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Research Paper

Role of Artificial Intelligence in Assets and Portfolio Management: Emerging Paradigms

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Abstract
Artificial Intelligence (AI) is entering a new phase in asset and portfolio management, moving beyond conventional machine-learning-based forecasting into emerging paradigms such as generative AI, large language model (LLM) based investment agents, and explainable, human-supervised hybrid decision systems. This article examines these emerging paradigms and their implications for investment research, portfolio construction and investor communication, and empirically tests investor readiness to adopt AI-supported portfolio management through 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 emerging paradigms such as LLM-based investment agents offer considerable analytical power but will only translate into investor trust if paired with transparency, explainability and continued human oversight, and it offers suggestions for asset managers, technology providers and regulators navigating this transition.

Keywords: ***Artificial Intelligence, Portfolio Management, Generative AI, Large Language Models, Explainable AI, Investor Adoption***

I. Introduction

Asset and portfolio management has passed through several distinct technological phases: from discretionary, judgement-based management, to quantitative and statistical portfolio theory, to machine-learning-based forecasting and risk modelling. A new paradigm is now emerging with the rapid advance of generative AI and large language models (LLMs), which can process unstructured financial text, generate research summaries, power autonomous investment agents and support natural-language interaction between investors and portfolio-management systems (Kong et al., 2024). Industry research similarly notes that generative AI adds a distinct new dimension to investment research beyond earlier machine-learning-based asset allocation, for instance by allowing analysts to attach asset-allocation implications directly to AI-generated narrative scenarios (Amundi Research Center, 2025).

This article therefore reviews the emerging technical paradigms in AI-based asset and portfolio management and complements this review with original survey evidence on investor willingness to adopt AI-supported portfolio management services.

II. Objectives of the Study

- To examine the emerging paradigms of Artificial Intelligence in asset and portfolio management, including generative AI, large language model (LLM) based investment agents, and explainable AI.
- To review how these emerging paradigms extend earlier machine-learning and deep-learning applications in return forecasting, portfolio construction and risk management.
- To examine investors' awareness of, and willingness to adopt, AI-supported portfolio management services in this emerging landscape.
- To empirically test the effect of perceived usefulness and perceived risk on investors' willingness to adopt AI-supported portfolio management.
- To offer suggestions for asset managers, technology providers and regulators for the responsible adoption of emerging AI paradigms in investment management.

III. Rationale of the Study

The rationale for this study stems from the pace at which AI paradigms in asset management are evolving. Only a few years after machine-learning-based forecasting and reinforcement-learning-based allocation became established research themes, generative AI and LLM-based investment agents are already being explored for tasks ranging from financial-document analysis and sentiment extraction to fully agent-based portfolio construction (Kong et al., 2024). Asset managers, regulators and investors risk falling behind this shift if academic research does not keep pace with it. At the same time, the behavioural literature on investor acceptance of AI-managed funds continues to show that transparency, not the sophistication of the underlying technology, is the decisive factor shaping investor willingness to invest (Perret, Mandic, & Herselman, 2025). It is therefore important to study emerging AI paradigms and investor readiness together rather than in isolation, particularly as regulators such as the Securities and Exchange Board of India begin framing guidelines for responsible AI/ML usage in securities markets (SEBI, 2025).

IV. 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.

V. Review of Existing Literature

5.1 Foundational Portfolio Theory

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. These foundational frameworks remain the benchmark against which every subsequent AI-based paradigm in portfolio management is evaluated.

5.2 Earlier AI Paradigms: Machine Learning, Deep Learning and Reinforcement Learning

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 by capturing nonlinear interactions among predictors such as momentum, liquidity and volatility. Sezer, Gudelek and Ozbayoglu (2020) reviewed deep-learning applications in financial time-series forecasting and found CNN, LSTM and hybrid deep-belief-network models to be the most widely applied architectures, while noting persistent criticism of their limited interpretability. Jiang, Xu and Liang (2017) proposed a deep reinforcement learning framework for continuous portfolio reallocation, reporting strong back-tested performance, though the study did not fully address real-world transaction costs and slippage.

5.3 The Emerging Paradigm: Generative AI and LLM-Based Investment Agents

Kong et al. (2024) provided a comprehensive review of large language model applications in financial and investment management, categorizing the literature into linguistic tasks, sentiment analysis, financial time-series analysis, financial reasoning and agent-based modelling, and compiling datasets and benchmarks associated with each application area. Their review positions LLMs not merely as text-processing tools but as a foundation for autonomous or semi-autonomous investment agents capable of financial reasoning, planning and decision support — a marked extension beyond the narrower forecasting role of earlier machine-learning models. Industry research similarly observes that generative AI allows asset managers to generate proprietary scenario-based insights and attach asset-allocation implications directly to AI-generated narratives, adding a qualitatively new research capability beyond earlier machine-learning-based asset allocation (Amundi Research Center, 2025).

5.4 Investor Acceptance, Trust and Explainability

Davis (1989) established perceived usefulness and perceived ease of use as the primary determinants of technology-adoption intention through the Technology Acceptance Model. König, Wurster and Siewert (2022) found, through a discrete choice experiment, 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. Taken together, the literature shows an accelerating technical frontier — from machine learning, to deep learning and reinforcement learning, to generative AI and LLM-based agents — running alongside a behavioural literature that consistently identifies transparency and explainability, not raw technical capability, as the condition on which investor trust and adoption depend.

VI. Research Gap

Two gaps are evident. First, the emerging technical literature on generative AI and LLM-based investment agents (Kong et al., 2024) is largely methodological and benchmark-oriented, with limited attention paid to whether investors are willing to trust or adopt systems built on these newer paradigms. Second, existing investor-acceptance studies (König, Wurster, & Siewert, 2022 & Perret, Mandic,) were conducted before generative AI and LLM-based agents became a visible paradigm in investment management, and therefore do not directly capture investor attitudes toward this newest wave of AI capability. This article addresses this gap by reviewing the emerging technical paradigms and pairing that review with a direct empirical test of perceived-usefulness and perceived-risk relationships among a sample of 120 investors.

VII. Research Methodology

7.1 Research Design

The study adopts a descriptive, analytical and empirical research design, combining a structured literature-based review of emerging AI paradigms 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.

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.

VIII. 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

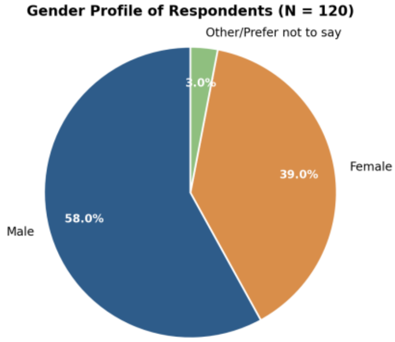

Figure 1: Gender Profile of Respondents (N = 120)

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.

8.2 Awareness of Emerging AI Paradigms in Portfolio Management

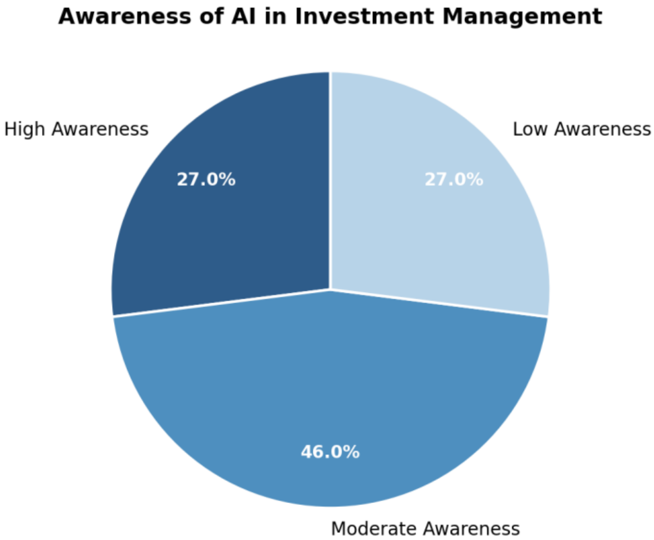

Figure 2: Awareness of AI (Including Emerging Generative-AI Paradigms) in Portfolio Management (N = 120)

Only 27 percent of respondents reported high awareness of AI use in investment research and portfolio management, including newer generative-AI and LLM-based tools, while 46 percent reported moderate awareness and 27 percent reported low awareness. This indicates that awareness of the emerging paradigm lags even further behind its technical development than awareness of earlier, more established AI techniques.

8.3 Willingness to Adopt AI-Supported Portfolio Management

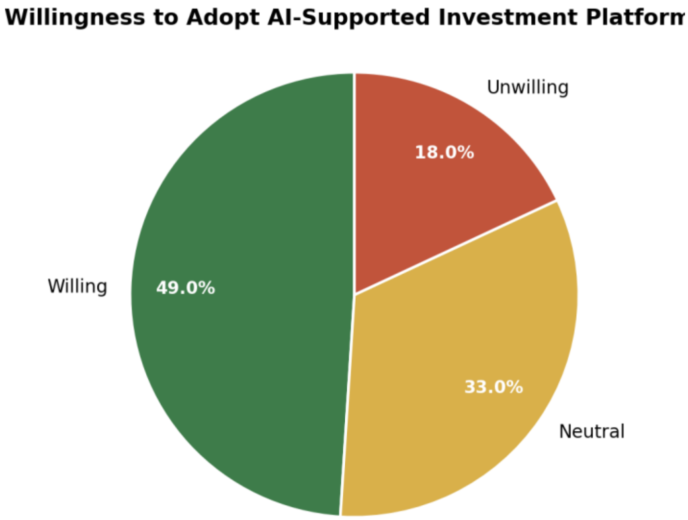

Figure 3: Willingness to Adopt AI-Supported Portfolio Management (N = 120)

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 even as the underlying AI paradigm continues to evolve rapidly.

8.4 Factors Influencing Trust in AI-Based Recommendations

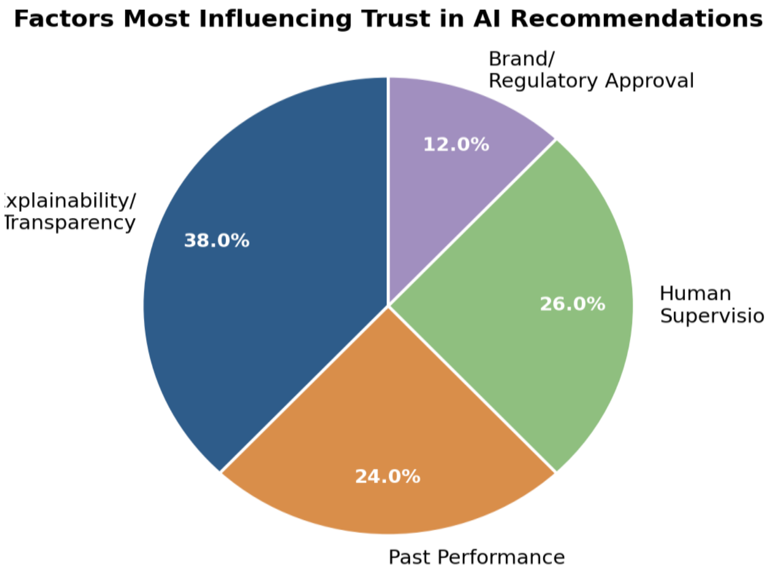

Figure 4: Factors Most Influencing Trust in AI-Based Investment Recommendations (N = 120)

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. This finding is particularly relevant to the emerging generative-AI paradigm, where systems can generate fluent natural-language explanations that may appear transparent without being verifiably accurate, reinforcing the continued need for human review (Kong et al., 2024).

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

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.

IX. Findings

- The emerging paradigm in AI-based asset and portfolio management is shifting from narrow forecasting and classification tasks toward generative AI and LLM-based investment agents capable of financial reasoning, planning and natural-language interaction (Kong et al., 2024).
- Investor awareness of these emerging AI paradigms is lower than awareness of AI in investment management generally, with only about one-quarter of respondents reporting high awareness.
- A majority of respondents (49 percent) are nonetheless willing to adopt AI-supported portfolio management, indicating cautious but net-positive acceptance.
- 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 remain the most cited trust factors, which is particularly significant for generative-AI systems capable of producing fluent but not always verifiably accurate explanations.

X. Suggestions and Recommendations

- Asset-management firms adopting generative-AI and LLM-based investment tools should pair them with explicit source citation and verification layers, since fluent natural-language output can create a false impression of transparency without genuine explainability.
- Firms should retain a hybrid human-AI model for emerging-paradigm tools specifically, given that these systems are newer, less understood by investors, and more prone to unverified or hallucinated outputs than earlier, narrower machine-learning models.
- Investor-education initiatives should specifically address generative AI and LLM-based investment tools, since awareness of these emerging paradigms lags even behind general AI awareness in this sample.
- Regulators should extend AI-governance consultations, such as SEBI's ongoing consultation on responsible AI/ML usage (SEBI, 2025), to address the specific risks of generative and agentic AI systems, including hallucination, prompt manipulation and automation bias, alongside the risks associated with earlier predictive AI models.
- Future research should track investor perception of generative-AI and LLM-based investment tools longitudinally as awareness and usage of these emerging paradigms grow, and should combine survey evidence with controlled experiments comparing investor trust in LLM-generated versus human-written investment explanations.

XI. Conclusion

This article examined the emerging paradigms of Artificial Intelligence in asset and portfolio management, tracing the technical progression from machine learning and deep learning through reinforcement learning to generative AI and large-language-model-based investment agents (Kong et al., 2024), and paired this review with empirical survey evidence on investor readiness to adopt AI-supported portfolio management.

Based on a sample of 120 respondents, the study finds that awareness of these emerging paradigms remains limited, but that a majority of investors are nonetheless open to adopting AI-supported portfolio management, provided that recommendations are transparent, explainable and subject to human oversight. Both hypotheses tested were supported: perceived usefulness significantly and positively influences adoption intention, while perceived risk significantly and negatively influences it. As AI in asset management moves toward more autonomous, conversational and generative capabilities, the central lesson from this study is that investor trust continues to depend less on the sophistication of the underlying model and more on the transparency, explainability and human accountability built around it. The study is limited by its convenience-based sampling and modest sample size, and future research tracking investor attitudes as generative-AI-based investment tools become more widely deployed would further strengthen the evidentiary basis for responsible adoption of these emerging paradigms.

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