Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-3 | March 2026
Original Researcher Article

Transforming Portfolio Management Through Artificial Intelligence: Smarter Allocation, Risk Control, And Collaborative Intelligence

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ABSTRACT
This research work explores the use of Artificial Intelligence (AI) in personalized portfolio management and its effectiveness in asset allocation, risk management, and decision-making for investors, besides exploring the possibility of Human-AI collaboration. The primary data was collected from 100 active individual investors. This research uses correlation analysis, linear regression, and chi-square tests to determine the investor preferences for AI-based portfolio management systems and human financial advisors on eight decision-making criteria: financial literacy, risk tolerance, investment horizon, liquidity, taxation, macroeconomic awareness, behavioural biases, and ESG preferences. The results show a clear demarcation of portfolio management variables based on their automatability. Financial literacy, risk tolerance, investment horizon, tax benefits, liquidity, and macroeconomic awareness have strong positive correlations with AI preference, indicating high automation possibilities for algorithmic systems. Behavioural biases and ESG preferences have weak or negative correlations, indicating limitations of AI in dealing with psychological and value-based investment issues. Regression analysis shows that while income positively affects investable capital, it explains only a small variation, thereby emphasizing the need for multi-factor profiling in personalized portfolio management. Chi-square tests show a statistically significant overall preference for human financial advisors, with most investors preferring hybrid Human-AI advisory models over fully automated systems. The findings of this research work provide empirical validation to the behavioural finance and fintech literature by showing that AI improves efficiency in asset allocation and risk management but cannot fully replace human judgment in behavioural and ethical aspects. This research work concludes that the future of personalized portfolio management lies in AI-based advisory systems that leverage the power of human and artificial intelligence together, rather than in fully automated systems
Keywords: Artificial Intelligence, Personalized Portfolio Management, Asset Allocation, Risk Management, Behavioural Finance, Human-AI Collaboration, Robo-Advisory, Investor Decision-Making, Financial Technology, Correlation, Regression, Chi-Square.

INTRODUCTION:

This paper places traditional portfolio management in the context of established financial theory, specifically focusing on Modern Portfolio Theory (MPT). These theories concentrate on diversification, asset allocation, and risk and return trade-offs. These theories rely on systematic financial variables such as income, investable funds, risk tolerance, and time horizon for decision-making. Although popular and widely used, the current literature shows that these theories rely on rational investor behaviour and linear relationships between variables, which may not be as effective in complex and dynamic market environments.

At the same time, research on behavioural finance shows that actual investor decision-making is often influenced by cognitive biases such as loss aversion, overconfidence, and affective factors that may result in suboptimal portfolio performance, especially in turbulent markets. This implies that traditional portfolio management techniques may not be adequate to capture actual investor behaviour in real-world markets.

With the increasing complexity of markets and increasing amounts of available data, recent literature has explored the application of Artificial Intelligence (AI) to improve portfolio management. Empirical studies have shown that AI-based models perform better than traditional models in managing big data, identifying non-linear relationships, and dynamically allocating assets and managing risk. AI-based methods have also been shown to increase accuracy in risk profiling and portfolio rebalancing efficiency.

However, the current literature warns against overdependence on fully automated models. In all studies, investors have shown a consistent preference for human financial advisors to counter behavioural biases, make sense of macroeconomic uncertainty, and align investment decisions with personal values, including Environmental, Social, and Governance (ESG) factors. Therefore, the literature increasingly supports the use of hybrid human-AI advisory systems, where AI can support analytical work and human advisors can provide contextual insights and behavioural advice.

In this context, this study explores investor preferences between AI-based portfolio management systems and human financial advisors on fundamental decision-making parameters. By analysing investor preferences on asset allocation, capital evaluation, and risk management, and synthesizing these findings with traditional financial variables, this research seeks to add to the existing understanding of effective Human-AI collaboration in personalized portfolio management.

2. Literature Review

Ng Kok Wah (2025) goes through the transformative nature of AI-driven wealth management systems with the specific examples of robo-advisors, predictive analytics, and personalized investment recommendations showing that AI-based systems are far more efficient at decision-making because the AI can process large volumes of data and detect market trends and patterns that are beyond human abilities. Other researchers as well also explored the different factors that influence investment choice of consumers. In the same way, Alfzari et al. (2025) investigated the application of predictive analytics and artificial intelligence to portfolio management with the aim to optimize the risk-return trade-offs. The findings revealed that the use of AI has a positive and significant effect on the performance of the portfolio and the effectiveness of decisions, and the behavioural biases and the perceived ease of use determine the technology acceptance. The article adds a practical measure of the interaction between human judgment and governance systems with AI-based portfolio systems. Nonetheless, the role played by researchers on the identification of variables that influence the decision making was minimal. Therefore this paper clarified the variables involved in a decision made by consumers in relation to investment.

The study by Chawla et al. (2025) on Risk Tolerance and Capacity raises the issue of the applicability of artificial intelligence in measuring the risk appetite of individuals as investors, and the validity of AI-driven financial recommendations is questionable. Among other factors, their analysis points to the inconsistencies and demographic biases in AI-based risk estimation, which indicates that automated systems may be weak in subjective financial decisions. One of the most important lessons learned is that more model sophistication does not always help in making a better decision in areas of personal preferences and behavioural traits. The paper finds that in the absence of a universal set of assessment standards and regulatory controls, AI-related advisory services are at risk of reinforcing inequality and misclassification in the investment decision-making process.

The article by ASU News (2025) on Financial Goals and Investment Horizon, focuses on how artificial intelligence is being used in financial planning and how to balance technological efficiency and human judgment. The article mentions that AI is excellent at data processing and business modelling, but financial decision-making is still highly subjective and value-based. The experts claim that AI is not emotional and lacks contextual insight, which are essential during long-term financial planning. The article therefore concludes that the future of financial planning services will likely be characterized by the hybrid human-AI advisory models.

Capital Availability is an important determinant of financial system stability. Danielsson and Uthemann (2025) state that financial systems have become increasingly reliant on the application of artificial intelligence (AI) and that AI has the potential to fundamentally alter the dynamic of a financial crisis. AI can improve the quality and speed of information flow and support the speed and quality of decision-making by market participants; however, it may also encourage a tendency towards homogenised decision-making and increase the occurrence of leverage cycles leading to a decrease in financial system stability. Additionally, the authors report that AI-driven networks may increase feedback loops that occur during periods of financial instability, resulting in more rapid and severe crises. The article concludes with the recommendation that regulatory frameworks need to be developed to specifically address systemic risk resulting from AI, in order to support the long-term stability of the financial systems.

In 2025, Lucid Blog published an analysis entitled Behavioural Biases, in which they examined how Artificial Intelligence (AI) could potentially assist both researchers and investors in eliminating cognitive biases that have an impact on investing. Using AI to identify examples of loss aversion, overconfidence, and other examples of cognitive bias will help people make better decisions when investing. Although this avenue of technological advancement may also incur problems through the practices of automation bias due to the overreliance on AI's assistance, it is imperative for future development of AI to be transparent and explainable so that responsible and adaptive use can occur.

Ponoselvi & Rajathilagam (2025) conducted research to explore the effectiveness of AI-driven educational platforms in terms of increasing financial literacy amongst young people and found that AI-driven educational platforms have been successful at increasing general learner engagement, knowledge, and motivation through the use of adaptive learning techniques to personalize learning experiences with respect to the feedback being provided. Additionally, the researchers concluded that AI-driven financial literacy resources and initiatives provide participants with an opportunity to develop long-term decision-making skills around finance by providing individuals with greater autonomy and have the potential to complement traditional educational practices.

The study from MIT's Department of Economics (2024) regards AI as a general purpose technology that has broader macro socio-economic effects. The study reviews and assesses AI's expected long-term productivity and economic growth benefits and also the short-term adjustment problems of job displacement and inequality. A significant conclusion of the study is while AI is expected to create significant efficiency improvements, there are also likely to be costs associated with adjustment periods that will severely weigh on individual job / workforce segments. The authors emphasize the need for proactive/predictive policy measures to ensure the long-term economic growth resulting from the broader implementation of AI technologies is sustainable and inclusive from a social perspective.

PMC (2025) examines the correlation between AI implementation, corporate behaviours and corporate environmental, social and governance (ESG) sustainability performance. They indicate AI implementation may improve a corporate entity's financial transparency and governance reporting to the public and enhance the accuracy of corporate reports on environmental sustainability behaviours. Furthermore, they also warn of the possibility that AI will generate weak ESG performance reports due to ethical issues related to algorithmic bias or corporations simply complying through surface implementations of automated ESG reporting. The authors conclude while AI technology has the potential to enhance corporate entities' abilities to meet their ESG objectives, this is only possible through appropriate governance systems/oversight.

3. Methodology

This work uses quantitative, cross-sectional correlational research design to find the relation between the investment key decision-making factors and the investing's opinion about the AI replacing the interference in the portfolio management by human. Primary data was obtained from 100 individual investors who are actively engaged in investing in financial instruments such as equities and mutual funds. A structured questionnaire was applied under non-probability convenience sampling. Participants were voluntary and anonymous, and had to be at least 18 years of age and had to have made at least one personal investment decision. Investment decision factors were assessed on the basis of single item 5 point Likert scales . The factors that were taken into account were Risk Tolerance & Capacity, Financial Goals & Investment Horizon, Capital Availability / Liquidity, Behavioural Biases, Financial Literacy / Market Knowledge, Macroeconomic & Regulatory Awareness, ESG Preferences (Environmental, Social & Governance) and Taxation Benefit. The dependent variable, the perception by investors of AI replacing human interference in the management of their portfolio, was also rated on a 5-point Likert scale (higher scores are given to investors who are more accepting of AI-driven portfolio management). Responses were screened for completeness, coded numerically (1-5), and transformative described using descriptive statistics (frequencies, percent, means) in terms of each factor and a dependent variable. No cases with missing values on the main variables were kept for analysis. For this analysis we made various objectives and hypothesis which helps to concluded on a firm based decision, which are mentioned below:

Objectives

- To determine the correlation between Financial Literacy / Market Knowledge importance ratings and preference for AI portfolio management.
- To determine the correlation between Risk Tolerance & Capacity importance ratings and preference for AI portfolio management.
- The correlation between the ratings of Financial Goals and Investment Horizon significance and preference of AI portfolio management will be found.
- To test the correlation between Taxation Benefit importance ratings and preference of AI portfolio management.
- To test if Capital Availability ratings / Liquidity importance ratings predict preference of AI portfolio management
- To establish the relationship between Macroeconomic importance and Regulatory Awareness ratings of the importance and preference AI portfolio management.
- To establish the relationship between the ratings of Behavioural Biases importance and the preference of AI portfolio management.
- To identify the association between the ratings of ESG Preferences importance and the preference of AI portfolio management.
- To assess the predictive influence of monthly income on the availability of investable capital using linear regression analysis, and to evaluate the adequacy of income as a predictor in asset allocation decisions.
- To assess investor preference between AI-based portfolio management and human financial advisors using Chi-square goodness-of-fit testing and per-person preference index analysis, in order to evaluate the scope for effective human–AI collaboration in personalized portfolio management.

Hypothesis

- There is a significant positive correlation between Financial Literacy / Market Knowledge and preference for AI-driven portfolio management.
- There is a significant positive correlation between Risk Tolerance & Capacity and preference for AI-driven portfolio management.
- Financial Goals and Investment Horizon are significantly, in a positive way, related to preference of AI-driven portfolio management.
- Taxation Benefit Consideration and preference of AI-driven portfolio management have a significant positive correlation.
- Capital Availability / Liquidity and preference of AI-driven portfolio management have a significant positive correlation.
- Macroeconomic & Regulatory Awareness have a significant positive relationship with preference of AI-driven portfolio management.
- Behavioural Biases Awareness and AI-driven portfolio management preference do not significantly correlate.
- ESG Preferences and preference towards AI-driven portfolio management do not have significant or weak negative correlation.

We can critically analyse the sample data using further analysis using various methods,

Our Correlation Analysis shows critical information about which factors of portfolio management can be automated and which cannot, and which require human judgement. The data reveals a definite three-tier structure: 5 factors with strong correlations (> 0.77) which could be automated well, 1 factor with medium correlation resulting in a hybrid approach and 2 factors with weak/negative correlations that need a large degree of human supervision. The analysis is done based on significance level of 5%.

Tier 1: Very Strong Correlation (Highly Automatable Factors)
(a) Financial Literacy / Market Knowledge - 0.9746
Objective: To determine the correlation between Financial Literacy / Market Knowledge importance ratings and preference for AI portfolio management.
Hypothesis: There is a significant positive correlation between Financial Literacy / Market Knowledge and preference for AI-driven portfolio management.

Table 1: Correlation of Financial Literacy / Market Knowledge

	Column 1	Column 2
Column 1	1	
Column 2	0.974558629	1

Financial Literacy / Market Knowledge with the correlation of 0.9746, 73% of investors rated it Very Important (4-5 rating) and 46 of 100 respondents chose the highest rating. This is a strong relationship since financial knowledge is directly related to informed investment decision making and hence it is very quantifiable by use of questionnaires, test scores or data on investment experience. Here, AI will be superior as the profiling of risks and the calibration of complexity of a portfolio based on the level of knowledge of the investor is automated and will always produce data-driven decisions that the algorithm can effectively forecast. As the p value is >0.05 we accept the hypothesis.

(b) Risk Tolerance & Capacity - 0.9244
Objective: To determine the correlation between Risk Tolerance & Capacity importance ratings and preference for AI portfolio management.
Hypothesis: There is a significant positive correlation between Risk Tolerance & Capacity and preference for AI-driven portfolio management.

Table 2: Correlation of Risk Tolerance & Capacity

	Column 1	Column 2
Column 1	1	
Column 2	0.924388653	1

Risk Tolerance & Capacity with the rating of 0.9244 and 58% of the respondents of Very Important, even though the rating is spread across the levels. In order to establish the risk tolerance, standardized questionnaires and financial stress testing can be used, which underlies as a foundation of investment portfolio building. Machine learning is ideally positioned to compute accurate risk profiles and stress tests as well as to match portfolios to risk capacity so that the AI makes the reliable decisions to allocate portfolios on this basis of the same investor priority. As the p value is >0.05 we accept the hypothesis.

(c) Financial Goals & Investment Horizon - 0.9193
Objective: The correlation between the ratings of Financial Goals and Investment Horizon significance and preference of AI portfolio management will be found.
Hypothesis: Financial Goals and Investment Horizon are significantly, in a positive way, related to preference of AI-driven portfolio management.

Table 3: Correlation of Financial Goals & Investment Horizon

	Column 1	Column 2
Column 1	1	
Column 2	0.919250421	1

Financial Goals & Investment Horizon has the greatest level of consensus of 0.9193 with 79% of the respondents rating it as Very Important and none not important. These measurable, objective variables objectives and time periods would be the optimal algorithmic inputs, which will enable the AI to automatically optimize the allocation of assets as the situation changes. This is an investor priority universal and therefore acts as a strong anchor to the AI-driven strategies which highlights its automatability. As the p value is >0.05 we accept the hypothesis.
Tier 2: Strong Correlation (Hybrid Approach Recommended)
(d) Taxation Benefit - 0.8796
Objective: To test the correlation between Taxation Benefit importance ratings and preference of AI portfolio management.
Hypothesis: Taxation Benefit Consideration and preference of AI-driven portfolio management have a significant positive correlation.

Table 4: Correlation of Taxation Benefit Consideration

	Column 1	Column 2
Column 1	1	
Column 2	0.879593207	1

Taxation Benefit is highly correlated with 0.8796, 60% of the respondents consider it as Very important, but there are mixed answers. Tax optimization is measurable but location specific when it comes to jurisdictions, income level and type of investment. Tax-loss harvesting can be automated with AI and even efficient strategies can be found, but more difficult cases are those involving trusts or holdings across multiple jurisdictions, so the responsibility falls on a human to review and determine the suitable course of action, implying that a hybrid strategy exists when investors have vastly different tax needs. As the p value is >0.05 we accept the hypothesis.

(e) Capital Availability / Liquidity - 0.8777
Objective: Do Capital Availability ratings / Liquidity importance ratings predict preference of AI portfolio management
Hypothesis: Capital Availability / Liquidity and preference of AI-driven portfolio management have a significant positive correlation.

Table 5: Correlation of Capital Availability / Liquidity

	Column 1	Column 2
Column 1	1	
Column 2	0.87774726	1

Capital Availability / Liquidity is rated 0.8777; 57% weighted score on Very Important with a weight of 3.70, is moderately prioritized. Liquidity needs although measurable in terms of bank balances and cash flow are personal and unpredictable. AI must track occupations and propose modifications, yet human decisions must take final emergency reserve actions depending on the job security and life stage differences. As the p value is >0.05 we accept the hypothesis.

(f) Macroeconomic & Regulatory Awareness - 0.7690

Purpose To establish the relationship between Macroeconomic importance and Regulatory Awareness ratings of the importance and preference AI portfolio management.

Hypothesis: Macroeconomic & Regulatory Awareness have a significant positive relationship with preference of AI-driven portfolio management.

Table 6: Correlation of Macroeconomic & Regulatory Awareness

	Column 1	Column 2
Column 1	1	
Column 2	0.768963164	1

Macroeconomic/ Regulatory Awareness at 0.7690 has a 61% Very Important rating with a lower top-end rating. Being the weakest strong factor, it is a matter of contextual judgment in addition to data analysis. AI will be able to provide macro indications and regulatory signals but human experts have to interpret implications and make strategy changes because investors are aware of macro significance though not fully understand its effect on a portfolio. As the p value is >0.05 we accept the hypothesis.

Tier 3: Weak/Negative Correlation (Require Human Judgment)

(g) Behavioural Biases - 0.0142

Objective: To establish the relationship between the ratings of Behavioural Biases importance and the preference of AI portfolio management.

Hypothesis: Behavioural Biases Awareness and AI-driven portfolio management preference do not significantly correlate.

Table 7: Correlation of Behavioural Biases Awareness

	Column 1	Column 2
Column 1	1	
Column 2	0.01422776	1

Behavioural Biases displays a near-zero correlation (0.0142 which is significant as 33 percent rate it Very Important and 31 percent dismisses it). Investors do not always realize the effects of their biases on them, which poses a significant gap in which AI cannot be used to control unnoticed psychology. Although the use of AI can identify biased decisions such as panic selling, behavioural coaching needs to be offered by human beings, which is the inherent weakness of the algorithmic investor discipline. As the p value is >0.05 we reject the hypothesis.

(h) ESG Preferences - (-0.0523)

Objective: To identify the association between the ratings of ESG Preferences importance and the preference of AI portfolio management.

Hypothesis: ESG Preferences and preference towards AI-driven portfolio management do not have significant or weak negative correlation.

Table 8: Correlation of ESG Preferences

	Column 1	Column 2
Column 1	1	
Column 2	-0.052342392	1

ESG Preferences shows negative correlation (-0.0523), operating differently from rational optimization, with only 26% Very Important ratings spread across levels. ESG reflects personal values rather than data optimization, lacking standardization. While computers can scan ESG factors, it is necessary for humans to be aware of the particular values of each investor, as failure to align could lead to a breakdown in values-based investing by computers. As the p value is >0.05 we reject the hypothesis.

Table 9: Statistical Insights

Metric	Value
Mean Correlation	0.6633
Median Correlation	0.8787
Standard Deviation	0.3981
Correlation Range	1.0269
High Correlations (>0.8)	5 out of 8
Low/Negative (≤0.1)	2 out of 8

The median (0.8787) is higher than the mean (0.6633), indicating that most factors correlate strongly, with two outliers (Behavioural Biases and ESG) dragging down the average. This 62.5% strong correlation suggests AI can automate the majority of portfolio decisions, but critical gaps remain.

Table 10: Summary

Factor	Correlation	AI Capability	Recommendation
Financial literacy	0.9746	Full automation	Let AI analyse and profile
Risk tolerance	0.9244	Full automation	AI-driven risk assessment
Financial goals	0.9193	Full automation	Algorithm-based optimization
Taxation	0.8796	80% automation	AI with human exception review

Liquidity	0.8777	80% automation	AI monitoring, human decisions
Macro awareness	0.7690	Hybrid	AI alerts + human interpretation
Behavioural bias	0.0142	Requires human	AI flags + advisor coaching
ESG preferences	-0.0523	Requires human	AI screening + personal conversation

Key Takeaways:

The percentages of factors which are highly automatable (correlations above 0.8) support the use of AI in managing a portfolio, 25% would need hybrid methods (moderate automation, but with human oversight), 12.5% would need human judgment at their core (behavioural and values-based decisions). The gap in the correlation indicates the blind spots of AI: it is impossible to optimize psychology and values through algorithms. The total automatization cannot be made without losing the investor satisfaction and commitment. This is the reason industry best practice is hybrid AI-human models and not full automation.

Although the correlation analysis determines the extent of association between the most important factors of investors and the possibility of AI-driven automation, it does not evaluate the predictive sufficiency of either of the variables. Specifically, despite the general assumption that income affects investment capacity, correlation does not imply how much income may explain the differences in the capital that is available. Thus, to assess the validity of monthly income as a predictor of investable capital and to determine its usefulness in the decision-making of which asset to invest in a portfolio the analysis is furthered to a linear regression model.

Table 11: Regression Statistics

Multiple R	0.22584178
R Square	0.05100451
Adjusted R Square	0.04132088
Standard Error	1.09685636
Observations	100

Table 12: Anova

	df	**SS**	**MS**	**F**	**Significance F**
Regression	1	6.3368	6.3368	5.2670869	0.02386487
Residual	98	117.9032	1.203093878		
Total	99	124.24			

	Coefficients	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Lower 95.0%**	**Upper 95.0%**
Intercept	1.3328	0.21605565	6.168781148	1.5473E-08	0.9040446	1.7615554	0.9040446	1.7615554
Monthly Income (₹)	0.178	0.07755946	2.2950113485	0.02386487	0.02408578	0.33191422	0.02408578	0.33191422

Linear regression analysis was carried out on 100 data points to test the correlation between Monthly Income and Capital Available for Investment. The regression equation is: Capital Score = 1.33 + 0.18 (Income Score). The above model results indicate a positive and significant relationship between income and access to capital which is ($p=0.024$) and this means that the more income the more capital is available to invest. Nevertheless, the model is yet to be fully explained, and its R-squared is 0.051, which means that the income can only explain 5.1% of the variance in the available capital.

This relationship is further explained by the estimated coefficients. The income coefficient (= 0.18) indicates that average increase of 0.18 units in the capital score would occur as a result of every unit increase in the income score, which indicates a change of income to the next income bracket. As the capital variable is altered in no discrete and discrete steps of a unit, it can be implied by the value of the effect size, that there are small adjustments in the levels of investable capital; when there are large differences in income. The intercept (1.33) means that the respondents are expected to have an amount of investable funds at the lowest income category. This may incorporate any savings that people have made in the past, little finance and investments that have been made without considering the current income monthly.

Nevertheless, the strength of this relationship is not so great. This is statistically significant, but the R2 value suggests the poor quality of prediction of investment capital based on monthly income. This implies that nearly 95 percent of the variation in the availability of capital cannot be explained by income and then there are other unknown variables available. Such bad relationship can be explained by several reasons:

Expense and liability structure: Person A and Person B may receive similar incomes but have dissimilar expenses like loans, EMI or liability to dependents.

Effect of Time Horizon and Age: The accumulation of capital must be a time dependent process. The young people with high incomes might have amassed less capital as compared to the people of advancing age with medium and stable incomes.

Lifestyle Inflation: The higher the income earned by individuals, the higher the amount they spend. This kind of spending is a negative factor in terms of its ability to transform earnings into investable assets. All of these factors show that income is a necessary but not sufficient condition of capital accumulation.

The above findings have important implications for investment assessment.
This confirms the existence of a positive relationship between higher income and higher amount of money that can be invested though this is highly insignificant. In fact, the level of monthly earnings alone will not be sufficient to determine the investing capacity when one is alone.
In the case of financial profiling and investment advisory services, Net investment income would have to be put in combination with other variables such as age, saving, Debt risk, and level of expenditure. These variables should be taken into consideration in future research in order to enhance modelling on capital formation.
To complement the regression results and extend the analysis beyond predictive relationships, investor preferences regarding AI-based portfolio management versus human financial advisors are examined using a Chi-square framework.

Table 13: Individual Question Analysis

Observations			**Expected**	**Chi-square**	**Chi-square**	**Ideal**	**Analysis**
[Risk Tolerance & Capacity]	AI	23	50	14.58			
	Human Adviser	77	50	14.58	29.16	3.841	reject
[Financial Goals & Investment Horizon]	AI	35	50	4.5			
	Human Adviser	65	50	4.5	9	3.841	reject
[Liquidity]	AI	23	50	14.58			
	Human Adviser	77	50	14.58	29.16	3.841	reject
[Behavioural Biases]	AI	22	50	15.68			
	Human Adviser	78	50	15.68	31.36	3.841	reject
[Financial Literacy]	AI	49	50	0.02			
	Human Adviser	51	50	0.02	0.04	3.841	accept
[Macroeconomic & Regulatory Awareness]	AI	52	50	0.08			
	Human Adviser	48	50	0.08	0.16	3.841	accept
[ESG (Environmental, Social, Governance) Preferences]	AI	59	50	1.62			
	Human Adviser	41	50	1.62	3.24	3.841	accept
[Taxation Benefits]	AI	29	50	8.82			
	Human Adviser	71	50	8.82	17.64	3.841	reject

Table 14: Combined Analysis

Option	**Observation**	**Expected**	**Chi-square**	**Chi-square**	**Ideal**	**Analysis**
AI	292	400	29.16			
Human Advisor	508	400	29.16	58.32	3.841	reject

Table 15: Distribution Table

Distribution	**No. of People**
AI	5
Mixed	58
Human Advisor	36

Table 16: Mean Index

Mixed	0.635

(a) Factor-Wise Chi-Square Analysis
Each portfolio decision factor was tested individually using a Chi-Square Goodness-of-Fit Test (df = 1, critical value = 3.841).

Table 17: Key Findings

Factor	χ^2 Value	Decision	Interpretation
Risk Tolerance & Capacity	29.16	Reject H_0	Strong preference for Human advisors
Financial Goals & Investment	9.00	Reject H_0	Human judgment preferred
Liquidity	29.16	Reject H_0	Human advisors favoured
Behavioural Biases	31.36	Reject H_0	Clear dominance of Human advisors
Financial Literacy	0.04	Accept H_0	No significant preference
Macroeconomic & Regulatory	0.16	Accept H_0	No significant preference
ESG Preferences	3.24	Accept H_0	No significant preference
Taxation Benefits	17.64	Reject H_0	Human advisors preferred

Findings reveal that human advisors are in full control of areas of decision making that are judgmental, interpretational and behavioural in nature and thus the significance of having humans in the management of the emotions of the investors, the cognitive biases, as well as the context specific financial decision making. Conversely, there is no statistically significant difference in such technically quantifiable areas like financial literacy, macroeconomic awareness, and ESG considerations, which indicates that the specified areas are highly appropriate to be analysed by AI because of their data-driven and structured nature. This trend fits well with the behavioural finance theory, which assumes that psychological and context-based investment decisions cannot be completely automated and thus supports the supplementary position of human judgment and AI-based analytical skills in portfolio management.

(b) Aggregate Chi-Square Analysis

All 800 observations were pooled to test overall preference.

Table 18: Response Summary

Option	Observed	Expected
AI	292	400
Human Advisor	508	400

- χ^2 calculated = 58.32
- χ^2 critical (df = 1, α = 0.05) = 3.841

Result

Since 58.32 > 3.841, the null hypothesis is rejected.

Interpretation

There is an extremely strong and statistically significant overall preference between AI and Human advisors, with a clear dominance of Human advisors in portfolio management decisions. This confirms that the deviation from equal preference is not due to chance.

(c) Per-Person Average-Based Index

Table19: Distribution Table

Category	Number of Respondents
AI (0.00-0.33)	5
Mixed (0.34-0.66)	58
Human Advisor (0.67-1.00)	36

The distribution of the preferences among respondents shows that most of them (58) are in Mixed category in terms of their strong inclination towards hybrid AI-human models of portfolio management. Another 36% of respondents demonstrate a distinct interest in human advisors, which makes it clear that human judgment remains a significant factor in complex and context-oriented investment decisions. Conversely, according to the survey, only half of the participants support the complete AI-based management, which indicates that investors do not yet have complete confidence in full automation. Such distribution facilitates the fact that AI-based advisory models are not adopted as fast as they become more technologically advanced.

(d) Integration with Correlation Framework

When combined with the correlation analysis, the data show that such factors with high correlations with each other as risk tolerance, financial goals and taxation are associated with a strong inclination towards human advisors, whereas such factors as behavioural biases and ESG considerations have weak or near-zero correlations indicating the rejection of algorithmic standardisation. Additionally, the fact that a Mixed majority (58%) means that there is a distinct preference towards hybrid advisory methods instead of a full replacement by AI. On the whole, the analysis can be viewed as a strong statistical indicator that human advisors are much more preferred than AI advisors in behavioural, liquidity and taxation decisions. Simultaneously, the outcomes of correlation analysis prove that automation can still be used in data-driven portfolio operations, but at the same time, psychological and value-based investment decisions still need human intervention. Therefore, the results highly favour AI-enhanced advisory models combining both computational efficiency and human judgment than completely computer-based portfolio management tools.

4. Conclusion

This conclusion is based on grounds which is laid by analysing various methodology, which helped the research to be examined from every possible edges. Further we will examine each factor wise conclusion and how it can be useful in the market, In financial literacy / market knowledge, very strong positive correlation with AI preference shows that more informed investors are more willing to trust AI for portfolio construction and monitoring. It supports your claim that AI can deliver advanced, data-driven asset allocation to clients who understand markets, and that platforms should embed literacy assessments and educational modules to personalize algorithm complexity and interfaces.

In risk tolerance and capacity, strong correlation here demonstrates that risk profiling is a fully automatable core of personalized portfolio management. This directly underpins your risk management part: AI engines can continuously estimate risk tolerance from questionnaires, behaviour and market conditions, and then adjust portfolio volatility and drawdown limits in real time.

In financial goals and investment horizon, it indicates almost universal importance and very strong correlation, it validates goal-based, AI-driven asset allocation as central to your paper. AI can map each goal and horizon to model portfolios, update glide paths as time passes, and simulate probability of goal achievement, illustrating how AI personalizes long-term asset allocation better than static human plans.

In taxation benefit, strong but context-dependent correlation supports your argument that AI adds tangible value in after-tax optimization but still needs human review in complex cases. AI's ability to help with tax loss recovery, selection of tax-efficient investments, and determination of holding periods is illustrative of its capability to support the risk management and collaborative process of human advisors in relation to the management of special structures.

A strong correlation exists between AI's ability to assess a firm's capital availability/liquidity and AI's ability to monitor liquidity needs and cash reserves as part of a firm's overall risk management strategy, thereby supporting your statement that AI provides valuable data for cash flow tracking, predicting cash flow deficiencies and rebalancing or STP recommendations by monitoring cash flow from operational demands; however, sudden life-changing events will require human judgment in relation to AI's ability to partner with humans on a unified basis. In macroeconomic and regulatory awareness, a high but lower correlation shows that AI has the strength to process macro and regulatory information, but human input is required for interpretation and communication. This directly feeds your human-AI collaboration theme: AI can generate regime signals and risk alerts, while portfolio managers decide strategic shifts and explain them to clients.

In behavioural biases, non-significant correlation is crucial evidence that AI alone cannot manage investor psychology, even if it optimizes portfolios mathematically. This supports your conclusion that advisors remain essential for coaching against panic selling, overconfidence and herding, positioning human behaviour management as a complementary layer on top of AI-driven asset allocation and risk tools.

In ESG preferences, weak negative correlation shows that values and ethics do not map cleanly to algorithmic optimization, directly backing the argument that full automation is impossible. AI can screen and score ESG, but only humans can elicit and prioritise individual values, so ESG becomes a flagship use-case for human-AI collaboration in product selection and portfolio customization.

Taken together, the six strong, significant correlations i.e. 75% (literacy, risk, goals, tax, liquidity, macro) empirically justify that AI can and should be deeply integrated into personalized portfolio management for asset allocation and risk management, while the two non-significant ones i.e. 25% (behavioural bias, ESG) empirically justify that human judgment remains indispensable for psychology and values, making human-AI collaboration the optimal model rather than full automation.

The regression results allow a clear but nuanced conclusion about the role of income in determining investable capital. The model confirms that monthly income has a real, positive and statistically significant influence on the amount of capital available for investment, which supports the intuitive assumption that higher earners generally have greater capacity to invest. However, the very low explanatory power of the model indicates that income on its own is a weak predictor and cannot reliably capture how much an individual is actually able to allocate to investments. In the context of the study's objective, this means that income should be treated as a relevant but insufficient variable: it is useful as a starting point for profiling, but it cannot be the primary basis for asset allocation decisions. For industry and practice, the implication is that financial institutions, advisors and AI-driven portfolio systems must move beyond income-based segmentation and incorporate a richer set of variables such as expenditure patterns, debt obligations, savings behaviour, age and time horizon when estimating investable surplus and designing portfolios. In summary, the regression test further emphasizes the important point of this study: that responsible and effective portfolio personalization cannot be achieved through a single, easily measurable criterion such as monthly income.

The results of the Chi-square tests yield a definitive and consistent interpretation of how investors feel about AI's role in managing their investments. Simply put, the studies conclude that investors do not currently want to replace their human advisors with AI when it comes to managing their investments. For instance, even though there is no clear cut preference when it comes to using AI in areas that require significant judgement, emotionality and context; there continues to be an affirmation of the need for human judgement in practical investment decision-making. In contrast, the lack of a decided preference for using AI in more technically based and data rich spaces indicates that investors are open to the idea of AI working alongside their human advisors in well-structured and measurable areas.

As such, the results suggest a strong endorsement for creating hybrid models of AI-enhanced investment advisory services, which use AI as a highly analytical tool in investment decision-making, while retaining the ultimate authority for behavioural guidance, context-based interpretation and values-based decision-making with human advisors. The result of this study is consistent with behavioural finance theory. Additionally, this provides further evidence in support of one of the main arguments of this study, that the future of personalized investment portfolios lies in successful collaboration between both AI and human advisors rather than AI replacing human advisors entirely.

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