemble and hybrid models that combine multiple AI techniques to enhance accuracy in forecasting and for robustness is clearly seen (Chopra & Sharma, 2021). This includes combining traditional ML methods with deep learning architectures like CNNs, LSTMs, GRUs, etc, which are effective for time series forecasting (Mirete-Ferrer et al., 2022; Dakalbab et al., 2024). Hybrid models such as one combining LSTM for technical analysis with other methods for news sentiment analysis are proving to yield more reliable results (Li & Bastos, 2020; Dakalbab et al., 2024; Chopra & Sharma, 2021).
- **Dynamic and Adaptive Trading Systems:** The focus is shifting towards systems that can dynamically select the most suitable agent for certain market conditions. It is crucial for these systems to be designed for adaptability which allows them to respond effectively to frequent changes in the market environment, which can combat overfitting too (Sahu et al., 2023; Cohen, 2022).

2.4.2. Data utilization and multimodality

- **Broader data sources:** There is more exploration occurring to incorporate wider forms of data sources beyond the average traditional price data in strategies with ML. This includes technical and fundamental indicators, macroeconomic factors, industry policies, market news, and social media sentiment (Li & Bastos, 2021;). Multimodal learning which merges these different forms of data is being focused on to enhance model performance (Chen & Huang, 2021)
- **Multimodal Data Fusion:** A trend building from the point above involves fusing information from diverse modalities, such as combining quantitative price data with qualitative news sentiment. The primary challenge lies in developing effective methods to merge these data sources into an informative whole dataset (Mirete-Ferrer, 2022).
- **Advanced pre-processing:** As financial data is in nature noisy and high-dimensional, preprocessing is needed. This involves rigorous data cleaning, scaling, and transformation (Chopra & Sharma, 2021).

2.4.3. New computational paradigms:

- **Quantum computing and QML:** Quantum computing is emerging as a future solution for the computational challenges of HFT forecasting, offering new ways to manage massive datasets and reduce uncertainty (Palaniappan et al., 2024). The budding field of QML which merges quantum computing with ML has the potential to revolutionize financial data analysis and strategy development (Palaniappan et al., 2024)

2.4.4. Interpretability and Explainable AI (XAI)

- **Addressing the "Black Box" problem:** Due to complexity from ML models, particularly deep neural networks, the internal decision making is opaque to human users (Sahu et al, 2023). XAI is a critical area for future research, which will make the decisions made by ML clearer in trading strategies, which would easily satisfy regulatory concerns in the financial industry (Pagliaro, 2025; Dakalbab et al., 2024).

2.5. Synthesis and Identification of Research Gap

Following an extensive review of the relevant literature, this study has examined the current landscape of machine learning applications in financial trading and identifies both established techniques and nascent trends. This synthesis enabled the identification of the critical research gap that while existing literature describes various machine learning applications, there is limited analysis of how emerging trends like Explainable AI (XAI) and Multimodal AI can resolve core adoption barriers, particularly the complexity and the "black box" problem inherent in many advanced models. Building upon these insights, this study formulates a rigorous research methodology designed to address the stated research questions and hypotheses. The proposed methodology utilizes a qualitative case study approach employing the Diffusion of Innovations (DOI) theory as the primary analytical framework. This approach that aligns the methodological framework with the key gaps, ensures that the analysis is targeted and capable of generating structured conclusions on the adoption potential and future impact of transparent AI in financial markets.

3. Research Methodology

To investigate the identified research gaps, this study will use a qualitative, interpretive case study methodology. This approach is optimal for conducting an investigation into a complex real-world phenomenon such as the diffusion of advanced technological systems in financial markets. The Diffusion of Innovations (DOI) theory serves as the primary analytical lens for this research. The five core dimensions of the theory are Relative Advantage, Compatibility, Complexity, Trialability, and Observability. These dimensions will be used as a framework to systematically encode and analyse the characteristics of each case study to establish barriers and adoption potential of ML in financial markets.

3.1. Explaining the Diffusion of Innovations (DOI) Theory

The Diffusion of Innovations (DOI) theory, a seminal framework by Everett M. Rogers, provides a comprehensive explanation for how new ideas, practices, and technologies spread through a social system over time. Originating not from high technology but from sociological studies of agricultural practices in the 1930s and 40s, the theory defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (García-Avilés, 2020). At its core, DOI is framed as an "uncertainty reduction process." An innovation is any idea or object perceived as new, and this newness inherently creates uncertainty for potential adopters. While a technology is often designed to reduce uncertainty in cause-effect relationships like making an outcome more predictable, Rogers argues that its novelty parallelly creates another kind of uncertainty. This motivates individuals to seek information and engage in communication to evaluate the new idea which is the driver of diffusion (García-Avilés, 2020). Rogers identified five key attributes or dimensions of an innovation that directly influence an individual's decision to adopt. These attributes provide a robust framework for analysing the adoption process (García-Avilés, 2020).

IDT Dimension 1, Relative Advantage: This is the degree to which an innovation is perceived as being better than the previous idea that is directly related to this new innovation. The advantage can be measured in economic terms, social prestige, convenience, or satisfaction. A high perceived relative advantage reduces uncertainty about the innovation's value and provides a strong motivation for adoption. If the new method is clearly more profitable or efficient, then the risk of adopting it seems lower (García-Avilés, 2020).

IDT Dimension 2, Compatibility: Compatibility refers to how consistent the innovation is with the existing values, past experiences, and needs of potential adopters. If an innovation requires a significant change in an individual's or organization's established workflow, beliefs, or infrastructure, it will face greater resistance. High compatibility smooths the adoption path by reducing the uncertainty associated with integration and psychological friction (García-Avilés, 2020).

IDT Dimension 3, Complexity: This is the degree to which an innovation is perceived as difficult to understand and use. Innovations that are simple to grasp are adopted more rapidly than those that require the adopter to develop new skills and understandings; high complexity increases uncertainty as potential adopters may doubt their ability to use the innovation effectively (García-Avilés, 2020).

IDT Dimension 4, Trialability & Observability: These two dimensions are often considered together as they relate to seeing the innovation in action.

- **Trialability** is the degree to which an innovation may be experimented with on a limited basis. The ability to "test drive" an innovation before making a full commitment is a critical tool for reducing uncertainty. Pilot programs and free trials directly address this (García-Avilés, 2020).
- **Observability** is the degree to which the results of an innovation are visible to others. If the benefits are easily seen and communicated there is powerful social proof and encourages others to adopt. The more visible the positive results, the less uncertain the innovation appears to onlookers (García-Avilés, 2020).

3.2. Research Questions

1. How do emerging AI paradigms such as Explainable AI (XAI) and Multimodal AI address the primary adoption barriers of Machine Learning in the context of algorithmic trading?

2. What are the potential impacts of resolving the barriers of implementing machine learning in algorithmic trading, and consequently what are the future adoption trends of machine learning in financial markets from reduced barriers?

3.3. Hypotheses

1. The adoption rate of advanced machine learning models in trading is primarily constrained not by their performance (Relative Advantage), but by their perceived Complexity and low Observability (the "black box" problem).

2. The integration of Explainable AI (XAI) into ML trading systems directly mitigates these adoption barriers by significantly reducing perceived Complexity and increasing Observability, thereby enhancing user trust and institutional Compatibility.

4. Analysis and findings

4.1. Caselet 1: AI's Transformative Role in Modern Stock Trading Strategies

The application of Artificial Intelligence (AI) in stock trading was initially only available to large corporations. Recent advancements in deep learning (DL) and machine learning (ML) techniques have led to a transformation in how investors approach decision-making and portfolio management in financial markets. This evolution is critical for developing future trading strategies via machine learning (Chowdhury & Chittagong Independent University, 2019).

Key Impacts of AI in Stock Trading:

• **Objective and Expedient Decision-Making**: The fundamental goal of stock market trading is to generate profit. AI systems excel by making quick decisions with the highest accuracy especially since they do not experience emotional factors such as greed and fear that often lead to inaccurate and wrong human decisions. This capability is a significant advantage along with how AI systems can process information and execute trading decisions at incredible speeds, speeds at which a human cannot keep up with, and this results in superior trading strategies that generate more profit (Chowdhury & Chittagong Independent University, 2019).

• **Comprehensive Data Analysis**: AI's strength lies in its ability to consider diverse and pragmatic factors. This includes analyzing price variations, social media sentiment, macroeconomic data, financial news on listed companies, government decisions, and more. Advanced AI algorithms can monitor a number of these data sources in real-time, generating invaluable insights not normally possible through human or programmed algorithmic trading strategies. This allows trading strategies to react to a wide-range of data accordingly and swiftly, benefiting the trader immensely as it is impossible to monitor so many data-sources consistently and as widely as an AI system (Chowdhury & Chittagong Independent University, 2019).

• **Revenue Generation and Risk Mitigation**: The financial impact of AI is substantial. For instance, a UK-based research firm observed that 45 percent of revenues from stock trading on Wall Street are generated by AI-driven decisions. AI also plays a crucial role in alleviating risk by continuously analyzing market fluctuations, and advanced AI and deep learning can effectively spot and prevent risky transactions (Chowdhury & Chittagong Independent University, 2019).

• **Continuous Learning and Adaptation**: AI-powered trading systems are designed to learn and adapt from historical data, which continuously improves their decision-making capabilities. Through machine learning algorithms, these systems identify patterns and trends in stock prices and market behaviour while recognizing the effectiveness of specific trading strategies from historical data. This iterative learning allows AI models to fine-tune their predictions and recommendations over time, leading to higher accuracy rates and better trading outcomes, and to prevent overfitting to historical data, machine learning algorithms can be subject to more contemporary data too (Chowdhury & Chittagong Independent University, 2019).

• **Automation and Efficiency (High-Frequency Trading - HFT)**: AI significantly contributes to market speed and efficiency by automating trading processes. High-frequency trading (HFT), in particular, relies heavily on AI algorithms to execute trades at millisecond speeds (Chowdhury & Chittagong Independent University, 2019).

• **Specialized AI Tools**: Concrete examples of AI tools in action include "Trade Schedule," a smart tool used by traders in Asian stock markets to determine optimal buy and sell times, and "Aidiya," an AI-based tool in Hong Kong that forms a hedge fund without human intervention. These tools and others benefit traders without much cost specifically to traders (Chowdhury & Chittagong Independent University, 2019).

• **Challenges**: Despite these advantages, the rapid advances of AI in stock trading presents challenges. A significant concern is the potential for biased behaviour in AI models if they are trained on biased or incomplete data. Such biases can cause the models to miss critical market signals. Therefore, it is crucial to ensure that the data used to train AI models is representative and diverse to mitigate these inherent biases (Chowdhury & Chittagong Independent University, 2019).

AI systems driven by vast real-time data have revolutionised stock trading with the capacity to make fast, accurate, and emotionless choices. These systems' continuous learning and adaptability lead to improved efficiency, increased profitability, reduced costs, and enhanced risk management. Reducing overfitting and data biases is a critical area for further research and development to improve these AI systems' trading abilities (Chowdhury & Chittagong Independent University, 2019).

4.2. Caselet 2: Transparent Stock Prediction with AI Transformers for Financial Literacy

The effective interpretation of complex data and the utilization of advanced forecasting tools are paramount for informed decision-making in the dynamic and opaque realm of financial markets, which particularly concerns financial literacy. To address this challenge, a novel approach proposes the integration of transformer-based time series models with Explainable Artificial Intelligence (XAI) to enhance both the interpretability and accuracy of stock price predictions (Çalık et al., 2025). This methodology is explored in the context of emerging markets, specifically focusing on the daily stock prices of the five highest-volume banks listed in the BIST100 index alongside the XBANK and XU100 indices in the Turkish banking sector, spanning from January 2015 to March 2025. The core predictive models used include DLinear, LTSNet, Vanilla Transformer, and Time Series Transformer (TST), with their input features significantly enhanced by a wide array of technical indicators (Çalık et al., 2025). A key contribution lies in the adoption of XAI techniques, specifically SHAP and LIME, to provide crucial transparency into how individual features influence model outputs. This is particularly vital as traditional AI models can often function as opaque "black boxes", as detailed earlier. By detailing the internal mechanisms and the rationale behind predictions, XAI enhances user confidence and prevents investors from relying blindly on opaque systems and hence directly increasing financial literacy (Çalık et al., 2025). The results of this integrated framework demonstrate the strong predictive capabilities of transformer models and underscore the potential of interpretable machine learning to help individuals in making informed investment decisions and engaging in financial markets. This approach provides a policy-relevant framework for combining advanced AI technologies with financial literacy goals, and is tailored for the needs of developing and emerging markets (Çalık et al., 2025). This aligns with broader trends in quantitative finance where machine learning (ML), deep learning (DL), and reinforcement learning (RL) are increasingly utilized for tasks such as financial signal representation, trading, and portfolio management across various assets. The emphasis on interpretability and comprehensive validation remains a critical area of research as AI applications in finance continue to evolve (Çalık et al., 2025).

4.3. Caselet 3: AI Trading – Revolutionizing Financial Markets

The Evolution and Mechanics of AI-Powered Trading

Artificial Intelligence (AI) trading utilizes advanced technologies to analyse vast market data and generate financial predictions to automate trading signals, such as machine learning (ML), deep learning (DL), and natural language processing (NLP). This is a significant evolution from traditional algorithmic trading, which relies on static models that must be manually updated. In contrast, AI-powered systems are dynamic as they learn from both historical and real-time data while independently identifying patterns and adapting to market volatility to continuously improve their predictive accuracy. The sheer volume of information these systems can process far exceed the capabilities of human traders or older software (Khropatyy, 2024). The operations of an AI trading system is methodical. It begins with extensive data collection, gathering not only traditional market data like prices and volumes but also alternative data from non-traditional sources like social media sentiment or web traffic. This raw data then undergoes feature extraction, where it is cleansed and the most relevant predictive variables are isolated. In the model training phase, ML algorithms are trained on this historical data to recognize profitable patterns, with their reliability being verified through back-testing. Once deployed, the system analyses real-time data to generate trade signals and can execute them automatically, often within milliseconds. The AI's capacity for continuous learning, which involves constantly monitoring its performance and refining its models with new data, is a significant advantage (Khropatyy, 2024).

Transformative Impact and Core Technologies

AI is fundamentally reshaping the investment landscape by enabling powerful data analytics and bringing new applications. This includes high-speed algorithmic trading, high-frequency trading (HFT), automated robo-advisors for personalized portfolio management, and sophisticated predictive analytics. These tools allow firms to identify market patterns, evaluate strategies, and automate workflows with speed and efficiency (Khropatyy, 2024). This transformation is driven by a series of technological innovations:

Big Data Analytics: Provides the capability to process the enormous volumes of information required for real-time analysis.

Machine Learning (ML): Utilizes algorithms (supervised, unsupervised, and reinforcement) to identify trends and build predictive models.

Deep Learning (DL): Employs complex neural networks to uncover subtle relationships in data, ideal for portfolio management and analyzing market sentiment from news or social media.

Natural Language Processing (NLP): Enables the interpretation of human language from text-based sources to gauge market sentiment.

Cloud Computing: Offers the scalable and flexible infrastructure necessary to support the intensive data processing demands of AI platforms.

Practical Applications and Inherent Challenges

The real-world effectiveness of AI trading is evident in cases where platforms have accurately predicted corporate earning drops by analyzing alternative data, which were sometimes in direct contradiction to expert forecasts. Hedge funds like Renaissance Technologies and Bridgewater Associates have successfully integrated AI into their operations (Khropatyy, 2024). Despite its advantages, developing effective AI trading solutions presents significant hurdles. Key challenges include ensuring high data quality and volume, building a scalable infrastructure for real-time processing, and overcoming the lack of interpretability. Many advanced models function as “black boxes," making it difficult to understand the logic behind their predictions, which poses a risk management and trust issue (Khropatyy, 2024).

To mitigate these challenges, best practices in development include defining clear requirements, using high-quality data, selecting appropriate algorithms, and rigorously testing models in simulated environments before deployment. Monitoring and updating continuously are crucial to ensure the system remains effective over time (Khropatyy, 2024).

4.4. Explaining the Diffusion of Innovations (DOI) Theory

The Diffusion of Innovations (DOI) theory, a seminal framework by Everett M. Rogers, provides a comprehensive explanation for how new ideas, practices, and technologies spread through a social system over time. Originating not from high technology but from sociological studies of agricultural practices in the 1930s and 40s, the theory defines diffusion as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (García-Avilés, 2020). At its core, DOI is framed as an “uncertainty reduction process.” An innovation is any idea or object perceived as new, and this newness inherently creates uncertainty for potential adopters. While a technology is often designed to reduce uncertainty in cause-effect relationships like making an outcome more predictable, Rogers argues that its novelty parallelly creates another kind of uncertainty. This motivates individuals to seek information and engage in communication to evaluate the new idea which is the driver of diffusion (García-Avilés, 2020). Rogers identified five key attributes or dimensions of an innovation that directly influence an individual's decision to adopt. These attributes provide a robust framework for analyzing the adoption process (García-Avilés, 2020).

IDT Dimension 1, Relative Advantage: This is the degree to which an innovation is perceived as being better than the previous idea that is directly related to this new innovation. The advantage can be measured in economic terms, social prestige, convenience, or satisfaction. A high perceived relative advantage reduces uncertainty about the innovation's value and provides a strong motivation for adoption. If the new method is clearly more profitable or efficient, then the risk of adopting it seems lower (García-Avilés, 2020).

IDT Dimension 2, Compatibility: Compatibility refers to how consistent the innovation is with the existing values, past experiences, and needs of potential adopters. If an innovation requires a significant change in an individual's or organization's established workflow, beliefs, or infrastructure, it will face greater resistance. High compatibility smooths the adoption path by reducing the uncertainty associated with integration and psychological friction (García-Avilés, 2020).

IDT Dimension 3, Complexity: This is the degree to which an innovation is perceived as difficult to understand and use. Innovations that are simple to grasp are adopted more rapidly than those that require the adopter to develop new skills and understandings; high complexity increases uncertainty as potential adopters may doubt their ability to use the innovation effectively (García-Avilés, 2020).

IDT Dimension 4, Trialability & Observability: These two dimensions are often considered together as they relate to seeing the innovation in action.

- **Trialability** is the degree to which an innovation may be experimented with on a limited basis. The ability to "test drive" an innovation before making a full commitment is a critical tool for reducing uncertainty. Pilot programs and free trials directly address this (García-Avilés, 2020).
- **Observability** is the degree to which the results of an innovation are visible to others. If the benefits are easily seen and communicated there is powerful social proof and encourages others to adopt. The more visible the positive results, the less uncertain the innovation appears to onlookers (García-Avilés, 2020).

Table II: Innovation Diffusion Theory - Framework Mapping for each case study

Case Study	Innovation Type & Focus	IDT Dimension 1: Relative Advantage	IDT Dimension 2: Compatibility	IDT Dimension 3: Complexity	IDT Dimension 4: Trialability & Observability
Case 1: AI in Stock Trading	Regression-based trading strategies integrating expert knowledge for explainability and actionable insights.	Faster, emotion-free decisions improve accuracy and reduce costs.	Fits profit-maximization goals but clashes with traditional, human-led trading.	“Black box" nature and potential for bias create challenges in trust and understanding.	Financial returns are highly observable but the AI's decision-making process is opaque.
Case 2: Transformer + XAI for Financial Literacy	Advance transformer models with XAI (SHAP, LIME) for accurate, interpretable predictions to enhance financial literacy and stock trading	High predictive accuracy combined with transparency immensely helps investor decision-making.	Meets the demand for transparent, educational tools, especially for non-experts but clashes with human-led trading.	XAI techniques (SHAP, LIME) reduce model complexity, making it more accessible to wide audiences.	XAI makes the model's reasoning observable; performance is proven via benchmarking.
Case 3: ML, DL, NLP, and Ensemble Approaches	Integrated AI ecosystem (ML, DL, NLP) with diverse data streams and robust preprocessing.	Superior accuracy and real-time adaptation by learning from diverse data sources.	Works well with high-frequency trading and automates tasks for human analysts; complements expert input. Clashes extremely with traditional human-led trading.	High complexity from data, infrastructure, and expertise needs; "black box" issue persists, but modular design and robust testing reduce barriers.	Iterative model updates and visible portfolio gains permit staged adoption; Tested via backtesting so success is observable in tool performance.

4.5. Key Comparison and Contrast Patterns in the DOI Analysis of the case studies

High Advantage vs. High Complexity Trade-Off: The most dominant pattern is that the innovations offer a massive Relative Advantage in metrics like speed, accuracy, and profit, but this comes at the cost of high Complexity. The "black box" nature of AI is the single biggest barrier to adoption mentioned in case 1 and 3, but case 2's use of XAI is a direct attempt to mitigate this very issue, proving that Complexity is the key counter-force to the technology's inherent advantages. (Çalık et al., 2025; Chowdhury & Chittagong Independent University, 2019; Khropatyy, 2024).

The "Human vs. Machine" Compatibility Conflict: A consistent theme is the clash between the innovations and traditional, human-led trading. While the technology is highly compatible with goals of profit maximization and high-frequency trading, it creates significant friction with established human workflows and trust. This reveals a fundamental incompatibility with the institutional culture and norms of conventional human-centric trading. (Çalık et al., 2025; Chowdhury & Chittagong Independent University, 2019; Khropatyy, 2024).

Observability of Results, Not Process: All cases show that the outcomes of the innovation are highly observable (e.g., financial returns, benchmark performance), which drives interest in these innovations. However, the internal decision-making process remains opaque in cases 1 and 3, hindering full trust and adoption, especially policy and regulatory wise, that high returns alone cannot overcome. (Çalık et al., 2025; Chowdhury & Chittagong Independent University, 2019; Khropatyy, 2024).

The Role of XAI as a "Complexity Reducer": Case 2 stands out as a unique strategic response to the primary challenge. By using techniques like SHAP and LIME, the innovation in Case 2 makes the AI's reasoning process itself observable, directly addressing the "black box" problem. This XAI usage directly reduces the Complexity and improves the Observability of the AI's process, making it a solution to the main problem identified in the other cases. This suggests that the next wave of successful AI adoption may depend less on increasing predictive power and more on enhancing transparency and trust (Çalık et al., 2025; Chowdhury & Chittagong Independent University, 2019; Khropatyy, 2024).

5. Discussion

Existing literature widely emphasizes the predictive strength of machine learning in trading such as the superiority of ensemble and hybrid models over single classifiers. For instance, Pagliaro (2025) conducted a critical reassessment and found that ensemble methods like the Extra Trees Classifier consistently outperform other approaches, achieving directional accuracy as high as 86.1% for 10-day prediction windows. Further, Li et al. (2019) proposed a novel DRL framework that integrates Stacked Denoising Autoencoders (SDAEs) for robust feature extraction from noisy financial data and Long Short-Term Memory (LSTM) units to capture temporal dependencies. Their results demonstrate that this approach, particularly the SDAES-LSTM Asynchronous Advantage Actor-Critic (A3C) model, consistently outperforms baseline DRL agents, achieving an annualized return of 85.33% and a Sharpe ratio of 4.3 on APPL stock. These studies show high accuracy but sometimes little economic benefit; however, the largest concern is that these studies repeatedly show limited interpretability in many examined models, leading to concerns about algorithmic opacity, market fairness, and regulatory compliance (Pagliaro, 2025; Hansen, 2020; Hajj & Hammoud, 2023).

Our case-based analysis from the DOI framework transitions the scholarly discourse from a predominant focus on predictive accuracy toward the critical adoption dynamics that govern the integration of machine learning in financial markets. The investigation reveals that while the Relative Advantage of advanced AI is well-established, its diffusion is fundamentally constrained by high Complexity and a corresponding lack of Observability into the "black box" decision-making process. This study posits that emerging paradigms such as Explainable AI (XAI) and Multimodal AI are not merely incremental technological advancements but are strategic innovations that directly address these core adoption barriers. The primary barrier to ML adoption is the trade-off between Relative Advantage and Complexity, which is an aspect that XAI is uniquely positioned to resolve. XAI serves to reduce model complexity by transforming opaque processes into interpretable outputs, thereby enhancing trust and satisfying both institutional internal governance and external regulatory demands. Further, Multimodal AI improves Compatibility by fusing diverse data streams in a manner that can complement existing institutional workflows through the use of data streams that organizations use currently, thus lowering organizational barriers to implementation. The analysis suggests that firms adopting these transparent yet sophisticated models will report greater institutional compatibility and lower organizational inertia while implementing these models in financial markets.

Contrasting prior scholarship which is primarily focused on maximizing predictive accuracy and economic performance (Li et al., 2019), our study demonstrates that interpretability and institutional compatibility are becoming equally critical determinants of adoption. While previous authors identify the opaque "black box" nature of advanced models as a significant implementation challenge (Hajj & Hammoud, 2023), our DOI-based framework shows that the co-evolution of XAI and regulatory compliance can reposition this opacity as a solvable barrier. Furthermore, we posit that the application of XAI, as detailed in case 2, offers clear Trialability and Observability advantages that are largely unexamined in prior technical studies. XAI enables institutions to validate the model's reasoning along with the outcomes, which reduces potential risks from decision errors and fosters trust. Thus, this paper's framework extends beyond a narrow focus on accuracy toward the broader socio-technical dynamics of ML adoption, while aligning the technological potential of ML with the practical requirements of policy compliance and governance standards in financial markets.

5.1. Limitations

This paper is limited by its qualitative nature and reliance on case-based analysis of diffusion, which limits empirical confirmation. The findings remain bounded by the contexts of the cases analysed, and so generalizability across all financial markets, investor demographics, and institutional settings requires quantitative validation for more robust analysis. Additionally, systemic risks such as herding effects from large-scale AI use were considered in a conceptual manner but not measured longitudinally. The analysis on QML is highlighted as a potential future trend; however, as the technology is still in its early stages, analysing its diffusion characteristics and potential market effect remains conceptual.

5.2. Future scope

Several avenues for future research extend naturally from this work. First, the qualitative findings presented here invite quantitative validation through surveys of financial institutions to statistically measure the impact of DOI dimensions such as complexity, compatibility, and trialability on adoption decisions. Beyond the firm level, a longitudinal analysis of systemic risk is needed to assess the long-term effects of widespread AI and XAI adoption on market stability, especially in financial environments prone to algorithmic herding. Further, as QML matures, research will be required to investigate how its diffusion could redefine relative advantage while amplifying complexity, which could potentially disrupt established adoption trajectories. Finally, the dynamic interplay between technology and governance needs further exploration through regulatory co-evolution studies to examine how policy requirements for AI explainability and XAI implementations co-develop to shape the future of algorithmic trading.

6. Conclusion

This paper identified that adoption barriers tied to opacity and complexity of ML models in trading remain underexplored since existing literature emphasizes the technical superiority of ML in trading. Applying the DOI framework, the analysis shows that XAI directly addresses these barriers by increasing interpretability and hence reduces potential attached risks when compared with opaque ML model adoption. Multimodal AI also addresses adoption barriers by increasing compatibility of these technical models with data structures that organizations may already use. The proposed framework reframes the conversation around ML adoption, shifting the focus from a singular pursuit of predictive accuracy toward an integrated approach that balances technical performance with transparency, regulatory alignment, and institutional trust. By positioning interpretability as a central pillar for sustainable financial innovation, this work contributes to both the academic literature and the practical discourse on deploying trustworthy and effective AI in modern trading environments. Future research should build upon this qualitative foundation through quantitative validation, longitudinal systemic analysis of market risks, longitudinal systemic analysis, and deep examination into the diffusion of frontier technologies such as QML and the co-evolution of XAI with financial regulation.

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