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TRANSFORMING ASSET ALLOCATION THEORY THROUGH ROBO-ADVISORY AND ARTIFICIAL INTELLIGENCE

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Abstract
This study synthesises the global literature on the transformation of traditional asset-allocation theory, particularly Modern Portfolio Theory (MPT), toward decision models based on Artificial Intelligence (AI) and Robo-Advisory. Using a Systematic Literature Review (SLR) with the PRISMA 2020 protocol, 46 Scopus-indexed articles (2016–2026) were analysed. The findings document a paradigm shift from static mean-variance optimisation toward Deep Reinforcement Learning (DRL), hybrid FNN–DRL architectures, and the integration of alternative data such as ESG sentiment, Vision-Language climate perception, and digital assets. The study proposes an emerging "Algorithmic Portfolio Theory" and underlines the need for Explainable AI to secure accountability and investor trust in increasingly autonomous asset management.

Keyword: *Asset Allocation; Robo-Advisory; Artificial Intelligence; Portfolio Optimization; Machine Learning*

INTRODUCTION

For more than seven decades, global asset allocation has been dominated by Modern Portfolio Theory (MPT) and its emphasis on mean-variance efficiency. Its core assumptions—normally distributed returns and static parameters—frequently break down during extreme instability, failing to capture *fat-tail* risk and dynamic asset correlations during crises (Kim & Enke, 2018). This has motivated a shift toward more robust approaches such as distributionally robust optimisation (Costa & Iyengar, 2023) and constrained optimisation that keeps portfolios investable amid turbulence (Al Janabi, 2022).

The transformation is radical rather than incremental. Artificial Neural Networks have evolved from volatility-prediction tools into systems that autonomously classify market-stability regimes (Kim & Enke, 2018), while Deep Reinforcement Learning with actor–critic architectures reconcile the Markowitz and Kelly paradigms (Aboussalah et al., 2022) and hybrid FNN–DRL designs strengthen fundamental pre-selection (Sun et al., 2026). The information frontier has also expanded to unstructured alternative data—NFT sentiment (Baklanova et al., 2024), Vision-Language climate perception (D. Liu, 2025), and ESG news sentiment (Tan et al., 2025).

AI adoption through Robo-Advisory has not only reshaped institutional strategy but also democratised financial access for households and retail segments. Robo-advisor development has been shown to increase the share of household financial assets by improving employment quality and macroeconomic efficiency (H. Liu, 2025), while for the banking industry this strategic shift has raised profitability, particularly through higher non-interest margins after the global financial crisis (Zogning & Turcotte, 2025). Yet successful adoption

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still depends on investor psychology; personality traits, optimism, and especially an internal locus of control are decisive determinants of the decision to use automated advisory services (Oehler et al., 2022).

At the same time, integrating AI into asset allocation faces serious challenges of transparency and accountability. The rise of Generative AI introduces powerful personalisation of financial services alongside risks of algorithmic bias and data security that demand strong ethical frameworks (Ali & Aysan, 2026). Investors must also navigate policy uncertainty in environment and technology, which exerts heterogeneous effects on risky and safe-haven assets (Lin & Luo, 2026), as well as extreme risk spillover between AI-related assets and traditional or sectoral indices (Billah, 2024; Ngene & Wang, 2024). This fragmentation underscores the urgency of a systematic review that consolidates scattered findings into a single, coherent conceptual framework.

Despite this rapid growth, the literature remains technical and fragmented, and the accuracy–transparency trade-off of black-box models hampers institutional adoption (Zhao et al., 2026). A systematic synthesis is therefore needed to map how these technologies transform the theoretical structure of asset allocation. This study aims to synthesise that transformation, identify the dominant algorithm families, examine how alternative data reshape optimisation, and surface the research gaps emerging with Agentic AI. Practically, it offers a strategic guide for developers and young retail investors on the capabilities and limits of AI-based allocation.

THEORETICAL REVIEW

MPT, introduced by Markowitz in 1952, rests on mean-variance efficiency through diversification. Yet returns display non-linear, fat-tailed behaviour, and Bekiros et al. (2017) show that ignoring higher-order moments such as skewness and kurtosis undermines optimisation. Sensitivity to estimation error (model risk) further distorts weights, motivating Distributionally Robust Optimization that considers an ambiguity set of distributions (Costa & Iyengar, 2023) and machine-learning approaches that control estimation error (Ban et al., 2018).

Within this study, algorithmic asset allocation is understood as the process of setting portfolio weights using machine-learning algorithms to process multidimensional data adaptively. Robo-Advisory is understood as a low-cost advisory-delivery mechanism that automates risk assessment, asset selection, and rebalancing, while Explainable AI refers to a set of techniques that make model decisions interpretable to humans. These three constructs serve as the main lens for interpreting findings across articles and for linking the theoretical review to the research questions.

Classical theory also collides with operational reality in emerging markets, where the assumption of unlimited liquidity rarely holds. Al Janabi (2022) stresses constrained optimisation that integrates liquidity risk, without which theoretically optimal portfolios may be non-investable or non-executable during crises. Incorporating higher-order moments and liquidity constraints thus reframes efficiency itself: a portfolio is efficient not only when it minimises variance but when it remains tradable and resilient under stress—a requirement that AI-based models are increasingly designed to satisfy.

The evolution of machine learning has reshaped portfolio management. ANN with a Stability-Oriented Approach improves dynamic target-volatility allocation (Kim & Enke, 2018); hybrid FNN–DRL performs fundamental pre-selection before optimisation (Sun et al., 2026); and actor–critic DRL unites risk control with long-run growth (Aboussalah et al., 2022). Wavelet–LSTM decomposition (Abolmakarem et al., 2024), shrinkage-based forecast

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combination (Roccazzella et al., 2022), ensemble learning (Yao & Wan, 2025), and online-learning frameworks (Paskaramoorthy et al., 2020; Zhang et al., 2022) widen the toolkit.

Robo-Advisory has democratised wealth management and raised bank profitability through non-interest margins (Zogning & Turcotte, 2025; Kobets, 2022), while enabling alternative assets such as energy cryptos (Gurrib et al., 2020) and NFTs (Baklanova et al., 2024). Adoption depends on investor psychology (Oehler et al., 2022). ESG integration has become a risk-management necessity (Ben Hamadou & Boujelbène Abbes, 2025; Vo et al., 2019), and the frontier now includes visual data through Vision-Language Models (D. Liu, 2025). Explainability via categorical factors and SHAP (Zhao et al., 2026; Ben Jabeur et al., 2025) is prerequisite to the rise of Agentic AI within a human-plus-AI model (Chen, 2025).

The literature further stresses the handling of non-stationary data and cross-asset risk transmission as part of theoretical renewal. Combining the Wavelet Transform with LSTM decomposes stock prices into cleaner coefficients for more accurate prediction (Abolmakarem et al., 2024), while time-frequency decomposition shows that shocks to Real Estate Investment Trusts (REITs) are transitory even as their volatility connectedness persists over long horizons (Ngene & Wang, 2024). Alternative assets such as energy cryptos are likewise validated as effective diversifiers for conventional energy-equity portfolios through hybrid ARMA–GARCH and machine-learning models (Gurrib et al., 2020). Together these findings show that modern asset-allocation theory is moving from the assumption of perfect markets toward modelling that explicitly accounts for liquidity, non-stationarity, and cross-asset risk connectedness.

Methodological development also includes online-learning and ensemble frameworks that address sequential decision-making under transaction costs. Strategies such as exponential-gradient expert-advice aggregation (Zhang et al., 2022) and online investment-decision frameworks (Paskaramoorthy et al., 2020) let portfolios adapt continuously to incoming information, while ensemble models such as cost-sensitive Random Forest–AdaBoost (Yao & Wan, 2025) and unsupervised shape-based clustering (Lim & Ong, 2021) enrich diversification. Controlling estimation error through regularisation (Ban et al., 2018) confirms that the advantage of data-driven models lies in stability and generalisation rather than architectural complexity alone.

Building on this review, the study is qualitative and formulates no hypotheses; instead, it poses the following research questions:

RQ1: How does the literature document the transition from classical MPT toward autonomous AI-based decision models?

RQ2: Which algorithm families are most dominant in mitigating volatility and risk spillover across assets?

RQ3: How does alternative data (ESG, NFT, media sentiment) reshape optimisation within Robo-Advisory ecosystems?

RQ4: What research gaps emerge from the transition toward Agentic AI in institutional asset management?

METHOD

This study applies a Systematic Literature Review (SLR) following the PRISMA 2020 protocol (Page et al., 2021) to ensure a transparent, structured, and replicable process. Literature was retrieved from the Scopus database over 2016–2026 using the Boolean string combining asset-allocation terms, AI/Robo-advisory terms, and transformation terms. Inclusion and exclusion criteria (Table 1) restricted the corpus to English peer-reviewed articles integrating asset-allocation theory with AI.

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Table 1. Inclusion and Exclusion Criteria

Parameter	Inclusion	Exclusion
Topic	Asset-allocation/portfolio theory integrated with AI/ML/Robo-advisory	Single-commodity or non-financial infrastructure
Document	Peer-reviewed journal & review articles	Books, reports, non-blind-review proceedings
Period	2016–April 2026	Before 2016
Language	English	Non-English

Source: processed by authors, 2026

The selection followed four PRISMA stages: 62 records identified in Scopus; 8 excluded at screening (out of scope); 8 excluded at eligibility (no access/incomplete); leaving 46 articles included (Figure 1, Table 2). Each article was coded into a synthesis matrix (provided separately) capturing authorship, year, methodology, focus, and key findings, with quality appraisal prioritising SJR Q1/Q2 journals. Each article was additionally screened for methodological clarity, transparency of data sources, and reproducibility of results before inclusion in the thematic synthesis. This standardised extraction aims to preserve inter-coder consistency and minimise selection bias, so that the resulting synthesis can be traced back to the primary evidence in each article.

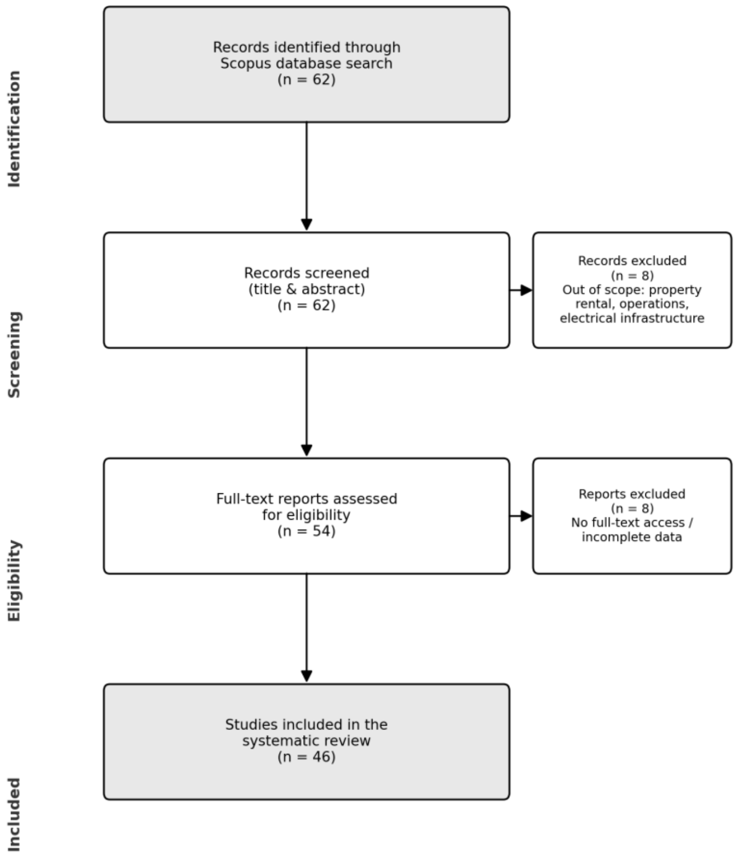

Figure 1. PRISMA 2020 Flow Diagram

Source: processed by authors, 2026

Table 2. PRISMA 2020 Study-Selection Summary

Stage	Retained	Excluded
Identification (Scopus)	62	–

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Stage	Retained	Excluded
Screening (title & abstract)	54	8 (out of scope)
Eligibility (full-text)	46	8 (no access/incomplete)
Included (final corpus)	46	—

Source: processed by authors, 2026

RESULTS

Analysis of the 46 articles reveals strong growth, with a peak of 17 articles in 2025 and five already recorded through April 2026, confirming the topic as a research frontier (Table 3). The years 2016–2020 mark an exploratory phase averaging one article per year, followed by moderate growth in 2021–2023 as Robo-Advisory platforms gained popularity, and an exponential surge in 2024–2025 driven largely by ESG-sentiment research. The corpus concentrates in reputable quantitative-finance journals (Table 4), and four methodological approaches emerge, dominated by quantitative modelling and optimisation (Table 5).

The dominance of quantitative modelling and optimisation (23 of 46 articles) indicates that reinforcing classical models with intelligent algorithms remains the mainstream, whereas fully autonomous reinforcement-learning studies are still relatively few (four articles). Empirical and general-AI applications (11 articles) focus on adoption effects on banks, households, and firms, while deep-learning and ANN studies (eight articles) target time-series prediction. This pattern suggests that AI-based asset allocation is in a transitional phase, in which methodological innovation grows faster than full adoption of autonomous systems, leaving wide research space on reinforcement-learning architectures and the governance of Agentic AI.

Table 3. Annual Publication Distribution (2016–2026)

Year	Articles
2017	1
2018	2
2019	1
2020	3
2021	1
2022	6
2023	2
2024	8
2025	17
2026 (to April)	5
Total	46

Source: processed by authors, 2026

Table 4. Distribution of Leading Journals

Journal	Articles
International Review of Financial Analysis	3
International Review of Economics and Finance	3
Quantitative Finance	3
Global Finance Journal	2
Pacific-Basin Finance Journal	2
Risks	2
Other journals (1 each)	31
Total	46

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Source: processed by authors, 2026

Table 5. Methodology and Algorithm Map

Approach	Articles	Representative studies
Quantitative modelling & optimisation	23	Costa & Iyengar (2023); Al Janabi (2022); Yao & Wan (2025)
Empirical & general AI applications	11	Zogning & Turcotte (2025); H. Liu (2025); Oehler et al. (2022)
Deep learning & ANN	8	Kim & Enke (2018); Abolmakarem et al. (2024); D. Liu (2025)
Reinforcement learning	4	Aboussalah et al. (2022); Sun et al. (2026)
Total	46	—

Source: processed by authors, 2026

DISCUSSION

The first theme is algorithmic evolution from static optimisation toward robust autonomy. DRL agents learn proactively through market interaction, and Distributionally Robust Optimization addresses model risk and estimation error (Costa & Iyengar, 2023), while neural networks accommodate fat-tail phenomena that linear models cannot (Bekiros et al., 2017). Future allocation therefore depends on algorithmic adaptation to non-linear, path-dependent dynamics.

More fundamentally, this shift changes the nature of the efficient frontier itself. Whereas classical models produce a static frontier, DRL and robust-optimisation approaches yield a frontier that moves with market regimes. Consistency appears in studies that combine two-stage stochastic models with neural networks (Bekiros et al., 2017) and in robust forecast combination via shrinkage and constrained optimisation (Roccazzella et al., 2022), both confirming that controlling estimation error is the principal source of advantage over conventional mean-variance optimisation. Unlike prior research that treats predictive accuracy as the ultimate goal, this synthesis shows that AI's greatest contribution at this stage lies in portfolio resilience to model error and distributional ambiguity. Hybrid architectures such as FNN–DRL (Sun et al., 2026) and actor–critic strategies (Aboussalah et al., 2022) thus do more than raise returns; they offer risk-control mechanisms that adapt to shifting market structures.

The second theme is the redefinition of investment variables through ESG and a new information frontier. Non-financial signals become integral portfolio inputs; ESG integration is a risk-management necessity (Ben Hamadou & Boujelbène Abbes, 2025), and Vision-Language Models extract market perception from imagery with predictive power exceeding text analysis (D. Liu, 2025)—a shift from pure financial utility toward value-based utility.

These findings are consistent with studies positioning sustainability as a determinant of resilience rather than a mere ethical option (Ben Hamadou & Boujelbène Abbes, 2025; Vo et al., 2019; Banyai et al., 2025). At the corporate level, extracting ESG news sentiment through Natural Language Processing restrains excessive financialisation and channels capital toward productive long-term innovation (Tan et al., 2025; Li et al., 2024; Deng & Qin, 2026). Extending the information frontier into the visual domain reinforces the argument that relevance is now multimodal; a visual-perception index even outperforms macroeconomic variables and text-based sentiment in predicting strategic-commodity returns (D. Liu, 2025). Unlike conventional theory that struggles to explain assets without traditional fundamentals, hype-index construction and sentiment analysis allow healthy growth to be distinguished from speculative bubbles in digital assets such as NFTs (Baklanova et al., 2024). The implication is

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that future optimisation criteria must accommodate structured, textual, and visual data simultaneously.

The third theme is democratisation and behavioural transformation. Robo-Advisory lowers entry barriers for retail investors but introduces an "algorithmic psychology" of trust; Explainable AI opens the black box (Ben Jabeur et al., 2025) as the field moves toward Agentic AI within a human-plus-AI corridor (Chen, 2025; Oehler et al., 2022).

This behavioural dimension underscores that the transformation is not merely technical but also sociological. The traditional advisor–client relationship shifts into a transparent, data-driven human–machine interaction, making trust the new "currency" of the digital investment ecosystem. Prior studies show that although automation can dampen emotional biases such as loss aversion, its effectiveness hinges on algorithmic openness and investors' understanding of the decision logic (Ben Jabeur et al., 2025; Oehler et al., 2022). Explainable AI is therefore not merely a technical need but an institutional and regulatory prerequisite, especially when uniform algorithm use across institutions can trigger herding behaviour that threatens systemic stability (Herdt & Schulte-Mattler, 2025; Poufinas & Siopi, 2024). This complements earlier research by positioning governance and transparency as determinants of sustainable adoption rather than optional add-ons.

Synthesising these themes, MPT is not abandoned but evolves into an "Algorithmic Portfolio Theory" characterised by probabilistic flexibility (robust modelling of extreme risk), data multimodality (structured, textual, and visual data), and controlled autonomy (intelligent agents under human oversight).

These three characteristics reinforce one another. Probabilistic flexibility keeps models resilient to extreme events; data multimodality widens the information base from numbers to text and imagery; and controlled autonomy ensures that fast execution stays within ethical limits and the client mandate. This framework answers the four research questions in an integrated way: the transition from classical MPT is documented through the shift toward DRO and DRL (RQ1); the dominant algorithm families are identified in quantitative modelling, deep learning, and reinforcement learning (RQ2); alternative data turn optimisation criteria multimodal (RQ3); and the principal gaps arise in the governance and accountability of Agentic AI (RQ4).

Compared with prior reviews that tend to treat algorithms, data, and behaviour separately, this synthesis places all three within a single continuum of theoretical evolution. Its main contribution is therefore not only to map techniques but to offer a conceptual lens for understanding the direction of asset management in the algorithmic era, while marking a new frontier in the role of Agentic AI for maintaining the stability of autonomous portfolios under extreme market volatility.

In an emerging market such as Indonesia, these findings carry high practical relevance. Developers of investment applications should embed Explainable AI so that young investors do not merely receive "black-box" recommendations but understand the rationale behind their allocation, allowing trust in autonomous systems to be built gradually. Digital financial literacy likewise needs to move beyond product familiarity toward understanding how algorithms work, mitigating over-reliance on automated systems and curbing behavioural bias among retail segments new to the capital market.

At the policy level, the autonomy granted to AI demands more dynamic regulation. Uniform algorithm use across many institutions risks triggering herding behaviour that threatens financial-system stability, so standardising model reporting and algorithmic transparency becomes crucial, especially for highly regulated institutions such as banks and insurers (Poufinas & Siopi, 2024; Herdt & Schulte-Mattler, 2025). Developing inclusive AI

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ethics and governance standards will ensure that technological innovation remains aligned with consumer protection and the stability of global capital markets.

Taken together, the four thematic clusters are not independent but sequential stages of a single transformation: robust algorithms provide the computational backbone, alternative data supply richer inputs, behavioural and democratisation dynamics shape adoption, and governance mechanisms determine whether the resulting autonomy is sustainable. Reading them as a continuum clarifies why isolated performance gains reported in individual studies do not automatically translate into institutional trust or systemic resilience, and why an integrative framework such as Algorithmic Portfolio Theory is needed to connect technical capability with responsible practice.

CONCLUSION

This review of 46 reputable articles shows that AI does not replace Markowitz's diversification principle but revolutionises it through Distributionally Robust Optimization, a methodological shift toward Deep Reinforcement Learning and hybrid architectures, and the integration of ESG and visual data that reorients portfolio management toward sustainable, value-based utility—supporting the emergence of an Algorithmic Portfolio Theory with a dynamic, multimodal efficient frontier.

Theoretically, the study introduces "Algorithmic Portfolio Theory" as an extension of Modern Portfolio Theory, demonstrating that the efficient frontier is now dynamic and multimodal and that non-financial and unstructured variables carry significant predictive weight in future portfolio optimisation. This shift calls for renewing the finance-management curriculum to integrate a Human+AI perspective and algorithmic transparency as core competencies.

Practically, financial-technology developers—especially those serving young retail investors—should embed Explainable AI so users understand allocation rationale, and digital literacy should move beyond product familiarity toward understanding how algorithms work. The study is limited to a single database (Scopus) and English-language articles, so local capital-market dynamics may be under-represented.

Future research should conduct local empirical tests using Indonesian capital-market data to validate DRL and local ESG scoring, examine the ethics and legal accountability of Agentic AI, and explore multimodal analysis using local social-media visual data as a sentiment predictor for retail investors.

In addition, subsequent studies could extend the corpus beyond a single database and language, incorporating Web of Science and regional publications to capture practices specific to emerging markets. Comparative work contrasting the performance of reinforcement-learning and ensemble models under local market microstructure, transaction costs, and liquidity constraints would also help translate the conceptual Algorithmic Portfolio Theory into testable, context-specific propositions for practitioners and regulators.

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