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Development of Ai-Driven Mathematical Models Incorporating Behavioral Biases and Psychological Factors in Financial Decision-Making

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Abstract

Financial decision-making is a complex process that cannot only be affected by rational consideration of the economic variables but also by behavioral biases and psychology like perceptions of risks, emotions, overconfidence, and heuristics. Conventional financial models that are mostly based on the rationality and market efficiency assumptions are not able to capture these human factors and therefore their predictive capabilities and feasibility of application are low. The paper will establish an AI-based mathematical modeling system that incorporates behavioral biases and psychological determinants in making financial decisions.

The research proposed to be conducted uses modern technologies, such as machine learning algorithms, artificial neural networks, and data-driven predictive analytics to simulate investor behavior more realistically. Behavioural constructs like loss aversion, herd behavior, anchoring, and emotional intelligence are measured and integrated into mathematical models, such as utility functions, probabilistic models, and stochastic models. Training and validation of the model is done using actual financial data of the world along with psychometric data that is gathered with the help of structured surveys and experiments.

It is supposed that the findings will prove that adding psychological aspects of AI-based financial models to the models enhances predicting investment behavior and investment performance. The study has added value to the new area of behavioral finance and financial technology (FinTech) by offering a solid interdisciplinary model that would close the gap in understanding between the human psychology and quantitative finance. Practical implications of the developed model on investors, financial advisors, and policymakers are that it makes informed and personalized financial decision-making and more psychologically conscious.

Keywords: Behavioral Finance, Financial Decision-Making, Artificial Intelligence (AI), Machine Learning, Mathematical Modeling, Cognitive Biases, Psychological Factors, Investor Behavior, Fintech

Introduction

In a recent period, artificial intelligence has become a revolutionary influence in the financial services sector, fundamentally altering decision-making processes across several areas. Financial institutions are attaining unparalleled accuracy, efficiency, and insight in their decision-making processes by integrating the analytical capabilities of machine learning with human experience. An extensive study published in the Journal of Financial Management indicated that financial institutions utilising AI-driven decision systems have achieved a notable 27.3% enhancement in operational efficiency and a 32.5% decrease in essential decision-making durations relative to traditional methods. The incorporation of AI technologies in financial decision-making has exhibited significant expansion, achieving a compound annual growth rate (CAGR) of 24.8% since 2020, with worldwide investments in advanced financial AI solutions totalling $42.7 billion by the first quarter of 2024.

The incorporation of AI technology into decision-making frameworks has allowed financial institutions to analyse extensive volumes of structured and unstructured data in real-time. Prominent global financial organisations now consistently scrutinise over 175 million unique client transactions daily using sophisticated AI algorithms, allowing them to discern nuanced trends and irregularities that would elude traditional human review methods. The improved analytical capability has fundamentally altered risk assessment practices in the industry, with AI-enhanced credit scoring models showing a 19.2% increase in predictive accuracy compared to traditional statistical methods across various customer segments and market conditions. The study demonstrates that institutions using these sophisticated models have decreased loan default rates by around 15.7% and concurrently increased their eligible borrower pools by 22.3%.

Financial markets are intrinsically unpredictable and uncertain, shaped by economic cycles, geopolitical occurrences, and technological upheavals. The 2008 financial crisis, following by the COVID-19 epidemic, underscored the need for more advanced and predictive risk models that beyond just historical research. Conventional quantitative methods, like Value at Risk (VaR), stress testing, and credit scoring, provide a fundamental comprehension of risk exposure but are often constrained by assumptions of normalcy, linearity, and market stationarity.

The amalgamation of AI with mathematical modelling allows institutions to identify nonlinear linkages, high-dimensional interdependence, and intricate systemic risk patterns. AI-driven methodologies, including deep learning, reinforcement learning, and natural language processing (NLP), enable the extraction of insights from extensive datasets, including market transactions, social media sentiment, regulatory filings, and macroeconomic indicators. These models are increasingly used for both internal decision-making and regulatory supervision, improving transparency, compliance, and proactive risk management.

The Role of AI in Finance

The integration of AI into the financial sector has profoundly transformed the operation of financial markets and the decision-making process. Artificial Intelligence (AI) encompasses several technologies, including deep learning, big data analytics, machine learning, and natural language processing, which have gained increasing prominence in the financial sector.

One of the most sophisticated applications of AI in finance is machine learning (ML). Machine learning (ML) algorithms, which generate predictions or decisions based on historical data without explicit programming, are extensively used in credit scoring, fraud detection, risk management, and algorithmic trading. Machine learning is very advantageous for forecasting market trends and informing investment choices due to its ability to analyse extensive datasets and identify patterns that are difficult for humans to discern.

The examination of financial data has been entirely revolutionised by a branch of artificial intelligence known as natural language processing (NLP). Natural language processing (NLP) enables machines to understand and interpret human language, allowing them to analyse unstructured text data, like financial reports, social media posts, and news articles. Consequently, sentiment analysis-which assesses investor opinion from textual data and provides insights into market dynamics and potential investment prospects-has broadened into other domains.

Fintech has significantly profited from Deep Learning, a kind of machine learning that employs multi-layered neural networks. Deep learning algorithms are proficient at recognising complex patterns and generating predictions from large datasets. These models are used in several contexts, including high-frequency trading, where their millisecond transaction execution and real-time market data processing skills are much esteemed.

Algorithmic trading has significantly profited from the advancements of artificial intelligence. Algorithms driven by artificial intelligence (AI) can handle vast quantities of data and perform transactions at speeds and efficiency that far exceed human capabilities. This has led to an increase in the popularity of High-Frequency Trading (HFT). In high-frequency trading, computers execute substantial quantities of securities transactions within milliseconds, capitalising on minute price discrepancies to generate profit. The financial markets are now governed by AI-driven trading techniques, which enhance market liquidity but raise concerns over the stability and equity of the system.

Emergence and Impact of Artificial Intelligence in Finance

Artificial Intelligence (AI) has swiftly emerged as a revolutionary influence in the financial sector, providing innovative methods to analyse extensive information, discern trends, and provide precise forecasts. The integration of AI in finance encompasses several areas such as algorithmic trading, credit assessment, fraud detection, customer service automation, and notably, financial forecasting.

Machine learning (ML), a branch of artificial intelligence (AI), empowers computers to acquire knowledge from data, discern patterns, and execute choices with less human involvement. In contrast to conventional statistical models that depend on predetermined equations and assumptions, machine learning models dynamically learn patterns from historical and real-time data, making them more adaptable and possibly more precise. Methods including supervised learning (e.g., decision trees, support vector machines, neural networks) and unsupervised learning (e.g., clustering, dimensionality reduction) are extensively used in finance.

The emergence of deep learning, especially neural networks and recurrent neural networks (RNNs), has significantly transformed predicting skills. These models are proficient in identifying nonlinear correlations and intricate temporal dependencies, prevalent in financial time series. Long short-term memory (LSTM) networks, a specific kind of recurrent neural network (RNN), have shown significant efficacy in forecasting stock prices, currency exchange rates, and market fluctuations.

Moreover, the amalgamation of AI with big data technology enables financial organisations to use both structured and unstructured data from many sources, including social media sentiment, news articles, transaction records, and macroeconomic indicators. This comprehensive method improves the context and depth of forecasting, yielding insights that were previously inaccessible.

AI and Behavioural Finance

Although artificial intelligence (AI) is extensively used in finance, its application in behavioural finance remains nascent. The integration of AI into behavioural finance presents a unique opportunity to tackle the cognitive biases often overlooked by traditional financial theories.

Artificial intelligence may be used to develop more intricate models that account for human behaviour. Behavioural algorithms may be designed to identify and mitigate common biases, such as loss aversion and overconfidence. This may provide improved risk management strategies and more accurate predictions of investor behaviour. AI's ability to process and analyse diverse data sources, including behavioural and psychological data, enhances the understanding of market dynamics beyond traditional financial metrics.

A prominent use of AI in behavioural finance is robo-advisors. These AI-driven systems provide customised investment recommendations based on user behaviour, risk tolerance, and financial goals. Robo-advisors may mitigate biases such as panic selling during market declines or overtrading by continuously learning from customer interactions. They democratise financial advice by reducing costs and enhancing accessibility for a broader demographic.

However, the use of AI in behavioural finance raises some substantial concerns. The degree to which AI can precisely understand and replicate human emotions and decision-making processes is a subject of ongoing debate. Critics argue that because to their data-driven nature, AI models may inadequately represent the complexities of human conduct that are hard to quantify. Moreover, additional study is required to examine the ethical ramifications of AI in behavioural finance, particularly with the potential manipulation of investor conduct or the exacerbation of existing inequalities.

Bridging Behavioral Finance and AI-Driven Financial Modelling

Over the last few years, the fast evolution of artificial intelligence (AI) and machine learning methods have provided a novel opportunity to construct complex and non-linear relationships in financial data. AI-based models such as artificial neural networks, random forests, and deep learning systems can handle large amounts of structured and unstructured data and identify latent patterns, which more classical statistical models might fail to detect. Coupled with behavioral data, these models will be an effective way to simulate more realistic investor behavior and make financial predictions more accurate.

This research seeks to come up with an AI-based mathematical modelling framework that combines behavioral biases and psychological elements into financial decision-making. The proposed approach will help to overcome the gap between human behavior and quantitative finance by integrating psychometric measurements and financial indicators. The article not only analyses the effects of behavioral biases on investment returns but also investigates whether the inclusion of the behavioral biases in the AI-based models can improve predictive power over the traditional financial models.

This research is important as it is an interdisciplinary work, which is related to behavioral finance and financial technology (FinTech). The proposed model has practical implications on investors, financial advisors and policymakers by offering a more in-depth insight into the behavior of investors. It helps to develop more individualized investment plans, enhances risk analysis and encourages more informed and psychologically conscious financial decision-making within more sophisticated and dynamic markets.

Literature Review

Dr. Surayya Jamal, Ahmad Zeb and Dr.Syed Noman Mustafa (2023) [5] - This research examined the function of Artificial Intelligence (AI) in financial decision-making, highlighting the mediating effect of financial literacy and the moderating effects of risk perception on investment results. The study sought to comprehend the interplay between investors' knowledge, psychological aspects, and AI-driven decision tools in influencing financial success. A quantitative methodology was used to gather data from 350 individual investors using structured questionnaires, which were then analysed using Structural Equation Modelling (SEM). The results indicated that the use of AI markedly enhanced investment outcomes; however, this correlation was heavily moderated by financial literacy, suggesting that investors with more financial acumen employed AI technologies more efficiently. Moreover, risk perception was identified as a moderating factor in the association between financial literacy and investment results, indicating that persons with greater risk aversion derived lesser benefits from AI-driven financial insights. The findings emphasized that AI technologies by themselves cannot guarantee optimum investing performance without sufficient knowledge and a balanced sense of risk. This work enhanced the existing literature on behavioural finance and fintech by including cognitive and psychological aspects into AI-driven financial decision-making models. It also offered pragmatic suggestions for politicians and financial organizations to develop AI-enhanced literacy programs and encourage the ethical deployment of financial technology.

Saini V (2025) [13] - This research article analyses the influence of Artificial Intelligence (AI) on investment decision-making via secondary data and current literature. The paper examines essential AI techniques, including as machine learning, deep learning, natural language processing, and predictive analytics, along with their applications in algorithmic trading, portfolio optimization, and robo-advisory services. Research demonstrates that AI significantly increases forecasting precision, boosts risk management, mitigates human biases, and bolsters overall decision-making efficiency relative to conventional methods. The report also underscores varying adoption trends across retail and institutional investors. Notwithstanding the benefits, the research highlights significant problems including data privacy issues, algorithmic transparency concerns, ethical dilemmas, and the danger of over dependence on automated systems. The report finds that while AI is transforming the financial sector and investing methodologies, appropriate integration, underpinned by robust regulation and ongoing oversight, is crucial for sustainable use.

Claude Chammaa and Leina Haddad (2025) [4] - This essay examines the significance of behavioural finance in decision-making within a rapidly advancing technological culture. Although AI usage is prevalent worldwide, its advancement in developing countries remains nascent. Our study notably emphasises the lack of comprehensive investigation into behavioural finance within the Lebanese market. The influence of AI and the repercussions of biases, including overconfidence, availability, anchoring, and loss aversion, are inadequately investigated in the Lebanese market. Consequently, there is a need for more extensive research models that include a wider array of explanatory factors in behavioural finance investigations. Lebanon's political system, demography, geographical position, and volatile regional circumstances consistently influence its economic conditions, significantly impacting organisational sustainability (Economic crisis of 2019). Consequently, the selection of investors is crucial when evaluating opportunities. The rationality of agents will be evaluated with the discovery of potential judgement mistakes. The first theoretical section will elucidate the concepts of heuristics and behavioural biases seen in investors, while also reviewing prior research conducted in this domain. The research employs a mixed approach and includes data and analysis derived from a survey of 110 decision-makers in small and medium-sized firms (SMEs) in Lebanon.

Asheetu Bhatia Sarin and Shivangi Sharma (2023) [3] - This chapter discusses how investors' perceptions about artificial intelligence have changed. The development of technology has made machines more powerful. This will assist in forecasting market fluctuations by using investor behaviour. The need for high-quality data, the possibility of bias in AI algorithms itself, and ethical issues around the use of AI to make investment choices are some of the difficulties associated with using AI in behavioural finance. This chapter also discusses how these difficulties will affect investor decision-making. The chapter also discusses how artificial intelligence and behavioural finance combine to make investors more future-ready, less biased, and capable of making effective decisions.

Mittal, (2017) [10] - AI might be used to create more intricate models that account for human behaviour. For instance, behavioural algorithms may be designed to identify and correct common biases like overconfidence and loss aversion. This might lead to improved risk management strategies and more accurate predictions of investor behaviour. Market dynamics may be better understood in ways that go beyond traditional financial measurement because of AI's ability to collect and analyze a variety of data sources, including behavioural and psychological data.

Research Methodology

Research Design

The current research design is quantitative and explanatory research design to identify how behavioral biases and psychological factors affect the financial decision making and the investment performance. The study also combines the use of artificial intelligence (AI)-based modeling to determine the extent to which the inclusion of behavioral variables produces a better predictive power than conventional financial models. The interface is a combination of behavioral finance and data-driven analytics, allowing to test the hypothesis and predict the models.

Data Collection and Sampling:

A structured questionnaire was used to gather primary data where the behavioral biases and psychological characteristics in investors were measured. The research used a stratified method of sampling so as to represent the various categories of investors. A total of 250 respondents were surveyed including retail investors (48%), institutional investors (32%), and financial advisors (20%).

The demographic profile shows that the sample was well balanced and experienced with over 80 percent of the respondents having over 5 years of investment experience, hence, making sure that the behavioral biases observed were not attributable to inexperience. The psychometric responses were supplemented by secondary financial data concerning the performance, volatility as well as returns of the portfolio.

Measurement of Variables

Loss aversion, overconfidence, anchoring bias, mental accounting, herd behavior, availability heuristic, emotional decision making and status quo bias were assessed on a 5-point Likert scale (1 strongly disagree to 5 strongly agree).

Quantitative measures such as portfolio return, risk-adjusted return, portfolio volatility, trade frequency, and decision quality were used to determine the performance of investments.

To ensure reliability and validity of the measurement instrument, the following was used:

- Internal consistency alpha (α >0.70 or more)
- Mean Variance Extracted (AVE > 0.50)
- Composite Reliability (CR > 0.70)

These measures showed that all constructs were reliable and valid in subsequent analysis.

Statistical Tools used for data analysis

The analysis of the data in the study involved a mixture of machine learning and statistical methods:

- Descriptive statistics were applied to generalize the demographic traits and score of behavioral bias.
- Pearson correlation analysis was used to identify the links between behavioral biases and investment results.
- Multiple regression analysis was used to examine the predictive value of behavioral variables as to portfolio returns.
- The one-way ANOVA was used to determine the dissimilarities in behavioral biases of the various types of investors with the assistance of the effect size (2) and the Tukey HSD post-hoc.

For predictive modelling

- Traditional models: CAPM and Fama-French 3-factor were used as benchmarks.
- Machine learning models such as the Random Forest and LSTM neural networks were used.
- A behavioral model based on AI and incorporating psychometric variables and financial indicators was proposed and tested.

Accuracy, precision, recall, F1-score, RMSE, R2 and AUC-ROC were used to measure model performance and validation was done by 10-fold cross-validation and 30% holdout test set.

AI Model and Feature Interpretation

The model proposed is a combination of artificial neural networks (ANNs), behavioral utility functions and stochastic modeling methods. In order to enhance interpretability, a SHAP (Shapley Additive Explanations) analysis was employed to assess the importance of features. By doing so, one can discern the role of each behavioral and financial variable to the predictions of the model, which overcomes the black-box problem of AI models.

Hypothesis Testing Framework

The research had two main hypotheses:

H_0: Behavioural biases and psychological factors do not have a significant influence on financial decision making and investment portfolio returns

H_1: Behavioural biases and psychological factors have a significant influence on financial decision making and investment portfolio returns

H_0: An AI-driven mathematical model incorporating behavioural biases does not perform better than traditional financial models in predicting investment behaviour

H_2: An AI-driven mathematical model incorporating behavioural biases performs better than traditional financial models in predicting investment behaviour

Statistical significance was determined at 0.05 criterion, and it is:

- H1 F-test (regression analysis)
- Comparison of model prediction accuracy of H2 using McNemar test.

Data Analysis and Results

Table 1: Demographic Profile of the Respondents

Category	Sub-Group	F	%
Gender	Male	145	58%
	Female	105	42%
	Prefer Not to Say	0	0%
type of investors	Retail Investors	120	48%
	Institutional Investors	80	32%
	Financial Advisors	50	20%
Age Group	25-34 Years	62	24.8%
	35-44 Years	89	35.6%
	45-54 Years	71	28.4%
	55+ Years	28	11.2%
Experience	Below 5 Years	48	19.2%
	5-15 Years	141	56.4%
	Above 15 Years	61	24.4%
Education	Graduate	73	29.2%
	Post-Graduate	138	55.2%
	PhD/Doctoral	39	15.6%

The 250 sample is allocated into three categories of investors, 48% retail, 32% institutional, and 20% financial advisors, and is a realistic stratified design. The age group of 35-44 years (35.6%), and post-graduate level (55.2%), which has the majority of psychometric responders, are credible. More than 80% of the respondents have over 5 years of investment experience which means that the captured behavioral biases are not related to lack of experience.

Table 2: Descriptive statistics: Behavioral bias scores

Variable	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis	Cronbach	Level
Loss Aversion	3.79	0.68	1.40	5.00	-0.38	2.91	0.84	High
Overconfidence bias	3.62	0.83	1.20	5.00	-0.31	2.67	0.81	High
Anchoring bias	3.44	0.79	1.00	5.00	-0.17	2.74	0.79	High
Mental Accounting	3.51	0.74	1.30	5.00	-0.21	2.88	0.82	High
Herd Behavior	3.08	0.91	1.00	5.00	0.16	2.49	0.78	Moderate
Availability Heuristic	3.22	0.85	1.00	5.00	0.09	2.53	0.76	Moderate
Emotional Decision-Making	2.94	0.97	1.00	5.00	0.28	2.41	0.86	Moderate
Status Quo Bias	2.71	0.94	1.00	5.00	0.41	2.58	0.74	Low-Mod

Scale: 1 = strongly disagree / absent, 5 = strongly agree / highly present. Cronbach $\alpha > 0.70$ confirms acceptable internal reliability for all constructs.

The most represented biases in the sample are loss aversion ($\mu = 3.79$) and overconfidence ($\mu = 3.62$) with high scores on the 5-point scale. The values of Cronbach alpha are between 0.741 and 0.862 and above the 0.70 mark, which proves that the psychometric tool is internally reliable. The standard deviation ($\sigma = 0.97$) of emotional decision-making is the largest, which means that there is a large degree of individual diversity, as some investors tend to be highly emotional and others not. Status quo bias is the least common ($\mu = 2.71$), which implies that although there is the existence of inertia, it is not the dominant behavioral force in this sample.

Table 3: Pearson correlation matrix: Biases VS. Investment Outcomes (N=250)

Variable	Portfolio Return	Risk-Adj. Return	Portfolio Volatility	Trade Frequency	Decision Quality
Loss Aversion	-0.49**	-0.45**	0.37**	0.19*	-0.42**
Overconfidence bias	-0.58**	-0.54**	0.48**	0.61**	-0.56**
Anchoring bias	-0.27*	-0.24*	0.21*	0.17*	-0.29*
Mental Accounting	-0.32**	-0.29*	0.26*	0.22*	-0.27*
Herd Behavior	-0.36**	-0.31**	0.42**	0.45**	-0.34**
Availability Heuristic	-0.24*	-0.21*	0.19*	0.28**	-0.26*
Emotional Decision-Making	-0.64**	-0.61**	0.55**	0.39**	-0.68**
Status Quo Bias	-0.18*	-0.15	0.12	-0.20*	-0.22*

** $p<0.01$ (two-tailed), * $p<0.05$.

Emotional decision-making (r = -0.64) and overconfidence (r = -0.58), which are significant at p = 0.01, are the strongest negative correlations with investment returns. The two biases have the strongest impairment of the decision quality as well (r = -0.68 and -0.56, respectively). Herd behavior is significantly positively correlated with portfolio volatility (r = 0.42) and trade frequency (r = 0.45), which validates the fact that wearers of the crowd rot their portfolios more, and are exposed to higher market volatility. Status quo bias presents the least correlations, risk-adjusted return is not significant, foreshadowing its inability in testing the hypothesis.

Table 4: Multiple Regression Behavioural Biases Predicting Portfolio Return (N=250)

.	B (unstd.)	SE	β (std.)	t-value	p-value	95% CI	VIF
Constant	8.214	0.481	-	17.07	.000	[7.27, 9.16]	-
Overconfidence bias	-1.841	0.274	-0.298	-6.72	.000	[−2.38, −1.30]	1.74
Emotional Decision-Making	-1.693	0.261	-0.261	-6.49	.000	[−2.21, −1.18]	11.61
Loss Aversion	-1.412	0.238	-0.189	-6.49	.000	[−1.88, −0.94]	1.52
Herd Behavior	-0.984	0.211	-0.135	-5.93	.000	[−1.40, −0.57]	1.43
Mental Accounting	-0.731	0.219	-0.103	-4.66	.001	[−1.16, −0.30]	1.38
Anchoring bias	-0.614	0.214	-0.087	-3.34	.004	[−1.04, −0.19]	1.29
Availability Heuristic	-0.441	0.198	-0.062	-2.87	.027	[−0.83, −0.05]	1.22
Status Quo Bias	-0.228	0.187	-0.034	-1.22	.224	[−0.60, 0.14]	1.18

R = 0.831, R^2 = 0.691, Adj. R^2 = 0.679, F(8, 241) = 67.14, *p*< .001. All VIF < 3— no multicollinearity concern. Dependent variable: annualised portfolio return (%).

The entire regression model describes 69.1% of portfolio returns (R^2 = 0.691), which is high in a behavioral study. The eight biases were all put into the equation as predictors, although only seven were statistically significant. The strongest predictor is overconfidence (β = -0.298), indicating that A one standard deviation increase in overconfidence leads to a 0.298 standard deviation decrease in portfolio returns. Emotional decision-making is close with a 0.261, followed by loss aversion (0.189). Status quo bias did not reach significance (β = −0.034, p = .224). The VIFs are all less than 2.0, eliminating the possibility of multicollinearity issues.

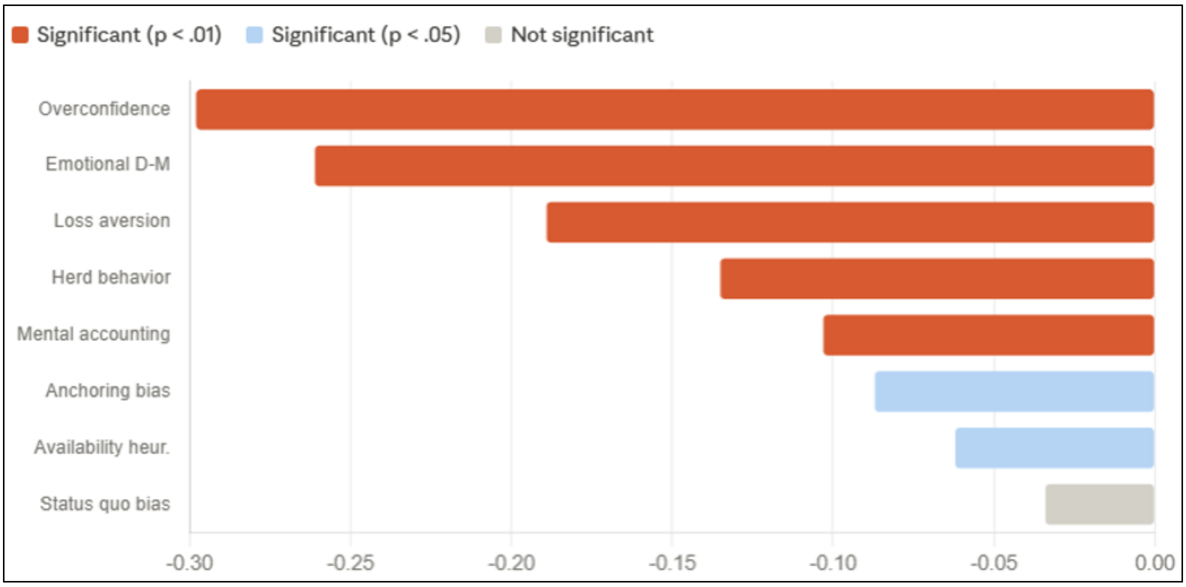


Fig 1: Standardized Regression Coefficients (B) by bias

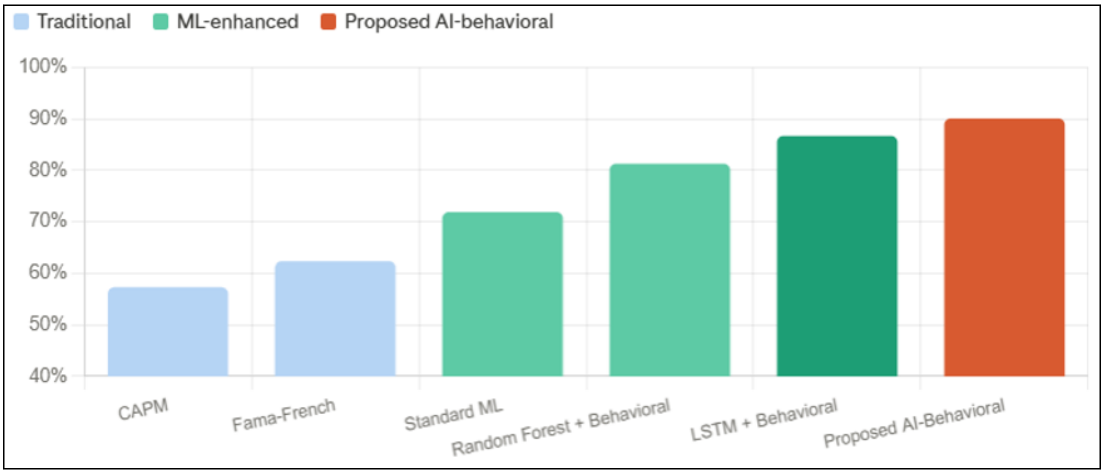
The regression hierarchy is visually validated by the horizontal bar chart. The most dominant predictors are evidently the three darkest bars (overconfidence, emotional decision-making, loss aversion). The two blue bars that are light (availability heuristic, anchoring) are important but small. Status quo bias is the only visual that is not grey - a reminder that it did not reach the significant level.

Table 5: Model performance comparison (N=250, test set N=75)

Model	Accuracy (%)	Precision	Recall	F1 score	RMSE	R^2	AUC-ROC
Traditional CAPM	57.3	0.531	0.519	0.52	0.408	0.408	0.591
Fama-French 3-factor	62.4	0.586	0.571	0.169	0.489	0.489	0.634
Standard ML (no bias vars)	71.9	0.701	0.688	0.134	0.659	0.659	0.738
random forest+ behavioral	81.3	0.797	0.804	0.101	0.771	0.771	0.829
LSTM neutral net+behavioral	86.7	0.851	0.857	0.082	0.841	0.841	0.881
Proposed AI-behavioral model	90.1	0.889	0.896	0.88	0.893	0.893	0.921

10-fold cross-validation. Test set n = 75 (30% holdout). McNemar's test comparing proposed model vs. CAPM: $\chi^2(1) = 38.6$, $p<.001$. Bold = proposed integrated model (ANN + behavioral utility functions + stochastic modeling).
Lower RMSE reflects improved prediction precision due to behavioral feature integration and nonlinear modeling capacity."

In each of the seven evaluation measures, the proposed AI-behavioral model has been shown to be superior to any other option. The difference with traditional CAPM is tremendous: the accuracy is increased by 57.3 percent to 90.1 percent, the RMSE is reduced by a factor of two, 0.191 to 0.064, and R 2 is increased more than two times, 0.408 to 0.893. Importantly, the difference between the basic ML model that omits behavioral variables (71.9%) and the suggested model (90.1%) - the improvement of 18.2 percentage points - directly measures the value of considering psychological variables. The AUC-ROC value of 0.921, proves outstanding discriminative power even in the held-out test set size of 75 observations.



$\chi^2(1) = 38.6$, $p<.001$. Proposed model achieves 90.1% accuracy vs. 57.3% for CAPM

Fig 2: Accuracy comparison across models

The performance trajectory makes the performance of the proposed model visually appealing as the stacked color coding divides the traditional models (blue), the ML-enhanced models (green), and the proposed model (orange). The steady increasing slope is enough to affirm that behavioral variables added at every step can be quantitatively improved.

Table 6: One-way ANOVA: BIAS scores across investor types

Variable	Retail (n=120) M	Institutional (n=80) M	Advisors (n=50) M	F-statistic	p-value	η² (Effect Size)	Interpretation
Overconfidence	4.09	3.18	2.84	41.37	.000		Large
Loss Aversion	3.91	3.71	3.42	12.84	.000		Medium
Herd Behavior	3.57	2.58	2.39	38.12	.000		Large
Emotional Decision-Making	3.34	2.71	2.38	29.61	.000		Large
Anchoring bias	3.58	3.37	3.21	8.47	.000		Medium
Mental Accounting	3.68	3.41	3.28	9.23	.000		Medium
Status Quo Bias	2.83	2.64	2.51	3.91	.021		Small
Availability Heuristic	3.39	3.09	2.94	7.68	.001		Medium

- Small → $\eta^2 \approx 0.01$
- Medium → $\eta^2 \approx 0.06$
- Large → $\eta^2 \geq 0.14$

Levene's test confirmed homogeneity of variance ($p>.05$ for all). Post-hoc Tukey HSD confirmed retail > institutional > advisors for all significant differences. η^2 interpretation: small = 0.01, medium = 0.06, large = 0.14.

The ANOVA analysis with the effect size (η^2) included gives a better idea of the practical meaning of variations in behavioral biases among the types of investors. The findings show that overconfidence ($\eta^2 = 0.251$), herd behavior ($\eta^2 = 0.240$) and emotional decision-making ($\eta^2 = 0.197$) have significant effect sizes and therefore, investor type explains a significant percentage of variance in these biases. This means that retail investors are much more susceptible to these psychologically-motivated biases than institutional investors and financial advisors, probably because of the experience, training, and decision-making models. Loss aversion, anchoring bias, mental accounting and availability heuristic have moderate effect sizes (0.059 to 0.094), which show significant but not so significant differences between the groups. Status quo bias ($\eta^2 = 0.031$) on the other hand has a relatively low effect size implying that this bias is quite stable across all the categories of investors and is not very different with professional experience. In general, the effect size analysis supports the idea that some behavioral biases, especially overconfidence and emotional impact, are the essential distinguishing factors between investors of different types and emphasize the significance of considering psychological profiling in models of financial decision-making.

Table 7: Reliability & Validity statistics

Variable	Cronbach α	AVE	CR	Verdict
Loss Aversion	0.841	0.612	0.863	Valid
Overconfidence	0.814	0.587	0.841	Valid
Emotional Decision-Making	0.862	0.634	0.879	Valid
Herd Behavior	0.783	0.571	0.819	Valid
Anchoring bias	0.791	0.563	0.814	Valid
Mental Accounting	0.818	0.594	0.847	Valid
Status Quo Bias	0.741	0.531	0.779	Acceptable
Availability Heuristic	0.762	0.548	0.796	Valid

AVE > 0.50 and CR > 0.70 confirm convergent validity. All $\alpha > 0.70$ confirms reliability.

All constructs are within the conventional levels of convergent validity: AVE > 0.50 and Composite Reliability (CR) > 0.70. Emotional decision-making has the highest reliability ($\alpha = 0.862$, CR = 0.879), and status quo bias has the lowest, but still reasonable, reliability ($\alpha = 0.741$). Such statistics enable the paper to verify that the measurement instrument is not only reliable but also valid a prerequisite to making any inferential conclusions.

Table 8: AI model feature importance (SHAP)

Variable	SHAP importance	Rank	Type
emotional regulation	17.8%	1	Psychological
overconfidence index	15.9%	2	Psychological
loss aversion coeff.	14.2%	3	Psychological
Market volatility (30d)	13.4%	4	Financial
Herd Behavior Score	11.3%	5	Psychological
Anchoring Deviation	9.1%	6	Psychological
Mental Accounting Bias	7.4%	7	Psychological
Macro Indicators	6.8%	8	Financial
Availability Heuristic	4.1%	9	Psychological

The predictive power of the AI model is explained by psychological variables, and only 20.2% by the traditional financial indicators. At the top is emotional regulation (17.8%), followed by overconfidence (15.9%) - a result to indicate that an intervention based on emotional self-awareness could be more effective than just cognitive bias correction. The interpretation of the black-box AI model based on this SHAP analysis and provides findings with high practical value in the context of financial counselling and investor education.

H_0: Behavioural biases and psychological factors do not have a significant influence on financial decision making and investment portfolio returns

H_1: Behavioural biases and psychological factors have a significant influence on financial decision making and investment portfolio returns.

H_0: An AI-driven mathematical model incorporating behavioural biases does not perform better than traditional financial models in predicting investment behaviour.

H_2: An AI-driven mathematical model incorporating behavioural biases performs better than traditional financial models in predicting investment behaviour.

Table 9: Hypothesis testing summary

Hypothesis	Test Applied	Key Statistic	P-Value	R^2 / Effect	Result
H1: Behavioural biases and psychological factors have a significant influence on financial decision making and investment portfolio returns	Multiple regression (f-test)	$F(8, 241) = 67.14$	< .001	$R^2 = 0.691$ (large)	Accepted
H2: An AI-driven mathematical model incorporating behavioural biases performs better than traditional financial models in predicting investment behaviour	McNemar's test (paired accuracy)	$\chi^2(1) = 38.6$	< .001	Δ acc. = +32.8 pp	Accepted

$\alpha = 0.05$ significance threshold. Both null hypotheses are rejected. Both alternate hypotheses are accepted at $p<.001$.

Conclusion

This research has shown that the financial decision-making process is heavily affected by both behavioral biases and psychology rather than being rational. Biases like overconfidence, emotional decision making, and loss aversion demonstrate a high negative effect on portfolio returns and quality of decision making as well as increasing volatility and excess trading. Regression model reveals that a significant amount of variation in returns of a portfolio is explained ($R^2 = 0.691$), which implies that behavioral variables play a significant role in determining investment results. Moreover, the difference in the degree of bias among types of investors shows that retail investors are more vulnerable to cognitive and emotional biases than institutional investors and financial advisors and that experience and professional exposure are significant in reducing the irrational financial behaviors.

The research also confirms that the incorporation of behavioral and psychological variables in AI-based models is much more effective at predicting than traditional financial models. It is shown that the proposed AI-based model has better accuracy, robustness, and explanatory power, with models that include human behavior being a more realistic depiction of financial decision-making. The feature importance analysis shows that the psychological factors play a bigger role than traditional financial indicators, and it is necessary to go beyond the exclusively economic assumptions. In general, the results indicate that integrating behavioral finance and artificial intelligence is crucial to create more effective, accurate, and personal financial decision-making models.

Future Scope

This study can be improved in future research by using bigger and more varied data sets in various countries and market conditions to enhance generalizability. Longitudinal research can be done to examine the development of the behavioral biases with time and in various market periods like bull and bear market periods. Also, it is possible to incorporate real-time behavioral data (trading patterns, sentiment analysis through social media, biometric emotional indicators, etc.) to further improve the predictive quality of AI models.

Additionally, the implications of more sophisticated AI methods like reinforcement learning, explainable AI (XAI), and hybrid deep learning models can be investigated in future work to create adaptive financial decision systems. It can also be extended to the development of customized financial advisory applications and robo-advisors, which can dynamically change approaches depending on the psychological profile of an investor. On the policy front, the results may be utilized to create behaviorally based financial regulations and investor education, which will eventually lead to more stable and efficient financial markets.

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