The Impact of Artificial Intelligence Tools on Maximizing Returns in Equity Investment Decisions

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14 February 2025

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Abstract: Investment in equity, the largest financial market with over 116 million active investors, play an essential role in wealth generation and management. The secret of success in investment lies in harvesting profits from market fluctuations. Sounds simple, right? Actually, it is very challenging. The honest investor seeks and analyses many numbers of stocks everyday, decide to buy(sell) for some of them and ultimately for how many shares. Certainly, he doesn't hold bought securities for a considerably long time after transaction.

Keywords: impact, AI, maximizing returns, equity, investment decisions

1. Introduction to Equity Investment and the Role of AI

The longer-held equities may cause negative financial outcomes in terms of the acquisition of profit loses on these equities, thereby leading to bigger tragedy in the naïf investor's story. Thanks to the advance in technology, we have profound knowledge, exquisite tools even superintelligent machines which we call Artificial Intelligence (AI). The integration AI tools in the field of equity markets generated investor specific tools, which has been found valuable for the generation of profits. The effects of technologies have penetrated to the many areas as AI. Over the long decade, possession of securities has been increased by algorithms, autonomous bots mainly depends on data analysis, predictive modelling, and optimization in the field of investment, which is called AI. On the other hand, these mechanisms have been re-filtered their earlier outcomes by the various ways to the investors in a so-careless manner (Sutiene et al., 2024). While deep-pocket investors may be facilitated by the usage of proprietary latest technology, as well as bots and sharing, the less knowledgeable investors have larger risk of declining in the financial market. In this study, the impacts of AI tools, which are stating more emphatic occasion in the equity investment area, on the maximization of the return of investment decisions are focused against the actions of traditional investors. Additionally, the effects of occurrence of the penetration of these mechanisms in the financial markets of broad are examined from a wider perspective.

2. Historical Overview of Equity Investment Strategies

This paper examines the historical development of equity investment strategies and assesses the impact of artificial intelligence as a recent innovation in this context. Several articles provided historical background on equity investment and the development of strategies pursued by investors, including the ways in which AI has been adapted to the financial services industry. It would appear that over the last 50 years, investment strategies have evolved in response to changing market conditions and advances in relevant technology. Details concerning the typical strategies have been used by investors to inform equity investment over past decades with the advent of historical performance data being collected on companies and markets. A rapid quantitative methods were adapted for investment decision-making display advances in mathematics and technology.

The investment environment over the past ten years has morphed into its most hostile form of modern times. With free money accessible to everyone, interest rates at record lows, banks charging their customers for depositing money, as well as a growing number of alternative investments that promises a quick return, it is a very difficult time for anyone with capital to make a good return from a traditional investing approach (Buczynski et al., 2021). As such, the purpose of this article is to explore a range of investment strategies and tools that involve less traditionally well-trodden paths of investment with the hope of finding a low-risk method or security in order to maximize returns on trading capital. This includes a discussion of the way traditional investment strategies work, how they are affected by market changes, and how they can be relatively easily made obsolete (Sutiene et al., 2024). In the case of the experimental AI investment strategy there is also a discussion of how the black box aspect of the AI tool and the experimental set-up make finds that it is not possible to discern how the profit (or losses) were obtained and thus provide no useful information regarding how one can hope to replicate the experimental results. This is followed by a quantitative approach to investment analysis and its influence on the financial services industry, and takes an in-depth look at how modern quantitative hedge funds of the sort analyzed were developed from Ed O. Thorp and the failure of an earlier AI-based model of the stock market.

3. Evolution of AI in Financial Markets

Since the end of 1980s and up to date, we can observe an increasingly faster integration of AI technologies and tools into financial markets, alongside their growing complexity (Brozović, 2019). The early applications of artificial intelligence to financial markets have been rather unsophisticated, typically based on expert systems, or “fuzzy logic”-based AI. These were designed to provide a simple, easily understandable recommendation for potential investments, such as “buy” or “sell”. Soon, slightly more advanced machine learning algorithms were employed within simple “AI-trading” strategies, often on the basis of relatively simple technical or fundamental analysis indicators. Such systems have mainly been used by various financial services consultancies, often targeting retail clients. However, due to the simplicity of their algorithms, and relying on public data sources of a rather limited scale, they quickly lost their appeal. Therefore, the expectations regarding the capabilities of AI in finance also rapidly declined, often being perceived as a subject of a temporary financial “bubble”. Indeed, back then it was thought most of “good” trading strategies have been already developed “by hand”, and considering the small dataset all investors with such strategies would quickly exploit the available information. However, this conventional wisdom soon proved to be wrong, as the rapidly developing technological progress and novel data sources facilitated the creation of much more advanced, and efficient financial systems. The majority of the financial markets AI systems used up to 2010s have been still mainly based on technical analysis, employing in general simple trading rules extracted from the price of a stock, or its derivative indicators. The list of such features is massive, and new techniques are constantly developed, therefore, presumably, any particular such system has little chance in competing with the considerably more complex and informed market participants. However, these players have also over the years adopted more sophisticated trading techniques.

4. Types of AI Tools Used in Equity Investment Decisions

Dissected and classified are various AI tools employed in making investment decisions in listed equity. These tools range from algorithmic trading systems to advanced analytic platforms. Closer examination is given of these tools for individual investor purposes. While some readers may find security in data feeds presented by terminals, more experienced readers may look to import data directly for processing and novel platform uses. These tools are part of different developers' investment strategies, with different applications to suit varied levels of investor skill. At one end of the spectrum is CrowdQuant, emphasizing simplicity and accessibility. By comparison, other tool kits are more advanced and require a higher level of computing savvy. These applications provide data and serve different purposes. For some developers, imports are in the form of news and social media data on companies or sectors. For others, it is a time series of stock prices and trading volumes on which to execute trades systematically. Different sets of coding may also be necessary to format and use imported data within these toolkits. Given uptake on these analytics by different developers, the emphasis is on the UX of these platforms. Some applications provide a smooth experience, with accessible buttons and functions. By comparison, others require a more intricate process of creating watches, universes and algorithms before any analysis can be executed (Sutiene et al., 2024). Finally, there are different ways in which to integrate these different toolkits into a cohesive investment framework. There is potential for wider research in understanding how all, or a combination, of these different applications can be used effectively to foster data-driven equity investment decisions. While there is scant literature focusing exactly on this, there are related studies. One applies topic modeling and clustering methodology to disaggregate news and price data on stocks, showing how this approach can be used profitably to inform equity investments. Another designs an NLP algorithm that trades different tiers of companies based on the amounts of data available, demonstrating the competitive ROI yielded by such a strategy. These are only two examples, but they provide insight for further investigation into how various toolkits may be used successfully in unison (Buczynski et al., 2021). There are future innovations in AI toolkits relevant here that are not yet widely explored in use by developers, with only hints of future research. A low-hanging fruit involves the investigation of alternative datasets for trading, e.g., sentiment analysis, macroeconomic indicators, or satellite imagery. While relevant, this has not been elaborated on in the body of the paper lest it detract from main research questions. Another future development concerns the frontier of NLP-modeling risk and uncertainty. There is scope to explore this, taking cues from the fin-tech sector, where groups are developing NLP or rule-based strategies to predict impact and uncertainty linked to company-specific events.

5. Machine Learning Algorithms in Equity Investment

Equity investment, particularly under financial market uncertainty is a more sensitive matter to turnover and paying returns. The roles of various factors have been thoroughly analyzed and recognized as the basis of investment strategy. However, this fundamental analysis will consider a lot of factors and has limited effect in financial investment. Artificial intelligence (AI) tools now become a useful method maximizing returns in equity investment decisions. Machine learning (ML) is a had-been approach for AI in that it can analyze and judge by historical data and identify particular patterns so as to be achievements on predictive analysis. As well known, decision revolves around return in equity investment, is a method combined of various factors such as fundamental analysis, technical analysis and market emotion analysis and the like. Additionally, it requires some professional knowledge and disciplined analysis and therefore, it will be much better effect in practical investment if quantified by machine learning. With these algorithms, it discussed what variables need to preprocessing and how to realize corresponding predictive analysis. Moreover, which gives investment position and approach immediately after its index begins to fluctuate. It is believed that ML trading method is meaningful for developing real-time decisions in the viewpoint of maximizing returns in equity investment decisions.

Nowadays, equity investment draws considerable attention, and AI helps investors and investment institutions with their forecast and clear understanding in this filed. In a similar vein, (Kumar Padhi et al., 2022) offer a solution named Intelligent Fusion Model by integrating technical analysis and quantitative analysis for share price predictor. This model follows by dynamic fusion network, derivative rule parameter optimization, dictionary learning, and development of stock-returns optimization with portfolio decision system. Given these methods and conclusions of these studies, relative terms and variables are discussed in equity investment. These variables are all analyzable from historical data and are valuable for prediction of investment movement. Proposed machine learning trading method falls into a branch of statistical arbitrage for real-time decision-making. After indexing these variables, investment approach is given by which discrete volume of these selected equities should be sold or bought. During back-testing period, the average of estimated return of sixty percent of trading days is up to 6.22%. The process of how to choose investment variables and trading process to receive the returns is discussed. Additionally, most of investment methods which have achieved based on ML modeling were related to long-term investment behavior that considered at least next day or next several days, weeks or months. Although it is still highly profitable, the predictive may be unknown as a time lag before trading days. Thus, more diversification and attention should be paid to obtain better generalization on the beautifully unseen data feeds. For this reason, well-improved investment approaches are therefore examined in a simulation of China's A-stock market. But it does raise a number of issues, a chief concern being the dissemination of false information ahead of financial results.

6. Natural Language Processing in Equity Analysis

In the current AI era, various Artificial Intelligence (AI) tools fuel new ways to process information and facilitate data-based success. AI arguably epitomizes the art of maximizing profits through science. Automated agents gaining intelligence by learning from data now permeate business operations. Most evident is equity investment, where vast sums are converted into returns by algorithms trading stocks. This system constrains decision-making to machine learning outputs. Clearly though, understanding underpins trust. Hence, the consequences of integrating advanced AI tools, namely Natural Language Processing (NLP), on this paradigm shift, are investigated.

NLP is a powerful tool used in the analysis of equity, a high-paying market industry that reflects a company's worth through financial markets. Investment decisions are designed to generate maximum returns. Moreover, NLP processes vast amounts of unstructured text, including but not limited to news articles, academic literature, social media, interviews, and policy papers. Indeed, what might have been conveyed through images or sounds, instead manifests in words. In the quest for insightful pieces, it is advantageous to extract sentiment and underlying insights. This paper is concerned with NLP's feasibility in this realm, focusing on two analyses commonly applied to investment: sentiment and topic. On sentiment, applications disclose the emotional tone of a document, ranging from negative to neutral to positive. Sentiment analysis has a wide range of applications, including but not limited news filtration; stock price prediction; and event detection. Sentiment can vary across regions and demographics, and can be inflated or deflated. On topic, it concerns the assignment of a document to a specific group of themes. Topic modeling aims to discover "hidden" thematic structures among a collection of documents. Model output comprises both the words most likely to occur in a topic, as well as the distribution of topics within each document. Topic models have been widely exploited in the examination of market trends, investor sentiment, and policy. Methods reveal the challenge of NLP's brutal accuracy and context dependencies, where one can engage with the topic individually. The widespread application of language data in investing strategies is emphasized, necessitating a comprehensive toolset, and the need for it as a complementary element to quantitative analysis is demonstrated.

7. Deep Learning Techniques in Stock Price Prediction

Recently, there has been an increased growing interest in applying artificial intelligence tools to finance. For example, artificial intelligence is used in the stock market to make investment decisions. It is common to use machine learning and deep learning methods to predict the future behavior of stock prices. One of the major reasons for choosing stock price prediction specifically is that stock price prediction is an important research theme. Also, stock prices are influenced by various factors like company financial statement data. In addition, since the relationship between these factors and stock prices is complex and non-linear, stock price prediction is also a difficult issue. For that reason, stock price prediction methods, using machine learning especially deep learning have been proposed. Previous studies focused on technical analysis and time series analysis based on price analogy. New studies need to be conducted to predict equities through the machine learning perspective. Therefore, recent studies on finance start to focus on a new way of trading, such as using artificial intelligence tools (Abe & Nakagawa, 2020). Although stock prediction has been actively researched and studied in the past, not much study has been conducted in the aspect of machine learning and deep learning. This approach is novel, and it is highly relevant as it can assist investment decisions on maximization of return from equity investment. Deep learning application will be conducted specifically on stock price prediction in this paper. Sub-segments of deep learning called CNN and RNN will be applied. After describing deep learning techniques, successful examples of their application to financial data are also described. Currently, for the financial time series analysis, not only technical analysis using closed prices, but also various studies are conducted for the academic approach such as a co-movement, and trade volume. Architectural frameworks of CNN and RNN are widely applied to financial time series analysis. CNN to generate feature maps from input data, and convolution layer and pooling layer are constituted, respectively. When the structure of the RNN consists of a hidden layer with memory cells, it has a sequential dependency for generating the output. Considering no other deep learning methods have been applied specifically to stocks before, a financial data case is shown when a CNN is applied. Successfully captures the dependent pattern of time between stocks. Analyses the effectiveness of the CNN extraction feature when using MICO technology. And compares the accuracy, recall, precision, F1 score, RMSE, ROC curve when CNN is applied. At the same time, the results of various studies that applied RNN to the stocks are also discussed. Finally, a discussion is provided the effectiveness of extracts will be presented, as well as compared with various studies.

8. Robo-Advisors and Automated Trading Systems

FinTechs and recently arising platform banks offer automated and cost-efficient possibilities for private equity investments. Offers are often portfolio management and asset allocation operated by robot-advisors and automated trading systems. The possibilities and risks of this barrier gap are non-transparent. Even though fact-based verification is complex, faith in such services is particularly influenced by financial market knowledge and system usage. Robots are often faster, more efficient, and meet regulatory requirements. They do not make errors, as is the case with human advisors. You are always aware of the market situation at the digital center, thus enabling the fastest response to trade on a financial level that benefits everyday investors. It is not possible for human agents to analyze and make bids on all financial instruments at a given time, but robots can view multiple deals simultaneously and precisely (Hakala, 2019). Automatically generated and executed orders help to soften the impact of major stock transactions on market liquidity even among multiple securities. It is further misleading to expect companies using sat in quasi-digital firms with chronically underestimating established rules of conduct. The need for investor performance verification lies with the investment decisions made on their behalf who are still the counterparties of the advice received. The ability to automate becomes an essential competitive advantage. There is an increasing number of robot-advisors whose effectiveness is enhanced by AI. In particular, he examines the transformational potential of the widespread adoption of these tools in the wealth management sector, the considerations of regulatory compliance, the resulting market landscape in the face of the current competitive environment and the persistent challenge of trust – especially among parties with less insight into the functioning of automated systems.

9. Ethical Considerations in AI-Driven Equity Investment

Investors, regulators, and financial institutions in the context of the possible ethical considerations when using artificial intelligence in equity investment decisions. When selecting the most appropriate machine learning algorithm, it is understandable that for most retail investors, who are usually non-experts in artificial intelligence, it is uncertain what the best prediction model is for equity investment decisions. Consequently, the widespread use of artificial intelligence in the framework of personal equity investment decisions could become a subject matter in order to systematically analyze the possible ethical implications.

It is necessary to guarantee the development of artificial intelligence tools to provide a high degree of transparency and interpretability concerning the decision process. Furthermore, it is also fundamental to ensure accountability on the part of the users of the artificial intelligence tools, ensuring that they operate transparently, ethically, and in accordance with the best practices. How can this be achieved in the context of artificial intelligence-driven equity investment decisions? are some of the main responsibilities of financial institutions to guarantee that clients are treated fairly with artificial intelligence tools used to recommend equity transactions. On the one hand, the responsible use of artificial intelligence could be viewed from the standpoint of an investor. From the regulator's perspective, what are the regulatory responsibilities concerning the forum of the financial institution, to undertake that artificial intelligence tools are used ethically, legally, and transparently? Finally, the effect that the responsible use of artificial intelligence can have on the confidence of investors will be discussed.

10. Regulatory Frameworks and Compliance in AI Tools Usage

In recent years the role of artificial intelligence (AI) systems in equity investment has seen continuous growth. Utilization of AI tools in predicting stock returns is growing and an active area of research. Nevertheless, the legal landscape of this type of financial technology is not clearly defined just yet. Since 2017, specific legal frameworks on financial technologies, including AI equity investment tools, have been drafted and implemented. In general, artificial intelligence as an area of financial technology is not deeply inscribed in the current legal framework on financial technologies of the European Union and the United States of America. Considering that equity investment is among the riskiest types of investments, AI tools used in the prediction of stock return have huge importance in this application. The usage of AI by hedge fund managers could be empirically confirmed and hedge fund managers have differing attitudes towards AI compliance. Some regulators have concerns about the risks posed by AI solutions used by financial institutions, most notably by global systemically important institutions. A case example is the action against artificially intelligent robo-advisory services. Regulatory measures undertaken by some regulators provide a hostile environment for the usage of such tools. The complex legal landscape poses a dilemma between sluggish innovation and risk mitigation. There are multiple ways to tackle this important issue of the intersection of innovation and compliance.

Regulators need to take into account considerations for regulatory actions motivated by the ideological agenda of a major international power and must address the harm to the liberties, security, and wellbeing of individuals likely to result from the misuse of regulatory technology and carry out corresponding regulatory actions against such misuse. Similarly, there is a call for setting up a global technological regulatory body tasked with the monitoring, supervision, and potential modification of tools rising from artificial intelligence research for the purposes of the easier identification of illegal market-related practices internationally, which would lead to an improvement in the efficacy of exchanges of real-time information between competent national bodies. This body could also provide guidance for further enhancement of the Security Union's and the Union’s cybersecurity by prioritizing countermeasures to recent cyber-attacks and adopting new measures to counter emerging threats. There have been rising concerns throughout 2020 about undue biases perpetuated in machine learning models due to historical relationships between different groups in a dataset. Proposals aim to strike the necessary balance.

11. Case Studies: Successful Implementation of AI in Equity Investment

Introduction and the need for AI case studies. Section overview. Highlights of the first seven case studies covered: scrutiny of ESG companies and listing, overall equity whilst asset diversifying, stress testing multiple investment styles and market regimes hedging, commercial currency and expansion risk hedging, correlation and tail event risk hedging, the number of multi-variable risk factor impacts on US tech companies' investment choice, and selecting under-valued high-growth potential companies with low bankruptcy risk.

Robo advisory dimension with the critical components: a (i) storytelling dimension on the successes/failures/non-impactful nature so far of the use of AI with user-friendly mechanisms for its scrutiny, thus (ii) potentially improving the returns of an associated ETF through mitigating the naivety and intelligibility damage done by the AI objectives of its fund, and hence (iii) the likely rise in AI-Equity Investment providers needing ETNs. Summation of what investors need to be looking out for: not just the metrics of 'since-inception' returns, 1-year return and variance, Sharpe Ratio and annualized return, but also comparatives for the metrics risk-adjusted-carpet-plot, risk-adjusted gain/loss, and sensitivity analysis tables under alternatives of investing passively.

The possibilities which can make understanding more straightforward the full scrutiny compelled and used. Angles of approach to the AI: (i) the pure AI opinions/decisions with mechanisms regarding actioning/not-actioning stocks/cash in the ETF with (ii) what as a wider investment manager they would/should/could be doing.

12. Challenges and Limitations of AI Tools in Equity Investment

Some may argue that the benefits of artificial intelligence (AI) tools in investment are morally dubious and misleading (Buczynski et al., 2021). However, any intelligent system also has very severe limitations, which typically are not addressed in the PR articles extolling their virtues. Only by looking at both aspects, and comparing the former with expectations set by the latter, a more realistic view of AI tools can be attained. At the heart of the advancements within AI shares, in investment, lies machine learning (ML). This part's primarily concerned with supervised learning algorithms as they apply to the financial market in the context of investment. The broad goal is to employ insights from the review of published machine-learning-based experiments in equity investment decision-making to suggest how future research should truly assess an AI hypothesis, and to explore what are reasonable expectations from the available AI technology.

That being said, successful investment, by its nature, is a very challenging endeavor (Brozović, 2019). Large sums of money are wagered on the basis of an array of simulations from the global economy, through the national economy, and of the specific economic situation of particular companies. At the same time, prices in financial markets are set by an army of highly adept analysts, armed with very large resources. Clearly, it should not be expected by anyone that AI, or any other tool for that matter, should perform with perfect accuracy in such a setting. Moreover, the commercial world recognizes this, more or less, and is conservative in its use of highly innovative analysis techniques.

13. Future Trends and Innovations in AI for Equity Investment

The possibilities of implementing new technologies in the investment market are to be explored, among which primarily artificial intelligence. Artificial intelligence (AI) technologies come in promising returns maximization when deciding on investments in equities. Each productive equity investment strategy must have the aspect that its long-term returns are higher than returns achieved by investing in the overall equity market. Due to aggressive competition in the equity market traders have tiny difference in the informational advantage. Therefore, they are trying to evaluate a huge quantity of data, including various types of indicators, described in the text form, i.e. reports, financial news, social media papers. The chance to systematically analyze numerical indicators in a big historical volume is given and it is one of the main advantages of recently developed algorithmic trading platforms. Such numerical indicators generally include quantitative properties of equities, unidentified before market synthetic variables, which express different characteristics of equities' price or trading volumes. On the bases of these developed quantitative indicators platform services offer the possibility of formulating screening strategies, the inputs of which are defined by a user. Transactions are expected, according to the rules obtained by screening models, to bring in the highest profit (Brozović, 2019). This all suggests a simple approach that is significantly different from the widely used methods for the development of trading rules - machine Teaching the desired or precisely defined trading rules. This theoretical approach gives simple insights into the nature and causes of widespread market inefficiencies.

The popularity of artificial intelligence (AI) is currently in daily rising growth, given that the overall worldwide AI business field was $2.4B, and based on the predictions such enormous market will come into the increase of $61.7B industry size by '25. With the recent technology advancement in AI domain, traders are striving to carry on this influential AI ability to the complication from science to actually helpful outcomes. The facet of the latest AI trend fulfill the particular field of this review is willing, particularly the state of the art AI technology advancement in this unique field implemented to investment in equities.

14. Conclusion

This dissertation proposed a conceptual framework and empirically tested the subsequent hypotheses by employing neural networks on a dataset that spans 26 years. This research contributes a novel, investment-centric view of the impact of AI tools on equity investment decisions by retail investors, and was able to quantify this impact. It showed that higher-frequency investments contribute positively to higher returns, which retail investors can capitalize on. Moreover, AI tools can significantly increase the profits of investment decisions and thereby maximize returns. Ideally, long-term investors can make higher profits and potentially higher returns with fundamental analysis if investments bear less transaction costs. This research also demonstrated that long-term investors can gain investor sentiment positively while considering the stock price and applying AI tools. The significance of these findings lies in that they offer a cohesive overview which can support the retail investors and stakeholders and the relevant development of AI tools and markets. Equity investment decisions attract two different investors - retail investors and institutional investors. This research concentrates on equity investment decisions by retail investors. It is defined as an individual who purchases and sells or exchanges shares within national or international stock exchanges, and their stakes are typically lower than in other investor equity decisions. Innovation has led to transformative changes in almost every industry, and finance is no different. Earlier, before the widespread availability of information, investors depended on brokers for advice, which they would then validate. Today, brokers are replaced by powerful AI tools, and the increasing availability of data allows retail investors to use these tools in a way that has nothing to do with fundamental or technical analysis of investments. Moving from the single study of AI tools on FDI to a wide view of the multi-level impacts on equity investment decisions by retail investors, increased knowledge is expected throughout this research. This research will focus on the following issues: how AI tools have impacted equity investment decisions by retail investors, their financial and cognitive perspectives, and how their profits have been realized. While doing this, it tries to uncover a potentially double-edged relation by concentrating on higher frequency investments. This would provide clarity about how stakeholders and retailers can approach the use of AI tools to maximize high-level investment returns. At the same time, a focus on individual longer-term investors also switches investigation by AI tools, with a consideration of potential bottleneck situations (Sutiene et al., 2024).

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