



ISSN: 2959-6386 (Online), Volume 3, Issue 3, September 2024

Journal of Knowledge Learning and Science Technology

Journal homepage: <https://jklst.org/index.php/home>



ROBO-ADVISORS: REVOLUTIONIZING WEALTH MANAGEMENT THROUGH THE INTEGRATION OF BIG DATA AND ARTIFICIAL INTELLIGENCE IN ALGORITHMIC TRADING STRATEGIES

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Abstract

This article explores how robo-advisors are transforming wealth management by integrating big data and artificial intelligence into algorithmic trading strategies. It discusses the ability of AI technologies, such as machine learning and natural language processing, to analyze vast amounts of data, identify market patterns, and optimize investment portfolios. Additionally, the article addresses the challenges of data quality, algorithmic transparency, and regulatory compliance, while highlighting the potential for AI-driven innovations to enhance investment decision-making and drive the future of financial services.

Keywords: Robo-Advisors; Big Data; Artificial Intelligence; Algorithmic Trading

Article Information:

Received: 22-Jan-24

Accepted: 20-March-24

Online: 30-May-24

Published: 25-Sep-24

DOI: <https://doi.org/10.60087/jklst.vol3.n3.p33-45>

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1. INTRODUCTION

The financial services industry is undergoing an unprecedented transformation, driven by the rapid development of artificial intelligence (AI) and advanced natural language processing technologies such as ChatGPT. Over the past few years, advances in AI technology have made many traditional financial services more efficient, intelligent, and personalized. From customer service to investment management, the application of AI is revolutionizing the way the financial industry operates, bringing significant efficiency gains and cost reductions. [1] One notable change is the rise of [2-3] Robo-Advisors. Robo-advisors use AI algorithms to provide users with automated, personalized investment advice and asset management services. These algorithms are able to analyze large amounts of market data, identify trading opportunities, and automate buying and selling operations based on preset strategies. With the continuous progress of AI technology, algorithmic trading has become more and more intelligent and can

adapt to market changes in real time, further improving the stability and efficiency of the financial market.

Technologies such as AI and ChatGPT are not only changing the way financial services are delivered, they are also profoundly impacting the customer experience. Using natural language processing technology, ChatGPT is able to have real-time conversations with customers, answer questions, provide financial advice, and even assist with complex financial transactions. [4][5]This highly personalized and responsive service model greatly improves customer satisfaction and enhances interaction and trust between customers and financial institutions.

Taken together, the emergence of AI and ChatGPT is profoundly reshaping the financial services industry. Innovative applications such as robo-advisors and algorithmic trading not only improve operational efficiency and service quality, but also provide customers with more intelligent and personalized financial services. With the further development of the technology, it is foreseeable that AI will continue to drive profound changes in the financial industry in the future, creating more new opportunities and challenges.

2. RELATED WORKS

2.1 Robo-Advisors

Robo-advisors are automated financial advisors and investment platforms, and robo-advisors' systems are combined using software algorithms. When you sign up for the robo-advisor, you will be asked to answer a number of questions, such as:

- Your age
- When do you plan to retire
- What type of investor are you (conservative or aggressive)

Robo-advisors use algorithms to manage your portfolio, rather than humans. Although some robo-advisors now require a minimum account, the threshold is usually very low, such as \$500[6].

A robo-advisor will let a computer manage your investment account based on your style and preferences. Most robo-advisers typically charge relatively low fixed fees, such as 0.25% of the total investment per year, while traditional financial advisers tend to charge higher prices. [7]Robo-advisors are great for automated investing because they use your preferences and style to invest and manage your money for you. However, traditional financial advisers don't make you a priority. Robo-advisors tend to invest in index funds and exchange-traded funds to keep costs low. A traditional financial advisor can guide you to invest in different types of securities, but at the same time, the cost will be higher.

1. Robo-advisor Benefits:

The rapid rise of Robo-Advisors in the financial services industry is largely due to their significant advantages. First, immediacy and diversity are the outstanding characteristics of robo-advisors. [8-10]While traditional financial advisers allow investors to choose their own stocks and other securities, this also carries the risk of potentially large losses. In contrast, robo-advisors diversify their portfolios by investing in index funds and exchange-traded funds

(ETFs), thereby minimizing investment risk. Second, robo-advisors typically don't have minimum investment requirements, and even if they do, they're usually around \$500 or less, making it easy for more investors to enter the market. In addition, robo-advisors have significantly reduced operating costs due to reduced reliance on human resources, thus charging lower fees, making the investment more economical.

Moreover, the robo-advisor platform interface design is simple and easy to operate, and most users can easily use it, which significantly improves the user experience. Another important benefit is that robo-advisors are socially responsible, often advising clients on socially valuable investments without paying a premium. Collectively, these advantages give robo-advisors a strong competitive advantage in providing efficient, economical and responsible investment services.

2. Disadvantages of robo-advisors:

However, robo-advisors also have some drawbacks that cannot be ignored. First of all, communication with people is very limited. Although robo-advisors' customer service systems are reliable, users rarely have access to personalized expert advice. Even if some robo-advisors provide expert advice, this usually requires an additional fee, which limits its popularity to some extent. Second, the investment options are limited. Most robo-advisors primarily invest their clients' money in ETFs[11], which are very effective for diversifying portfolios, but too narrow a range of options for investors who want to try different types of securities. So people who want to invest more broadly may still need to rely on a traditional financial adviser.

Finally, robo-advisors aren't for everyone. While robo-advisors are a good option for most investors, not everyone is suitable for such a service. If an investor has more complex financial needs, such as retirement planning, tax strategy, and future personal financial goals that need to be integrated, the standardized services of a robo-adviser may not be able to meet their individual needs. Therefore, for those investors who need comprehensive financial planning and professional advice, traditional financial advisers remain irreplaceable. To sum up, although robo-advisors have many advantages, their disadvantages also require investors to consider carefully when choosing.

2.2 Trading decision

Traditional financial decision-making is based on experience, while digital finance uses automatic data flow and intelligent algorithms to resolve the uncertainty of complex systems[12]. By building a decision-making system based on customer insight, the mode and link of decision-making will change greatly. Through continuous mining, aggregation and analysis of customer data, a new decision-making mechanism based on "data + algorithm" is built to replace traditional empirical decision-making, and decision-making will be more efficient, scientific, accurate and timely. Therefore, the collision between the "massive" customer information in the Internet environment and the "small" customer information mastered by financial institutions will undoubtedly have a major impact on the "industrial reengineering" of the future financial service model.

Through the collection of massive dimensions of data, customers are placed in various scenarios such as social networking and shopping, which is conducive to judging the

authenticity of customer behaviors, and it is easy to realize process tracking and accurately understand each customer [13-15]. Digital twin technology can also be used to build a digital twin system of interactive mapping, real-time feedback and decision optimization between the real economic system and the digital twin economy, and the rapid iteration of the digital world can be used to construct a digital financial decision optimization mechanism.

However, the normal low-frequency decision-making mechanism can not adapt to the high-frequency decision-making needs brought by the frequent emergencies, which requires the organizational decision-making mechanism in the digital era to adapt from the relatively determinative low-frequency decision-making to the uncertain high-frequency decision-making. In the process of trading decision making, it is not only a technical problem to move from relatively determinative low-frequency decision making to uncertain high-frequency decision making, which requires digital financial institutions to build a high-frequency, multi-center, short-link decision-making mechanism to meet the needs of high-frequency decision making.

2.3 Automated quantitative trading robots

Quantitative trading systems, also known as automated trading robots, utilize algorithmic strategies to analyze market data and execute trades with precision and speed. When engaging in quantitative trading, it is crucial to consider the following aspects [16]:

1. Selecting Appropriate Trading Strategies

The success of quantitative trading largely depends on the effectiveness of the trading strategy employed. When utilizing automated trading robots, it is essential to carefully select suitable trading strategies. Typically, quantitative trading strategies can be categorized into trend-following strategies, mean-reversion strategies, transaction cost strategies, among others [17]. Additionally, the applicability and risk management capabilities of the trading strategies should be considered to ensure stability and profitability.

2. Implementing Reasonable Risk Control Measures

Risk management is a critical component of quantitative trading. Appropriate risk control measures should be set based on individual risk preferences and market conditions. These measures may include limiting the trading amount, setting stop-loss orders, and controlling position sizes. Such measures help to prevent significant losses and safeguard capital.

3. Monitoring Market Volatility and Black Swan Events

Market volatility and black swan events are inherently unpredictable. Therefore, it is vital to continuously monitor these factors when using automated trading robots. In the event of unusual market conditions, traders should promptly adjust their trading strategies or execute stop-loss orders to mitigate potential losses.

4. Ensuring Data Accuracy and Integrity

Quantitative trading algorithms rely heavily on extensive data analysis and model construction. Thus, ensuring the accuracy and integrity of data is paramount. Reliable data sources and comprehensive data sets must be secured. Additionally, stringent data quality control and data cleansing procedures should be implemented to avoid errors and distortions that could adversely affect trading outcomes [18].

5. Maintaining Continuity and Timeliness in Trading

For quantitative trading to be effective, it must be conducted continuously to maintain stability and optimal performance. Therefore, appropriate trading frequency and timing should be established to ensure the persistence and timeliness of trades. Furthermore, it is crucial to keep track of data updates and model adjustments, and to revise trading strategies and parameters promptly to adapt to market changes.

In summary, the use of automated trading robots in quantitative trading requires careful consideration and meticulous execution. To ensure stability and profitability, traders must select appropriate trading strategies, implement sound risk control measures, monitor market volatility and black swan events, ensure data accuracy and integrity, and maintain the continuity and timeliness of trading activities.

3 The robot quantifies the trading operation process

By using computer technology to screen out high probability events from historical data as characteristic factors, investment strategies are formulated to reduce the impact of investor sentiment fluctuations. The era of big data provides sufficient and comprehensive analytical data for the application of artificial intelligence. As the core part of artificial intelligence, machine learning plays a role in three aspects: data extraction, data processing, and construction strategy [19-21]. Data extraction includes obtaining images, sounds, videos and other information from the Internet to improve research efficiency and accuracy. In terms of data processing, machine learning can reduce the dimension of massive data, store unstructured data as structured data and analyze it. In terms of building strategies, machine learning algorithms can be used to mine and analyze nonlinear relationships to build investment strategies that are expected to exceed the return on investment of linear relationships.

3.1 Common machine learning algorithms

In the traditional quantitative trading model, the decision tree can make predictions according to the characteristics of the data set, and build a tree-like decision model through the data to work, and each branch represents a different decision or result [22].

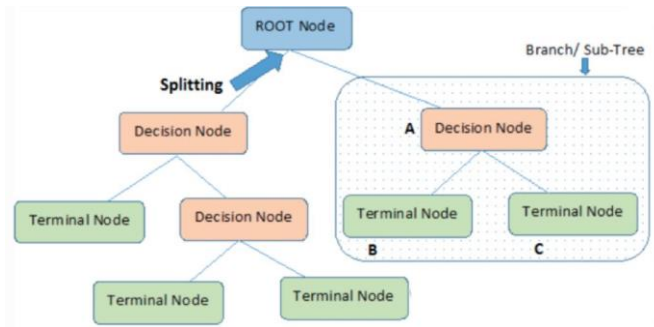


Figure 1. Prediction architecture of decision tree dataset

Decision trees are widely used for classification tasks in financial investment and quantitative trading. The main advantage is that the model structure is simple and easy to understand, and each decision path can be explained intuitively, thus making it very explanatory [23][24]. This transparency is particularly important in the financial sector, where investment decisions require a clear and unambiguous logic. In addition, decision trees can handle complex data sets and non-linear relationships, and are adaptable, able to capture important patterns and trends in the data.

However, decision trees also have some disadvantages. Decision trees that are not properly pruned often become too complex and capture noise in the training data, resulting in overfitting. [25]. This overfitting reduces the model's ability to generalize, making it perform poorly when dealing with new data. In addition, the decision boundary of the decision tree is based on a vertical and horizontal division, which may not be precise enough in some cases.

3.2 Bayesian statistical methods

Bayesian statistics is a statistical inference method based on prior probability and posterior probability. It updates the prior probability by combining the newly observed data, so as to calculate the posterior probability and realize the estimation of unknown parameters [26]. Bayesian statistical methods, including Bayesian networks and Bayesian classifiers, have wide application prospects.

In the financial field, Bayesian statistics can be used to assess financial risks, such as stock price fluctuations and attenuation rates, and can also be used to predict future spreads and assist arbitrage trading. Specifically, the Bayesian approach enables the model to be dynamically adjusted to quantitatively assess uncertainty based on historical data and changes in market conditions. This ability to update dynamically makes the Bayesian approach particularly important in financial investment.

The advantages and usefulness of Bayesian algorithm in the implementation of quantitative trading decisions by robo-advisors

1. Dynamic adaptation to market changes:

Bayesian algorithms are able to update the probability distribution in real time based on new data, so that the model always reflects the latest market conditions. This adaptive ability

is important in highly volatile financial markets and can help robo-advisors adjust investment strategies in a timely manner.

2. Dealing with uncertainty and risk management:

Bayesian method deals with uncertainty through probability distribution, which can reflect the real situation of the market better than traditional deterministic models [27]. In terms of risk management, Bayesian statistics can quantify the impact of various risk factors and provide more accurate risk assessment and management strategies.

3. Integrate multiple sources of information:

Bayesian methods can integrate multiple sources of information, including historical data, market news, economic indicators, and more. By building a Bayesian network, robo-advisors can take these factors into account to make a comprehensive assessment of market trends and investment opportunities.

4. Strong forecasting ability:

Because Bayesian method can update the posterior probability dynamically, it is outstanding in time series prediction. Robo-advisors can use Bayesian statistics to predict stock price trends, market volatility, etc., to provide strong support for investment decisions.

5. Transparency and interpretation of decisions:

The decision-making process of Bayesian method is based on explicit probabilistic inference and has good transparency and interpretation. This is essential for compliance and investor trust in the financial sector, where robo-advisors can clearly explain the logic and rationale for their decisions.

3.3 Deep learning algorithm

Deep learning, including deep neural networks (DNN), Transformer, multilayer deep autoencoders (DBNs), recurrent neural networks (RNNs), and short term memory networks (LSTM) [28]. In the financial sector, DL has been applied to algorithmic trading, cryptocurrency investment management, etc.

In addition, the current popular large models are mainly based on Transformer architecture, and the use of large models to make time series prediction of stock prices is also a popular direction.

Deep learning-based algorithmic trading models mainly focus on stock price prediction and classification based (Buy-sellSignal, or TrendDetection) algorithmic trading models.

Deep reinforcement learning combines the advantages of deep learning and reinforcement learning, using deep learning to extract features in the securities market as states of reinforcement learning to help AI make correct buying and selling decisions and improve returns. For example, the FRDNN algorithm uses deep neural networks to extract stock data features and input them into a cyclic reinforcement learning model to make trading actions. The TFJ-DRL model weights the features extracted by deep learning and adds the actions of

the last trading decision to the reinforcement learning algorithm to achieve better results [29]. DDPG algorithm is applied to portfolio management by limiting weight and diversifying risk.

Therefore, intelligent quantitative trading can obtain more and more extensive data, carry out logical deduction, and find out the characteristic factors that traditional quantitative trading does not pay attention to. It forms the machine's own investment decisions through a learning process that is constantly updated. Technologies such as artificial intelligence algorithms and knowledge graphs can predict markets and build more effective strategy models. Intelligent quantitative trading monitors the market environment 24 hours a day, grasps the market trend in time, and can automatically execute operational orders when encountering "black swan" events to reduce losses.

3.4 Robot intelligent trading system

Based on a large amount of corporate information, the automated trading system relies on big data analysis and modeling to predict the price trend of stocks, commodities and other markets. Also known as algorithmic trading, it is essentially a real-time decision-making system within the scope of enterprise information systems (EIS) [30]. With the development of technology, the underlying mechanisms of automated trading systems are increasingly diversified. Both academia and trading firms are digging into the underlying factors that could generate higher profits. Trading system methods are divided into technical analysis, text analysis and high-frequency trading.

1. Trading system based on technical analysis

Technical analysis trading system is a kind of trading method based on historical price and trading volume data, through charts and technical indicators to analyze and predict future market trends, and is widely used in financial market trading. This system can help investors find potential trading opportunities in the market and develop corresponding trading strategies.

Advantages. First, technical analysis trading systems can provide more accurate forecasts to help investors grasp market trends and fluctuations [31]. By analyzing the historical price data, the technical analysis trading system can find the rules and trends in the market, and provide a strong reference for investors. Secondly, the technical analysis trading system has high flexibility and adaptability, and can formulate corresponding strategies according to different market environments and investors' risk preferences. In addition, the technical analysis trading system can also automate trading through programmatic trading, improving trading efficiency and accuracy.

Disadvantages. First, technical analysis trading systems cannot completely avoid market risks and uncertainties. While technical analysis can provide predictions of future prices, market movements are influenced by a variety of factors, including policy, economic, and social aspects. Therefore, the technical analysis trading system cannot guarantee 100% accuracy and stability. Secondly, the technical analysis trading system requires a certain amount of professional knowledge and skills, and requires investors to have a certain amount of investment experience and risk awareness. In addition, the establishment and maintenance of technical analysis trading system needs to invest a lot of human and material resources, and the cost is high.

2. Trading system based on text analysis

Trading systems based on text analysis mainly use natural language processing (NLP) technology to process and analyze large amounts of text data, convert text information into structured data, and then use machine learning algorithms to train models to predict market trends and stock prices and other indicators. These models can be based on different data sets and different algorithms, such as linear regression, support vector machines, neural networks, etc.

Advantages. The trading system based on text analysis can automatically process a large amount of text information and improve the efficiency and accuracy of trading. In addition, through machine learning technology, the trading system can self-learn and self-optimize, constantly improving the accuracy of predictions and the efficiency of transactions.

Disadvantages. There are some difficulties in natural language processing, such as semantic ambiguity and grammatical irregularity, which may affect the accuracy and precision of text information. In addition, trading systems based on text analytics require a lot of data and algorithmic support, which consumes a lot of time and cost. Finally, trading systems based on text analysis may have some technical risks and vulnerabilities, such as model overfitting and data leaks, which may affect the reliability and security of the system.

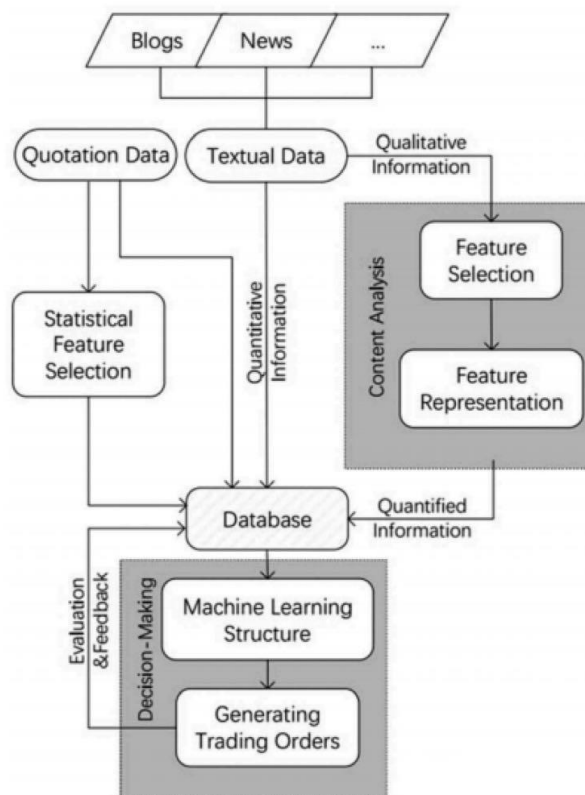


Figure 2. Automatic trading system architecture diagram

Among them, high-frequency trading is a highly automated trading strategy that makes a small profit by executing a large number of trades quickly. It typically utilizes high-speed computer systems and complex algorithms to analyze and predict short-term trends in the market and make buying and selling decisions in extremely short periods of time.

Advantages. High-frequency trading uses technology and algorithms to quickly catch small price differences in the market, making high profits in a short period of time. When there is a price difference between stocks on different exchanges, high-frequency trading can carry out arbitrage at the millisecond level, quickly respond to market fluctuations, accurately execute trades, and make full use of market liquidity. In addition, high-frequency trading avoids subjective emotional interference and improves trading stability through algorithms and data decision-making. At the same time, it can spread risk and quickly capture price differences in different markets for arbitrage.

Disadvantages. High-frequency trading needs to pay high fees and commissions, and the transaction cost is high. High-frequency trading requires advanced computer technology and algorithms, which is difficult and requires professional support. Although high-frequency trading can reduce risks, but at the same time there are regulatory risks and technical risks, once the wrong operation or abnormal market fluctuations, may lead to huge losses; High-frequency trading requires a certain amount of investment experience and risk tolerance, which is not suitable for ordinary investors. Investors need to understand its disadvantages and prudently carry out high-frequency trading at the right time.

4. Conclusion

We have an in-depth understanding of the application and impact of artificial intelligence in the field of financial quantitative investment. Artificial intelligence technologies, including machine learning, deep learning, and natural language processing, present unprecedented opportunities and challenges for financial investment. These technologies can process large amounts of data, spot potential patterns, predict market trends, and optimize investment strategies. For example, machine learning algorithms can develop efficient trading strategies by analyzing historical market data to identify hidden trading signals and trends. Deep learning can use its powerful feature extraction capabilities to process complex non-linear data, such as images and text, providing more accurate market predictions. Natural language processing can parse unstructured data, such as financial news and company reports, to extract valuable information that aids investment decisions.

However, the application of artificial intelligence in financial quantitative investment also faces some challenges and limitations. For example, data quality and integrity are key issues. Financial market data often contains noise and missing values, and the quality of this data directly affects the accuracy and reliability of the models. In addition, the interpretability of algorithms is also an important problem. Many machine learning and deep learning models, especially deep neural networks, tend to be "black box" models that struggle to explain their decision-making processes. This is particularly important in the financial sector, where investors and regulators need to understand and trust the decision-making logic of the models.

Regulatory and ethical issues cannot be ignored. With the widespread application of artificial intelligence in the financial sector, ensuring the fairness and transparency of algorithms to avoid potential market manipulation and fraud is a major challenge. Additionally,

artificial intelligence systems may amplify market fluctuations and increase the vulnerability of the financial system, necessitating the establishment of sound risk control mechanisms.

To address these challenges, a comprehensive approach is needed. For example, in terms of data quality, data cleaning and pre-processing techniques can be used to ensure the accuracy and integrity of input data. In terms of interpretability, interpretable models can be adopted or new interpretative tools can be developed to help understand the internal mechanisms of complex models. Financial institutions should also actively work with regulators to develop and comply with relevant regulations to ensure the compliance and ethical use of AI applications.

Despite these challenges, the potential of AI technology in financial quantitative investment remains enormous. With the continuous progress of technology and in-depth exploration of applications, it is believed that there will be more innovations and breakthroughs in the future. For example, emerging technologies such as federated learning can enable multi-party data sharing and collaborative modeling while protecting data privacy, further improving the performance and application scope of models. Additionally, the combination of quantum computing and artificial intelligence is expected to bring revolutionary improvements in computing power, promoting financial quantitative investment to a new stage of development.

In summary, artificial intelligence has significant application potential and promising prospects in the field of financial quantitative investment. By effectively leveraging its advantages and addressing its challenges and limitations, the efficiency and effectiveness of investment decisions can be substantially improved, fostering innovation and development within financial markets.

Acknowledgement

We thank Chao Fan, Zihan Li, Weike Ding, Huiming Zhou and Kun Qian for "Integrating Artificial Intelligence with SLAM Technology for Robotic Navigation and Localization in Unknown Environments [1]" for the outstanding contribution made by this article. Their research results have brought important innovations in the field of robot navigation and positioning in unknown environments, and provided valuable ideas and methods for promoting the integration of artificial intelligence and SLAM technology.

In addition, we also want to thank their research to inspire and help us. Their work provides us with a new way to deeply understand and explore the integration of artificial intelligence and SLAM technology, and provides an important reference for our future research. We are grateful for their hard work and outstanding achievements and look forward to working with them to advance this field in the future."

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