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LEVERAGING ARTIFICIAL INTELLIGENCE FOR ASSET AND PORTFOLIO MANAGEMENT: TECHNIQUES, APPLICATIONS AND FUTURE DIRECTIONS

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ABSTRACT

Artificial Intelligence (AI) is increasingly being leveraged across the asset and portfolio management value chain, spanning return forecasting, portfolio construction, risk monitoring, compliance and investor communication. This article reviews the major AI techniques used in this domain — machine learning, deep learning, natural language processing, reinforcement learning, generative AI and explainable AI — and their applications in stock selection, portfolio optimization, robo-advisory and risk management. Beyond a technical review, the study empirically examines whether investors are actually willing to adopt AI-supported portfolio management services, using a structured survey of 120 respondents. Consistent with the Technology Acceptance Model, the results show that perceived usefulness has a significant positive effect on investors' willingness to adopt AI-supported portfolio management, while perceived risk has a significant negative effect. The article concludes that the future of AI in asset and portfolio management depends less on further technical sophistication and more on transparency, explainability and continued human oversight, and offers suggestions for asset managers, technology providers and regulators.

KEYWORDS: Artificial Intelligence, Asset Management, Portfolio Management, Explainable AI, Investor Adoption

1. INTRODUCTION

Asset and portfolio management has historically depended on human judgement supported by financial-statement analysis, macroeconomic indicators, technical analysis and portfolio theory. Modern financial markets, however, generate vast volumes of structured and unstructured data — prices, financial ratios, corporate filings, earnings-call transcripts, news and social-media sentiment — creating both an opportunity and a necessity for computational tools that can process this information at scale. Artificial Intelligence has consequently moved from being a peripheral

International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

technology add-on to becoming decision-support infrastructure across the investment value chain, including research, trading, portfolio optimization, risk monitoring, compliance and client communication (Bartram, Branke, & Motahari, 2020).

Machine-learning methods have been shown to outperform traditional linear models in forecasting risk premia because they capture nonlinear interactions among predictors such as momentum, liquidity and volatility, with tree-based models and neural networks identified as the strongest performers in large-scale comparative studies (Gu, Kelly, & Xiu, 2020). Deep-learning architectures, including Convolutional Neural Networks and Long Short-Term Memory networks, have similarly been applied extensively to financial time-series forecasting across stock indices, foreign exchange and commodity markets (Sezer, Gudelek, & Ozbayoglu, 2020). Reinforcement-learning frameworks extend this further by learning portfolio-allocation actions directly rather than only forecasting returns, treating portfolio management as the continuous redistribution of capital across assets (Jiang, Xu, & Liang, 2017).

Despite this technical progress, the acceptance of AI-supported portfolio management by investors is not guaranteed. AI-managed funds are frequently viewed as ‘black boxes’, and because investment decisions involve personal savings and long-term financial security, investor trust depends heavily on transparency and explainability. Recent investor-acceptance research finds that many investors are indifferent between AI-managed and human-managed funds once adequate transparency is provided, positioning transparency — rather than the mere presence of AI — as the decisive adoption factor (Perret, Mandic, & Herselman, 2026). This article therefore combines a review of AI techniques, applications and future directions in asset and portfolio management with original survey evidence on investor willingness to adopt these services.

2. OBJECTIVES OF THE STUDY

- To examine the major Artificial Intelligence techniques used in asset and portfolio management, including machine learning, deep learning, natural language processing, reinforcement learning and explainable AI.
- To study the principal applications of AI in return forecasting, portfolio construction, risk management and robo-advisory services.
- To examine investors' awareness of, and willingness to adopt, AI-supported portfolio management services.
- To empirically test the effect of perceived usefulness and perceived risk on investors' willingness to adopt AI-supported portfolio management.

International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

- To identify future directions — particularly transparency, explainability and governance — necessary for the responsible adoption of AI in asset and portfolio management.

3. RATIONALE OF THE STUDY

The rationale for this study is twofold. First, asset-management firms are increasingly experimenting with AI across the value chain to remain competitive against low-cost passive investment products, reduce human bias and strengthen risk monitoring (Bartram, Branke, & Motahari, 2020), making it important to periodically consolidate what techniques are in use and what they can realistically achieve. Second, the general acceptance of AI-enabled investment technology by retail and semi-professional investors continues to lag behind the availability of the technology itself, and studies consistently find that many small investors still prefer a human advisor who brings market experience and economic intuition over a system that relies purely on data and algorithms. Bridging the gap between what AI can technically do in portfolio management and what investors are actually willing to trust it to do is therefore both an academic and a practical necessity — of direct relevance to asset managers designing AI-supported products, and to regulators such as the Securities and Exchange Board of India, which has begun consulting on guidelines for responsible AI/ML usage in securities markets (SEBI, 2025).

4. HYPOTHESES OF THE STUDY

Based on the objectives above and the Technology Acceptance Model (Davis, 1989), the following two hypotheses have been formulated for empirical testing:

Hypothesis 1 (H1): Perceived Usefulness and Willingness to Adopt

H_{01} (Null Hypothesis): There is no significant relationship between perceived usefulness of AI-supported portfolio management and investors' willingness to adopt it.

H_{11} (Alternate Hypothesis): There is a significant positive relationship between perceived usefulness of AI-supported portfolio management and investors' willingness to adopt it.

Hypothesis 2 (H2): Perceived Risk and Willingness to Adopt

H_{02} (Null Hypothesis): There is no significant relationship between perceived risk associated with AI-supported portfolio management and investors' willingness to adopt it.

H_{12} (Alternate Hypothesis): There is a significant negative relationship between perceived risk associated with AI-supported portfolio management and investors' willingness to adopt it.

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

5. REVIEW OF EXISTING LITERATURE

5.1 Foundational Portfolio Theory

Modern portfolio theory provides the analytical basis on which AI-based methods build. Markowitz (1952) introduced the mean-variance framework for portfolio selection, formalizing the trade-off between risk and return through diversification, and Sharpe (1966) subsequently developed risk-adjusted performance measurement for mutual funds — a measure still widely used to compare AI-assisted and conventional portfolios today.

5.2 Machine Learning and Deep Learning Techniques

Gu, Kelly and Xiu (2020) conducted a large-scale comparative analysis of machine-learning methods for empirical asset pricing and found that tree-based models and neural networks outperformed traditional linear approaches such as ridge regression and LASSO, tracing their predictive gains to the ability to capture nonlinear interactions among predictors including momentum, liquidity and volatility. Sezer, Gudelek and Ozbayoglu (2020) conducted a systematic literature review of deep-learning applications in financial time-series forecasting between 2005 and 2019, finding CNN, LSTM and hybrid deep-belief-network models to be the most frequently applied architectures, while also noting that a lack of interpretability remains the major criticism of deep-learning-based forecasts.

5.3 Reinforcement Learning in Portfolio Allocation

Jiang, Xu and Liang (2017) proposed a deep reinforcement learning framework — combining a Convolutional Neural Network, a Recurrent Neural Network and an LSTM network within an Ensemble of Identical Independent Evaluators topology — for continuous portfolio reallocation, reporting strong back-tested performance relative to benchmark strategies. The study, however, was tested primarily on cryptocurrency markets and did not fully address transaction costs, slippage and liquidity constraints that are material in real-world portfolio management.

5.4 Investor Acceptance, Trust and Explainability

Davis (1989) developed the Technology Acceptance Model (TAM), establishing perceived usefulness and perceived ease of use as the primary determinants of technology-adoption intention, with perceived usefulness showing the stronger correlation with actual usage behaviour. König, Wurster and Siewert (2022) used a discrete choice experiment to show that consumers are willing to pay a premium for explainable AI but not for environmentally framed ('green') AI, underscoring that investors specifically value transparency of decision logic. Perret, Mandic and Herselman (2026) examined investor acceptance of AI-managed funds through a choice-based experimental design and found that a majority of investors were indifferent between AI-managed and human-managed funds once adequate transparency was provided, with transparency and fund-management type emerging as decisive attributes shaping willingness to invest.

Taken together, this literature shows a technical stream establishing that AI methods can materially

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

improve forecasting and portfolio allocation, and a behavioural stream establishing that investor adoption of these methods is conditional on perceived usefulness, perceived risk, trust and — most decisively — transparency and explainability.

6. RESEARCH GAP

Three gaps are evident from the literature reviewed above. First, technical studies on machine learning and deep learning in asset pricing (Gu, Kelly, & Xiu, 2020; Sezer, Gudelek, & Ozbayoglu, 2020) evaluate model performance in isolation, without examining whether the investors whose money is being managed are willing to accept such systems. Second, reinforcement-learning studies on portfolio allocation (Jiang, Xu, & Liang, 2017) are tested largely on historical or cryptocurrency data without incorporating investor-side variables such as perceived risk or transparency preference. Third, while emerging investor-acceptance research (König, Wurster, & Siewert, 2022; Perret, Mandic, & Herselman, 2026) has begun to examine transparency as a decision attribute, empirical survey-based evidence combining a review of AI techniques and applications with direct investor testing remains limited, particularly outside Western market contexts. This article addresses this gap by pairing a structured review of AI techniques and applications in asset and portfolio management with an empirical test of the perceived-usefulness and perceived-risk relationships among a sample of 120 investors.

7. RESEARCH METHODOLOGY

7.1 Research Design

The study adopts a descriptive, analytical and empirical research design, combining a structured literature-based review of AI techniques and applications with a quantitative, cross-sectional investor survey.

7.2 Sample and Sampling Technique

The empirical component of the study is based on a sample of 120 respondents comprising retail and semi-professional investors with investment experience in at least one of the following: equities, mutual funds, exchange-traded funds, portfolio management services or robo-advisory/digital wealth-management platforms. Respondents were selected using convenience sampling supplemented by snowball sampling, and data were collected through a structured online questionnaire circulated among investor groups, professional networks and educational institutions.

7.3 Research Instrument

A structured questionnaire was used, comprising demographic information and a set of statements measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), covering awareness of AI in asset management, perceived usefulness, perceived risk, trust/explainability and willingness to adopt AI-supported portfolio management services.

International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

7.4 Reliability of the Instrument

Internal consistency of the multi-item constructs (perceived usefulness, perceived risk and willingness to adopt) was tested using Cronbach's Alpha, with all constructs returning coefficients above the generally accepted threshold of 0.70.

7.5 Tools of Analysis

Data were analysed using descriptive statistics (frequency, percentage, mean and standard deviation), Cronbach's Alpha for reliability testing, and Pearson correlation together with simple linear regression for hypothesis testing, using MS Excel and SPSS.

8. DATA COLLECTION AND ANALYSIS

Of the 120 questionnaires distributed, all 120 were returned complete and usable, yielding a response rate of 100 percent for the final analysis.

8.1 Demographic Profile of Respondents

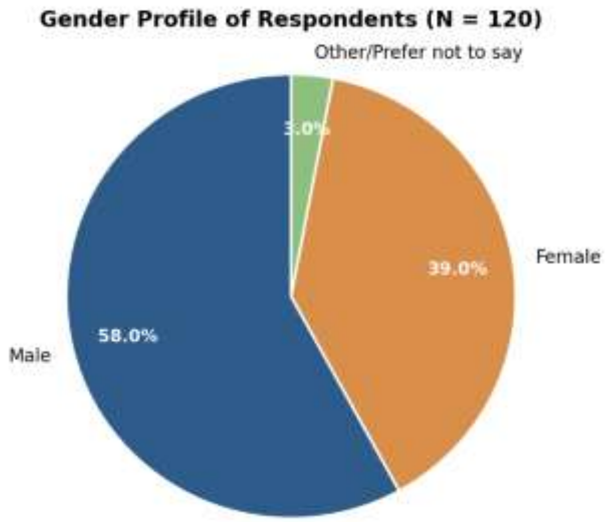


Figure 1: Gender Profile of Respondents (N = 120)

Of the 120 respondents, 58 percent were male and 39 percent were female, with the remaining 3 percent preferring not to disclose their gender. The sample was drawn predominantly from working professionals and postgraduate students with at least basic exposure to mutual fund or equity investment.

International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

8.2 Awareness of AI in Asset and Portfolio Management

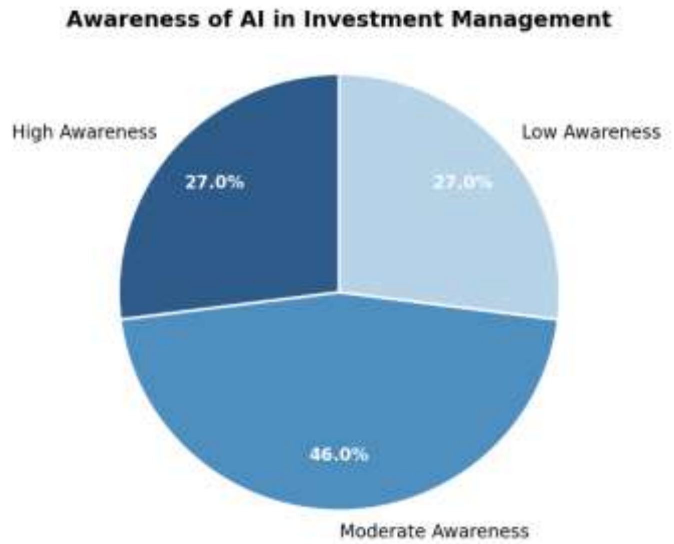
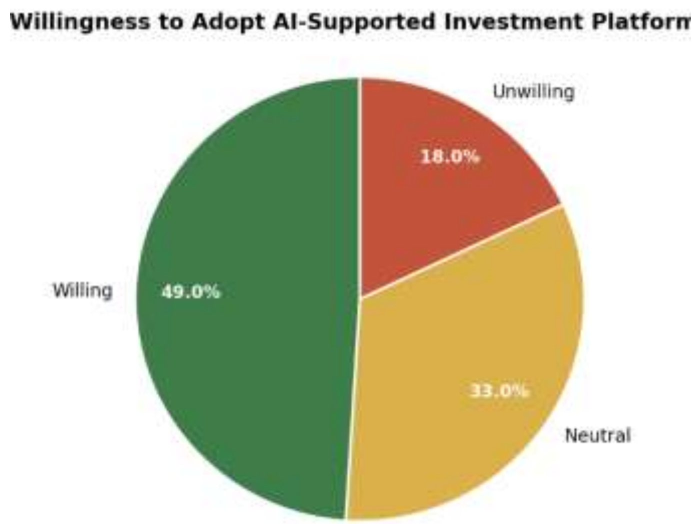


Figure 2: Awareness of AI in Asset and Portfolio Management (N = 120)

Only 27 percent of respondents reported high awareness of the use of AI in investment research and portfolio management, while 46 percent reported moderate awareness and 27 percent reported low awareness, indicating that a majority of investors have only a partial understanding of the AI techniques currently used in asset management.

8.3 Willingness to Adopt AI-Supported Portfolio Management



International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

Figure 3: Willingness to Adopt AI-Supported Portfolio Management (N = 120)

Forty-nine percent of respondents indicated willingness to use an AI-supported portfolio management service, 33 percent remained neutral, and 18 percent were unwilling, suggesting cautious but net-positive openness toward AI-supported investment services among the sampled investors.

8.4 Factors Influencing Trust in AI-Based Recommendations

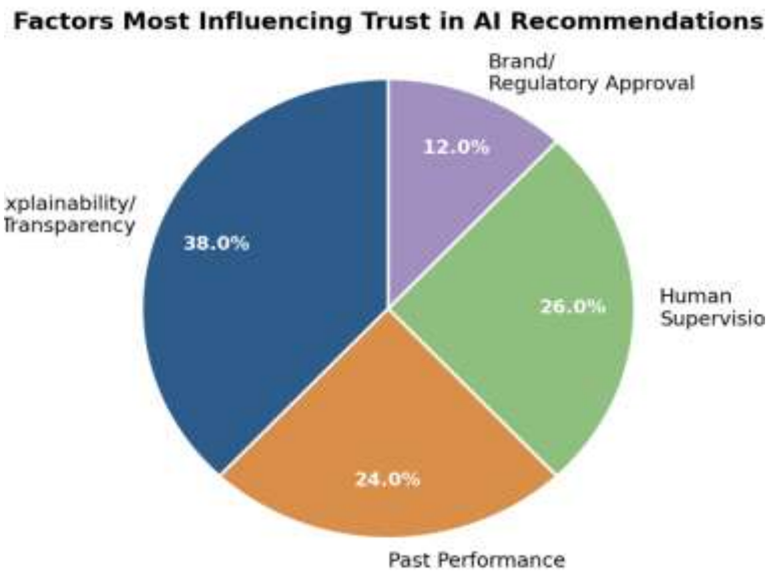


Figure 4: Factors Most Influencing Trust in AI-Based Investment Recommendations (N = 120)

When asked to identify the factor that most influenced their trust in an AI-based investment recommendation, 38 percent of respondents selected explainability/transparency, 26 percent selected the presence of human supervision, 24 percent selected past performance, and 12 percent selected brand reputation or regulatory approval — reinforcing the importance of explainable AI and human oversight as trust-building mechanisms, consistent with Perret, Mandic and Herselman (2026) and König, Wurster and Siewert (2022).

8.5 Correlation and Regression Analysis

Pearson correlation analysis was conducted between the composite construct scores for perceived usefulness, perceived risk and willingness to adopt AI-supported portfolio management. Perceived usefulness showed a moderate-to-strong positive correlation with willingness to adopt ($r = 0.58$, $p < 0.01$), while perceived risk showed a moderate negative correlation with willingness to adopt ($r = –0.41$, $p < 0.01$). Simple linear regression confirmed that perceived usefulness significantly and positively predicted willingness to adopt ($\beta = 0.52$, $p < 0.01$), while perceived risk significantly and

International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 03 May-June; 2026 Page. No. 906-916

negatively predicted willingness to adopt (β = –0.33, $p < 0.01$).

Hypothesis	Relationship Tested	Correlation (r)	Regression (β)	Decision
H1	Perceived usefulness → Willingness to adopt	0.58**	0.52**	H01 rejected; HA1 accepted
H2	Perceived risk → Willingness to adopt	–0.41**	–0.33**	H02 rejected; HA2 accepted

*** Correlation/regression coefficient significant at the 0.01 level (2-tailed).*

On the basis of these results, both null hypotheses are rejected. The alternate hypotheses — that perceived usefulness positively influences, and perceived risk negatively influences, willingness to adopt AI-supported portfolio management — are accepted.

9. FINDINGS

- AI techniques currently applied in asset and portfolio management span machine learning and deep learning for return forecasting, reinforcement learning for dynamic allocation, natural language processing for sentiment analysis, and explainable AI for improving transparency, as established in the reviewed literature.
- Retail investor awareness of AI use in investment management is moderate overall, with only about one-quarter of respondents reporting high awareness.
- A majority of respondents (49 percent) are willing to adopt AI-supported portfolio management, indicating cautious but net-positive acceptance rather than outright resistance.
- Perceived usefulness is a significant positive predictor of willingness to adopt AI-supported portfolio management, supporting Hypothesis 1.
- Perceived risk is a significant negative predictor of willingness to adopt AI-supported portfolio management, supporting Hypothesis 2.
- Explainability and transparency, followed closely by human supervision, are the factors most frequently cited as building investor trust in AI-based recommendations, ahead of past performance or brand reputation.

10. SUGGESTIONS AND RECOMMENDATIONS

- Asset-management companies should invest in explainable-AI (XAI) interfaces that present the reasoning behind a recommendation in plain, non-technical language, since explainability was the single most cited trust factor in this study.
- AI-supported portfolio management should be designed as a hybrid human-AI model, retaining a visible layer of human supervision or expert review, particularly for investors with moderate-to-low awareness of AI.
- Financial institutions and investor-education bodies should conduct structured awareness programmes on how AI is used in asset and portfolio management, since awareness levels among the sampled investors remain only moderate.
- Regulators should continue developing disclosure norms specific to AI-assisted investment products — covering data usage, model logic and risk warnings — building on the direction already indicated by SEBI's consultation on responsible AI/ML usage in securities markets (SEBI, 2025).
- Future research should extend this survey-based approach with an actual portfolio back-testing component, comparing AI-assisted and conventional portfolios on risk-adjusted performance measures such as the Sharpe ratio, to connect investor perception with realised outcomes.

11. CONCLUSION

This article reviewed the major Artificial Intelligence techniques, applications and future directions relevant to asset and portfolio management, and empirically examined investor willingness to adopt AI-supported portfolio management services using a survey of 120 respondents. The review confirms that machine learning, deep learning, reinforcement learning, natural language processing and explainable AI each contribute distinct capabilities across the investment value chain, from return forecasting to risk management and investor communication. The empirical results show that while awareness of AI in investment management remains moderate, a majority of investors are open to adopting AI-supported portfolio management, provided that recommendations are transparent and explainable and that human oversight remains in place. Both hypotheses tested were supported: perceived usefulness significantly and positively influences adoption intention, while perceived risk significantly and negatively influences it. These findings align with the broader academic consensus that the future of AI in asset and portfolio management depends less on further technical sophistication and more on transparency, explainability and responsible human-AI governance (Perret, Mandic, & Herselman, 2026). The study is limited by its convenience-based sampling and modest sample size, and future research combining investor perception with actual portfolio performance data would further strengthen the evidentiary basis for responsible AI adoption in this fast-evolving field.

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