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ARTIFICIAL INTELLIGENCE IN INVESTMENT DECISION-MAKING: BENEFITS, BIASES, AND MARKET IMPLICATIONS

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Abstract: *Artificial intelligence (AI) has become more and more central to modern investment management, as it promises faster information processing, better pattern recognition, and more adaptive portfolio strategies. Asset managers, hedge funds, investment banks and robo-advisory platforms now use machine learning, natural language processing and algorithmic optimisation techniques to assist with security selection, portfolio construction, execution and risk monitoring. But the rise of AI in finance also raised serious concerns about data bias, model opacity, overfitting, herding and systemic fragility. This article critically discusses the use of AI in investment decision-making from three interrelated angles: its possible practical benefits, its methodological and institutional constraints, and its overall effect on market behaviour. It argues that AI can materially improve analytical efficiency and decision support, but its value is often oversold where predictive power is confused with sound investment judgement. Investment decisions are not just statistical optimisation problems. They involve uncertainty, institutional constraints, behavioural responses, and the interpretation of economic meanings. AI should therefore not be viewed as a substitute for human judgement but as a sociotechnical decision system whose effectiveness is based on governance, interpretability, and disciplined use.*

Keywords:*Artificial intelligence; investment decision-making; machine learning; portfolio management; behavioural finance; financial markets*

1. INTRODUCTION

Investment decision-making has traditionally been a mixture of quantitative analysis and qualitative judgement. Historically, investors and portfolio managers have used valuation models, financial statements, macroeconomic indicators, industry knowledge and professional interpretation to decide where to allocate capital. However, the financial environment has evolved to become more data-intensive. Market participants today are confronted with vast streams of structured and unstructured information, including tick-level price data, corporate disclosures, earnings-call transcripts, news reports, social-media sentiments, and alternative

Latin American Journal of Education
www.lajoe.org

datasets. In such a context, artificial intelligence has become a powerful tool for extracting signals, finding patterns, and supporting investment decisions (Agrawal, Gans, and Goldfarb, 2018; Lo, 2017).

In finance, AI is not a single technique but rather a broad family of computational methods, including machine learning, deep learning, natural language processing, and predictive analytics. Currently, these technologies are used for security screening, market forecasting, sentiment analysis, portfolio optimisation, algorithmic trading, and robotadvisory services (Jabeur, Mefteh-Wali, and Viviani, 2023; Jiang, Kelly, and Xiu, 2020). They promise to process more information faster and more consistently than human analysts working alone.

However, the allure of AI in investment management has frequently led to conceptual inflation. There is a common implication in public and professional discourse that better prediction must lead to better investment decisions. This assumption is dubious. Investment is not a forecasting problem. It encompasses judgement under uncertainty, adaptation to changing regimes, the interpretation of ambiguous signals, and awareness of institutional and behavioural contexts. Models that do well on historical data can break down when market structures change, when liquidity conditions change, or when unexpected events break the relationships that existed in the past (Lo, 2017; Bailey et al., 2014).

This article critically discusses the role of AI in investment decision-making and raises three key questions. The first question is, “What are the benefits of AI for the investment process?” Secondly, what are the biases, limitations, and governance issues associated with its use? Thirdly, what are the implications of the wider adoption of AI for market behaviour, competition, and systemic risk? AI can significantly improve analytical support in investment management, but it cannot replace sound human judgement and institutional oversight. Far from eradicating the problems of investment decision-making, AI reshapes them into new technical and governance forms.

2. Conceptual foundations: AI, finance and the meaning of decision quality

The traditional classical finance theory has connected better market outcomes to better information processing. The Efficient Market Hypothesis states that asset prices incorporate all available information, and Modern Portfolio Theory formalises the risk-return trade-off in the construction of a portfolio (Fama, 1970; Markowitz, 1952). From this point of view, the appeal of AI is that it promises to process more information faster and on a larger scale, allowing for better investment decisions.

But the relationship between information processing and quality of decisions is more nuanced than this framework suggests. Financial markets generate useful signals, but they also

Latin American Journal of Education
www.lajoe.org

generate noise, instability and context-dependent regularity. More data does not necessarily mean more insight. In fact, big datasets can increase the risk of false discovery, particularly when models have a strong tendency to search for patterns that may not be present out of sample. In adaptive markets, relationships change as participants learn, imitate and respond strategically to each other (Lo, 2017).

Therefore, AI should be viewed not so much as a predictive technology but as an epistemic system that delineates what constitutes valid financial knowledge. It favours measurable correlations, machine-readable information, and computational optimisation. This can be advantageous when complexity exceeds the limits of human attention. But it can also constrain investment thinking by favouring what can be measured over what is economically meaningful. Management credibility, regulatory fragility, geopolitical exposure, and institutional quality are important for long-term investment outcomes but are difficult for machine learning systems to see.

So, a critical standpoint has to distinguish prediction from judgement. Prediction is a statistical estimate of what will happen in the future; judgement is how much confidence to have in those estimates, how they should affect portfolio choices, and how they interact with broader strategic objectives. Furthermore, an AI model may reduce investment quality even if it improves the accuracy of short-term forecasts if it incentivises overtrading, underestimates structural breaks, or hides uncertainty behind technical sophistication (Kahneman, 2011; Rudin, 2019). So, the relevant question is not whether AI can generate better signals in narrow terms but rather whether it can enable more robust, accountable, and resilient investment decisions.

3. The analytical benefits of AI in investment decision-making

The strongest case for AI is that it can increase analytical capacity. Financial professionals need to handle more and more information that goes well beyond the traditional spreadsheet-based or purely discretionary analysis. AI systems can simultaneously ingest price histories, accounting variables, macroeconomic indicators, textual narratives and other data. This expands the information base for investment decisions and shortens the time to identify potential opportunities or risks (Agrawal, Gans and Goldfarb, 2018; Gu, Kelly and Xiu, 2020).

Another big plus is pattern recognition. Machine-learning techniques are especially useful when relationships are nonlinear, high-dimensional or unstable. In asset pricing and portfolio management, AI can find interactions between variables that traditional linear models sometimes miss. This can potentially lead to improved factor identification, return prediction and dynamic allocation, particularly in situations where relevant information is spread across many data sources (Gu,

Latin American Journal of Education
www.lajoe.org

Kelly and Xiu, 2020; Jiang, Kelly and Xiu, 2020).

The informational frontier of investing has widened with natural language processing, as well. Qualitative information from earnings-call transcripts, analyst reports, news articles and central bank communications can affect market expectations but is hard to encode using traditional methods. NLP extends the reach of systematic analysis by transforming such text into measurable variables of sentiment, tone or topic (Tetlock, 2007; Fisher, Garnsey and Hughes, 2016). This is especially useful in markets where valuation is influenced by narrative, tone and managing expectations.

AI may also improve operational efficiency. Automation can cut research time, algorithms can help optimise order routing and timing, and robo-advisors can make portfolio recommendations at a lower cost. AI may enhance access to investment services and reduce some of the fixed costs inherent in traditional advisory models (Sironi, 2016; D'Acunto, Prabhala and Rossi, 2019). AI could enhance monitoring efficiency for institutional investors, for example, by flagging deviations, risk concentrations or unusual market conditions in real time.

AI can bring value to another domain as well – risk management. AI systems can detect emerging risks faster than periodic human review alone, because they are continuously processing changing volatility, correlation structures, liquidity conditions and market microstructure signals. This does not remove uncertainty but may improve the speed and granularity of risk detection (Boukherouaa et al., 2021). Such responsiveness is economically meaningful in a highly connected or fast-changing market.

Still, these benefits should be taken with a grain of salt. Faster processing does not necessarily translate into better investment performance. More signals does not mean better judgement. AI can increase the efficiency of information processing, but whether it leads to better decisions depends on how outputs are interpreted, constrained and embedded within portfolio processes. Critical analysis is therefore crucial at this point.

4. Bias, opacity and the fragility of AI-based investment systems

The first big limitation of AI in investment management is data bias. Machine-learning models are trained on historical data, but financial history is not a neutral or stable record. It is shaped by particular monetary regimes, regulatory conditions, political interventions, market structures and behavioural episodes. If those conditions change, the learned relationships can degrade quickly. Accordingly, historical data can encode transitory regularities as permanent truths (Kahneman, 2011; Boukherouaa et al., 2021).

The problem is particularly acute in finance, where structural change is common. Interest rate regimes change, policy regimes evolve, sector weights change; and crises suddenly reprice risk.

Latin American Journal of Education
www.lajoe.org

A model trained in times of abundant liquidity might falter in tightening cycles. A strategy that seems to work in stable market conditions may fail in crisis regimes when correlations converge and liquidity dries up. In those cases, AI does not so much discover objective laws of the market as it extrapolates from historically contingent patterns.

A second limitation is opacity. Many AI models, and particularly deep learning systems, are challenging to interpret. This presents a serious governance problem in investment management. Portfolio managers, risk officers, clients, and regulators often enquire about the rationale behind a position or the reasons for adjusting a portfolio. A model that provides a recommendation with no intelligible reasoning might be statistically impressive but institutionally weak (Rudin, 2019). This is especially problematic in fiduciary settings, where accountability is emphasised.

Opacity also raises a deeper epistemological problem. But when investors use black-box systems that they do not understand, they may treat machine outputs as objective simply because they are produced by computation. This can lead to a dangerous inversion of judgement: instead of models supporting investment reasoning, human decision-makers begin to defer to models whose assumptions they cannot adequately challenge. The outcome is not the end of subjectivity but its hiding in technical systems.

The third problem is overfitting. AI models tend to do well in-sample, as they pick up complex patterns in historical datasets. But financial markets are adaptive and reflexive: as soon as a pattern is known and exploited, its profitability may diminish or disappear. A model can thus discover relationships that are statistically impressive but economically fragile (Bailey et al., 2014). In finance, numerical sophistication can exacerbate this fragility by providing a false sense of reliability. Investors may trust precise outputs without adequately questioning if the underlying process is stable.

Another major weakness is that AI often formalises a narrow conception of rationality. The models typically optimise for expected returns, volatility, drawdowns, or classification accuracy. These are important, but real investment decisions also involve liquidity constraints, governance issues, long-term strategic positioning, regulatory obligations and tail-risk resilience. Things that cannot be simply reduced to an objective function may receive a lower rating or be forgotten. AI may thus take technically elegant decisions that are economically incomplete.

Finally, hindsight confidence is fuelled by the popularity of backtesting. Historical simulation is a must but can never simulate the uncertainty of live markets. The problem with back-testing is not that it is useless, but rather that it is often overrated. Strong past performance under model conditions is not the same as

Latin American Journal of Education
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robustness to open-ended future uncertainty.

5. AI and human judgment: substitution or augmentation

One of the main questions in the literature is whether AI should replace or augment human investment professionals. Claims that machines are less emotional, more consistent, and better able to process data than humans often imply the alternative view. Behavioural finance certainly shows that human investors are overconfident and subject to availability bias, loss aversion and herd behaviour (Kahneman, 2011). And such behaviour, in turn, makes AI look attractive as a fix for the flaws of human cognition.

But this contrast is too simplistic. AI may reduce some human biases, but it also introduces its own technical biases, such as training-data bias, optimisation bias and black-box dependence. The relevant comparison is then not between irrational humans and rational machines, but between different configurations of error in humans and machines. Human judgement may be uneven, but it can also perceive context, ambiguity, and structural change in ways that purely statistical systems find difficult.

So, the model that is most defensible is that of augmentation rather than total replacement. In this system, AI takes on the data-intensive tasks of screening, signal generation, text analysis, and risk monitoring while human professionals interpret, challenge model assumptions, and make final allocation decisions. This hybrid structure is more realistic because investment management is not only computational. It is also interpretive, strategic and institutional (Lo, 2017; Rudin, 2019).

But hybrid models are not necessarily safe, either. There is a real risk that human oversight becomes more symbolic than substantive. If investment committees or portfolio managers defer to algorithmic outputs on a routine basis, then human control is only in name. Effective augmentation, then, is more than just sticking a person at the end of the process. It demands organisational cultures, governance processes, and incentive structures that foster challenge, validation, and independent thought.

This is an important point, because many failures in quantitative finance are not caused by the absence of humans, but rather by the passivity of humans towards models. When models have institutional authority, judgement is not eliminated but merely displaced and made more difficult to scrutinise.

6. Market implications: concentration, herding and systemic risk

The use of AI in investment management goes beyond individual portfolios and has implications. One possible effect is more informational efficiency. If AI systems process disclosures, macroeconomic releases and market signals quicker than traditional analysts, then some information may be priced in more quickly. In this narrow sense the AI could improve some aspects of market efficiency.

Latin American Journal of Education
www.lajoe.org

But the broader picture is less cheerful. AI could increase competition by boosting the value of proprietary data, computing infrastructure and engineering talent. This may favour large institutions and lead to increased concentration in asset management and trading. Firms with better access to alternative data and high-quality technical teams may develop durable advantages that smaller participants cannot easily replicate (Allen, Gu and Jagtiani, 2022). Such developments can result in a market that is technologically more advanced but less equal in terms of access and capability.

A more serious concern is herd behaviour. If many firms use similar datasets, model architectures or optimisation routines, then their investment behaviour may converge. This can result in crowded trades, correlated exposures and destabilising exits during periods of stress. AI may, therefore, improve efficiency at the level of the individual firm but increase fragility at the level of the market. This tension is at the heart of the issue: what may be rational for one investor can become destabilising if it is replicated across the system (Boukherouaa et al., 2021; Lopez de Prado, 2018).

AI flattens decision-making's temporal structure too. Markets may favour speed over reflection because signals are processed more quickly and execution is more automated. This can exacerbate short-termism and reduce the time for interpretative judgement. In extreme cases, automated decision cycles could amplify volatility, not because models are wrong in a narrow sense, but because too many actors react similarly and too quickly to the same inputs.

There is also a regulatory problem. Algorithmic systems are governing ever larger volumes of capital. Explainability and accountability become public interest issues, not only internal management issues. The existence of big portfolios driven by opaque interacting and partly similar AI systems might open new channels of systemic risk. Governance of AI in finance is therefore not only a matter for firms but also for regulators concerned with market integrity and financial stability.

7. Critical discussion

The above analysis shows that AI offers real benefits in investment decision-making, particularly large-scale data processing, pattern recognition, textual analysis and continuous risk monitoring. These strengths make it an important tool in modern finance. But the gravest flaw in much of the pro-AI discourse is that it confuses technical capability with economic wisdom. Better optimisation does not always mean better investment decisions, and better predictions do not always mean more resilient portfolios.

A more pessimistic perspective is that AI does not address the basic epistemic and institutional problems of investment. Instead, it shuffles them. In some cases, human bias is reduced, but technical bias, opacity, and governance risks are introduced. In the same way, AI

Latin American Journal of Education
www.lajoe.org

can increase the efficiency of individual decision processes by creating collective vulnerabilities through herding, concentration, and model similarity. Therefore, AI neither is a cure nor a threat per se. Its effects depend on the way it is embedded in institutions, incentives and market structures.

This situation has two important consequences. First, investment managers should not just consider whether AI can enhance returns or improve signal extraction. They should also ask if it constrains their view of risk, promotes over-reliance on backup tests, or reduces accountability. Second, scholars need to move beyond simplistic comparisons of "human versus machine". A more useful question is: How do different forms of human-machine interaction affect decision quality, resilience, and market stability?

AI in investing is a powerful yet flawed socio-technical infrastructure. It should ultimately be treated as such. Its value rests less on technological novelty than on whether firms govern it with scepticism, interpretability and institutional discipline.

8. Conclusion

Artificial intelligence is reshaping investment decision-making by scaling the scope of analysis, finding patterns, assisting execution, and managing risk. Its contribution to modern finance is significant, especially in data-rich and fast-moving markets. But these benefits come with some major caveats, such as data bias, model opacity, overfitting, narrow optimisation logic, herding and systemic dependency.

The paper argues that AI should not be seen as a replacement for human investment judgement. Instead, it is a sociotechnical decision system whose performance depends on interpretability, governance and disciplined use. So, the most productive future for AI in investment management is likely to be one of augmentation rather than replacement.

Future research should go beyond the simple question of whether AI is better than human investors. More valuable questions include whether AI improves risk-adjusted performance across different market regimes, when it intensifies systemic fragility, and how understandable models can support more accountable investment decisions. These questions better reflect the true importance of AI in finance today and provide a better starting point for both academic research and professional practice.

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Latin American Journal of Education
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