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The Trustworthiness of AI Algorithms and the Simulator Bias in Trading

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Abstract

The application of AI technology is changing dramatically investment decisions in the financial and banking industry. Neural networks (NN) are a special type of machine learning algorithm employed in training trading robots. They might be associated with advanced analysis of the specific software simulators used fundamentally in algorithm training and testing to alleviate risk in the trading activities. Our research focuses on a couple of key aspects: a methodical literature review using Natural Language Processing (NLP) tools, to delve into major themes directing to the efforts of understanding of the role of algorithms and NN in trading and investment banking. We discovered that these technologies play a major role in reducing risk and effectively taking up the mission of forecasting market fluctuations and evolving shortly in automatic trading strategies. The paper examines the possibility of harnessing simulation tools utilised in the capital investments markets for practicing and examining algorithms as well as methods for reducing biases and enhancing decision-making process. The discoveries have revealed that NN rules can be efficient in attaining patterns in historical data while forecasting stock prices precisely. In terms of large applicability, this research emphasises the requirement for countering emotional and cognitive behaviours that may impact trading results, and it exposes the most effective types of NN for designing trading algorithms. An algorithmic framework for improving biases innated in a financial banking trading activities is recommended, to improve impartiality, risk management, and trading execution.

Keywords: risk management, trading algorithms, bias mitigation, trustworthiness.

JEL Classification : C11, C15, C45, D53.

1. Introduction

Taking into consideration the transition from Industry 4.0 to Industry 5.0 economy, it is vital for the financial sector to embrace the ethical AI technology

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and enhance its capability. The industry has traditionally been defined by instances connected to volatility, regulations, cybersecurity threats, technological limitations, and the disruption of settled economic activities (Goodell et al., 2021).

It is evident that, in the last ten years major studies in economics has concentrated on artificial intelligence (AI) technology. Moreover, it has experienced an acceleration in recent years and is now being implied on a large scale in all Fortune Global 500 companies as well as smaller companies across all industries. Mostly, AI has been associated with process automation in so-called "secondary sector" or manufacturing and processing sector. Recently, the scholars and the business community have observed the inception of positive applications of the technology, particularly in finance. The exponential growth of advanced analytics connected to the usage of machine learning (ML) and neural network (NN) algorithms, influenced dramatically investments. These evolutions enhance the newest methodologies and stimulate the application of data science to algorithmic trading strategies. Consequently, it is imperative for the industry to integrate algorithms aimed to calculate vulnerabilities of the market, in real time, for all types of risk. In that event, this will help to significantly avoid the magnitude of the emotional and cognitive behaviours that interfere in the trading process in the capital markets. The first objective of algorithmic trading is to generate a cost-effective trade execution process, and at the same time, harnessing risk management. This is accomplished by the utilisation of trading strategies software simulators. These software programmes cleave to preestablished mathematical rules, which mandate the entry and exit points for trades, thereby diminishing the requirement for human action (Chan, 2013).

Our paper is structured in sections: Section 2 summarises the problem under investigation, while Section 3 provides a review of the justification behind this research; Section 4 describes the methodology of the paper, while Section 5 presents the findings. Section 6 proposes a conclusion and suggests avenues for future research.

2. Problem Statement

The scholarly and major authors on the subject include an extensive array of topics, including the domain of algorithmic trading strategies (Aloud & Alkhamees, 2021), as well as the practical application of machine learning (Gerlein et al., 2016), market microstructure analysis (Osler, 2012), risk management, and regulatory considerations (Friedman, 2011). At the same time, it is imperative to assimilate concepts from finance, computer science, mathematics, and recently, emergent regulations on Artificial Intelligence formulated by the E.U and the U.S authorities.

A major proportion of research in the domain of algorithmic trading strategies is focused on to the expansion and evaluation of different types of algorithmic trading strategies. Illustrations of such strategies include those involved in market in general, trend following, statistical methods, and execution of algorithms (Hu, 2018). Simultaneously, the latest research is focused on neuronal networks as well as random forests used in the development of predictive models for risk assessment and portfolio optimisation in the context of machine learning applications (Kissell, 2020).

One of the major verdicts after of the scientific literature review is the constant concern of risk management. Without considering the author, risk management is constantly described in a comparable practice, with specific methodologies specific to algorithmic trading. A successful trading framework can be defined as one that assimilates an assortment of advanced analytics techniques with a predesigned system that can "understand" the importance of each information and how to use it in the prediction process. The above methodology demands diligent algorithmic selection and design. The consideration of algorithmic trading strategies includes a mandatory analysis of the current regulations. This involves an examination of market supervision, compliance regulations, regulatory frameworks, and the role of the regulatory framework impacting the market structure (Pereira et al., 2019). Nonetheless, the studied research does not examine the role of trading biases in the financial industry and the final outcomes that these have in this field. Hence, our research aims to nurture the knowledge related to trading tendencies, also known as biases, determine their nature, and identify software trading simulators and neural network applications that could be engaged to enhance the trading activity in the industry.

3. Research questions. Aims of the Research

The main purpose of this research is to closely inspect the process framework engaged in trading algorithms, which utilise advanced analytics solutions that facilitate the ethical AI best practices. Moreover, the design of these processes must take into consideration an extensive awareness of biases, with an emphasis on the cognitive biases. Finally, the design will address the vital role of the latest trading simulator software systems, with the final objective of successfully countering the most important trading biases.

The research question applied in this dissertation is: How might we project a framework for a successful and responsible AI trading process that will enhance transparency, sustainability, and durable profits to financial market players?

To successfully respond to this question, we must embrace a holistic approach that can be applied to any financial ecosystem. This should be qualified as mediating the internal capacities of the ecosystem in extension to its inputs and outputs. The main objective of the financial industry is to generate stable profits through a flowless process of allocating resources. The execution of the correct measures in one market has a positive impact on other markets and on the global market as well. This law is not limited to a single market; it can be observed in a multitude of contexts.

Our objective in this study is to initiate a comprehensive research project with the aim of providing major answers to several significant questions:

- What are the main cognitive biases that have been identified and which are their characteristics?

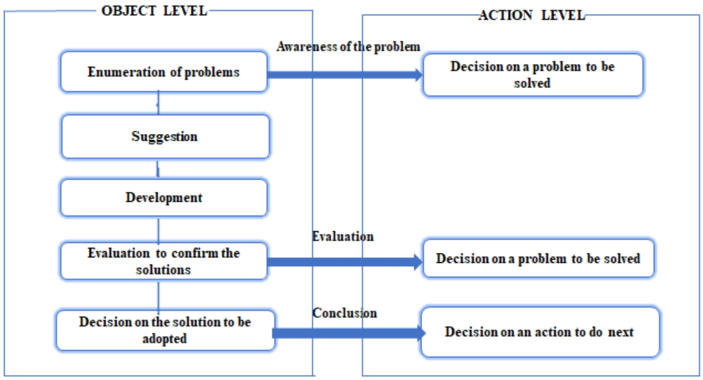
- What methods can be engaged to enhance effective information recovery within the context of the financial market?

At the same time, it is beneficial to determine which AI mechanisms are employed and which are the boundaries applied in the case of neuronal network applications that promote the implementation of transparent, ethical, and responsible trading strategies between market participants.

4. Research Methods

As part of this research study, the research method called *design experiment* (Takeda et al., 1990) is involved. We will follow specifically step (1) awareness of the problem, and step (2) suggestion, i.e. suggesting key concepts needed to solve the problem at hand.

Figure 1. The research methodology



Source: adapted from Takeda et al. (1990).

The research methodology is concentrated on the investigation of the framework designed for the various types of neural networks that can be utilised for transactions in the investment capital markets. It also contains the analysis of the complexities of trading algorithms, the implementation of complete algorithms in trading, and the development of a realistic model for the entry of the programme. The research methodology involves an analysis of the trends in decision biases and trading algorithms, based on the data they are trained with. The vital discovery of the research is the requirement to manage emotional and cognitive biases that might obstruct optimal trading behaviour (Ward, 2014). The final part of the paper is dedicated to the examination of bias reduction strategies and decision-making methodologies inherent within trading algorithms based on AI models. At the same time, our investigation proposes a potential solution (Kordzadeh & Ghasemaghaei, 2022).

The analysis of patterns in decision biases and trading algorithms is dependent on the data that determine their model. Therefore, the research methodology, as previously defined, is to address the role of emotional and cognitive processes in the trading process, with the aim of improving decision making. The paper provides an inclusive interpretation of these tendencies. Secondly, we analyse the simulation tools employed in the financial industry for training and testing algorithms, as we chose to investigate a software solution simulator. Thirdly, our research focuses on the reduction of negative trends and the methodologies engaged in the decision-making processes of trading algorithms based on artificial intelligence models.

From a definition and scientific standpoint, *cognitive bias* refers to methodical divergences from rationality in judgment, causing people to draw unreasonable conclusions about others and situations. These biases often emerge from the brain's effort to simplify the information process. Moreover, cognitive biases might precede perceptual deformation, misleading decisions, or largely, *irrational thinking*. There are several key aspects of cognitive bias: “systematic deviation” (they follow predictable patterns, they are not occasional, and they are highly repeatable); influence on decision-making; heuristics or trial-and-error methods (mental shortcuts that can lead to errors); emotion and motivation (these influence cognitive biases, affecting the objectivity of our thinking).

Trading biases establish a specific category of cognitive bias, particular and inherent to the financial sector. This theory was first defined by the Israeli psychologists Amos Tversky and Daniel Kahneman (Kahneman & Tversky, 1974). They have described this type of bias as “the systematic error in thinking, judgement and decision-making” that happen in the process of the information interpretation by humans. We advocate on the profound understanding of the biases that allows traders to predict efficiently market changes. A profound understanding of these concepts empowers traders to acquire resilient strategies and traverse the complexities of financial markets. That means that the process of conscious comprehension of their own emotional responses and those of others, allow traders to manage stress more effectively, maintain discipline, and tap into a better performance. The most common bias among those engaged in financial trading is a propensity towards optimism or pessimism. The performance of a specific trading activity is influenced by the outcomes of historical and current transactions. In the case of a successful trade, traders might experience a sense of conviction and optimism. This bias may result in overconfidence in decision making, which translates to riskier trades. On the contrary, a history of poor performance can turn out in unnecessary pessimism, which may block traders' capacity to capitalise on profitable opportunities. The most important element is to achieve a balance between these emotional behaviours to maintain a logical strategy to trading process.

Our research perspective indicates that artificial intelligence (AI) technologies, could play a major role in avoiding these biases. The utilisation of advanced analytics enables traders to decrease the influence of emotional biases and promote rational decision making.

Another element is that of *overconfidence bias*. A considerable correlation of the population exposes a trend to overestimate their expertise and abilities. Equally, traders demonstrate similar behaviours within the context of market operations. Overconfidence among traders can have a consequence in excessive risk taking and market volatility. Self-serving bias can lead to a lack of accountability and poor decision making. Education and the individual and global level foster self-awareness and enhance the inception of a more durable and rational trading process. In pursuit of reducing the cost price, traders employ a *double-down trading strategy*. Unfortunately, the market does not have the memory of its own, in other words, it does not keep the information regarding past prices and neglects the cost price. Our perspective is that the absence of a software simulator embodying historical data and cost-price algorithms will result in negative results for the trader and their company. An understanding of these tendencies can assist traders in developing more effective and less risky trading strategies. However, all these elements are to be incorporated in the simulator software system.

The notion of "loss aversion" is well known in the case of trading and market investment activities. The simple definition of loss aversion is the tendency of individuals to choose avoiding losses to gain accumulation of an equal value. The fear and the pain of losing are approximately 200% more significant than the pleasure of gaining. This bias can determine irrational decision making in the market space, such as maintaining losing positions for an extended period or selling winning positions early to avoid realising a loss. Our research demonstrates that AI technologies and more specifically algorithms can efficiently master loss aversion through a range of processes integrated into trading software simulators. These include equitable decision making, consistent strategies, risk management, behavioural analysis, which enhance active feedback and real-time adjustments, and ultimately, *backtesting.* This latter process empowers AI to simulate trading strategies using historical and current data, thereby assisting traders in understanding the long-term effects of their strategies and eliminating loss-averse behaviours.

"The fear of missing out" is another in key concept in trading biases and it refers to the emotional response that rolls out when traders experience anxiety about missing possible profit opportunities. As a result, investors manifest impulsive and irrational decision-making – a classic example is entering trades without sufficient analysis in pursuit of instant gains. In this case, the fear has an immediate consequence in the form of lack of clarity in decision making. As a proposed solution through this research, the trading simulator can facilitate data-driven decision making avoiding all the biases. As a functionality mechanism, algorithms continuously monitor market conditions and execute trades based on predefined criteria and rules, historical and present data, thereby avoiding the impulsive decisions driven by concepts such as "the fear of missing out". This has the effect of reducing the emotional influence on trading activities, which in turn may result in more rational and potentially more profitable outcomes.

The last concept that we would put forward is the one of the "law of small numbers". This bias interferes in the trading activity by applying the outcomes from a limited sample of data to a larger scale. In other words, humans have a significant tendency to extrapolate their decision to a limited number of situations that manifested a specific result. In the context of trading, this bias can result in traders overestimating the reliability of recent gains, assuming that they are indicative of long-term trends. This can result in incorrect decisions based on insufficient data, which may lead to implicit losses. Using AI technology to develop very high-performing software simulators, the algorithms sort through massive data analysis and huge historical data. As a result, traders can reduce their reliance on small samples. There is also an element of pattern recognition such that the advanced algorithm identifies real patterns across large data sets, distinguishing what is random noise and what contains meaningful patterns. Adaptive algorithms and feedback processes within the system enhance continuous learning. Taking into consideration the key findings presented in the dissertation, it can be concluded that utilization of the ethical AI-driven technologies augmented by the incorporation of neural networks and machine learning methodologies, assisted all the time by the human decision depict one of the most effective methodologies for the reduction of behavioural and trading errors. The primary reason behind this is that these superior technologies can analyse huge datasets, detect patterns that the human eye would miss, and then complete the trades with accuracy and consistency. Time and again, our research brings out the suggestion that software trading simulators be improved as a way of overcoming biases. Such a system, embedded with ethical algorithms, will effectively train and guide the trader on processing all available market information and assist them on preventing cognitive biases; aiming for more justifiable and rational decisions on trading to be made in a hybrid (human-machine) approach.

5. Findings

Our results suggest that there has been quite some advancement in the capabilities, volumes, mechanisms, and techniques in trading activities over the past 60 years. The introduction of systematic advanced analytics-driven strategies into trading has changed the domain very significantly and provided a big competitive advantage, powered by increases in computing power and data availability and the development of statistical methods. This section will provide a brief summary of the findings in the research. With increasing uses of artificial intelligence systems to aid humans in making their decisions, it becomes of utmost importance to have the full understanding of the potential for these systems to guide human behaviour in ways that can be either inadvertent or harmful. Regardless of their high predictive capacity, algorithm models may lack sufficient explainability, robustness, and fairness. Consequently, they may not be regarded as trustworthy by the traders, business users, auditors, and regulators. The trustworthiness of AI algorithms in trading requires at the same time the growth of sophisticated statistical techniques to quantify associated risks. This demand is correlated with recently proposed regulations, such as the

European Artificial Intelligence Act (EU, 2022) and the American Artificial Intelligence Risk Management Framework (United States National Institute of Standards and Technologies, 2022). For a fair evaluation of the trustworthiness of AI applications in trading, it is mandatory to define a set of quantifiable indicators that are specific to AI systems in this domain. Our straightforward observation is that classical statistical metrics and descriptive indicators are inadequate or, in the most optimistic scenario, insufficient for this purpose. As a next step in our research, we will define the blend of the most suitable combined statistical metrics that can be employed to measure, manage, and mitigate the risks associated with the use of artificial intelligence in trading.

Table 1 and Table 2 depict an example of a trading algorithm simulator system (we will name it "TASS") that leveraged the market data and applied machine learning algorithms. The trading biases, as described in the paper, have been eliminated by the algorithms. Table 3 shows the result when using TASS compared with the trader's decision. This is an alternative trading system or a trading simulator system. The research results inarguably validated that the trading simulator system, developed based on the advances of AI technology and algorithms, has generated profits. To illustrate this, we selected three positions from the overall study, all of which were profitable. The similar profitable results have been obtained for all the positions that have been studied.

Table 1. The list of trades created by the trading algorithms simulator system (buy)

Symbol	Trade Side	Buy Trade no.	Buy Price Trader	Buy Price TASS
CMP	BUY	12	0.87	0.98
ALU	BUY	13	0.65	0.67
BRD	BUY	10	11.7	11.99

Source: adapted from Vinte et al. (2019).

Table 2. The list of trades created by the trading algorithms simulator system (buy)

Symbol	Trade Side	Sell Trade no.	Sell Price Trader	Sell Price TASS
CMP	BUY	12	0.87	0.99
ALU	BUY	13	0.65	0.68
BRD	BUY	10	11.7	12.00

Source: adapted from Vinte et al. (2019).

Table 3. The return obtained by using the trading algorithm simulator system.

Symbol	Variance Buy	Variance Sell	Return %
CMP	+0.11/12.65%	+0.012/13.79%	1.14
ALU	+0.02/3.07%	+0.03/4.61%	1.54
BRD	+0.29/2.48%	+0.03/3.0%	0.52

Source: adapted from Vinte et al. (2019).

6. Conclusions

In the financial and banking industry and particularly in the investments domain, the plethora of information and data are defined by a significant level of complexity, noise, nonlinearity, and nonstationary and sometimes extremely versatile. In such a sophisticated environment, it is demanding and in most of the cases impossible for traders to develop a reliable strategy. Our research revealed that an extensive usage of a hybrid approach of ethical AI technology - which implies neuronal networks and machine learning algorithms, fostering continuous learning and feedback mechanism enhanced finally human decision - to overcome the identified biases. The algorithms, integrated as part of a software trading solution, have shown significant results in multiple areas, proving to be effective tools for the extraction of market characteristics and the avoidance of cognitive biases. Consequently, deep learning methods, neural networks, and machine learning techniques assisted by human decisions are employed in the new phenomenon of profitable and stable trading domain which will portray the characteristic of a future market imperative. At the same time, the incorporation of these algorithms might assist predictive precision, optimised decision making, and accelerated trading strategy efficiency. The research revealed that the development of a high-fidelity simulator software solution for the capital markets infused with AI algorithms will positively influence the behaviour of traders and investor bankers by allowing them to learn and test their skills in a “sandbox” like the trading environment they operate in. Such an established system can be subsequently extended to all trading markets with potential applications in other industries.

Declaration of Generative AI and AI-assisted technologies in the writing process: "During the preparation of this work the authors used *DeepL Write* in order to improve readability and language of the work. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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