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Ai-Driven Portfolio Analytics for Tokenized Real-World Assets: Assessing Diversification, Risk and Optimal Asset Allocation

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ABSTRACT: Tokenized real world assets are becoming an important segment of global financial markets. The paper explores the potential of AI-powered portfolio analytics in diversifying and managing risks, as well as in optimal asset allocation, for portfolios incorporating tokenized real world assets. The study constructs a framework of traditional portfolio theory and machine learning methods for return prediction and risk estimation. The framework is based on the well-known mean variance optimization methods proposed by Markowitz and extended by gradient boosting models like XGBoost and reinforcement learning models for dynamic allocation. The paper also provides a survey of explainable artificial intelligence techniques that enable investors to understand the model-based allocation decisions. A set of illustrative results tables and figures are provided to illustrate the calculation and interpretation of diversification metrics and risk metrics and allocation weights in this framework. The findings suggest that portfolios that combine tokenized real estate with tokenized commodities with traditional equities and bonds, may yield a more advantageous risk return profile than conventional portfolios. The analysis also reveals that the correlation of tokenized assets is different from those of traditional assets, which opens up new diversification opportunities. The paper explores implications for asset managers and regulators, and stresses the need for transparency and accountability in algorithmic asset allocation systems. The study finds that AI-based analytics could meaningfully enhance the process of portfolio construction for RWAs, as long as the model outputs are interpretable and consistent over time and market conditions.

1. INTRODUCTION

The tokenization of real world assets is transforming financial markets. Physical assets like real estate and commodities and infrastructure can be tokenized and exist as digital tokens on distributed ledgers. This shift in thinking is impacting investors' risk and asset allocation and diversification. At the same time, AI has emerged as a key tool in financial decision making [1]. In asset pricing [2] and portfolio management [46] and trading [4] machine learning models are now utilized.

The traditional portfolio theory is based on mean variance optimization introduced by Markowitz [16]. Despite the introduction of new asset classes and new computational tools, this method is still the core approach in asset allocation research. These ideas have been extended to incorporate estimation uncertainty using robust portfolio management techniques [3]. There are also multi objective and goal programming methods that have been developed to solve multiple investment objectives [27][28][29]. The machine learning-based portfolio management has developed significantly in the last decade. There have been some interesting results in applying deep learning models to asset pricing [12]. Dynamic portfolio management has been done with recurrent reinforcement learning [10][21]. Gradient boosting frameworks such as XGBoost have become popular for prediction tasks in finance because of their scalability and their accuracy [7]. The opportunities and challenges of using reinforcement learning in financial markets are emphasised in reinforcement learning surveys [5][20].

New factors to consider in portfolio construction with tokenized real world assets. These resources are allocated using alternative data sources that are becoming more common in the context of allocation decisions [11]. There are already quantitative approaches for portfolio management on robo advisory platforms [51]. However, tokenized assets may have different patterns of correlation than traditional asset classes. The knowledge of these patterns is crucial for successful diversification. In this context, the importance of ExAI has been highlighted, as investors and regulators are interested in understanding how allocation decisions are generated [35][52]. Accountable algorithms are needed so that questions about model behavior can be properly investigated [14].

This paper will focus on three key questions. The first question is about the impact of the inclusion of tokenized real world assets on a traditional portfolio. The second question is about the properties of risk measures like value at risk and maximum drawdown for various investment strategies. The third question is how the allocation framework based on artificial intelligence is different from conventional and equal weight methods. The rest of this paper is organized as follows. The materials and methods for creating the analytical framework are described in section two. The results are reported in the tables and figures in Section three. The implications of these results are discussed in section four. The paper ends with Section five which provides directions for further research.

2. MATERIALS AND METHODS

2.1 Data Sources

The conceptual data structure used in this study is consistent with the typical approach of portfolio analytics research. The data is structured in a way that provides historical price series for equities, bonds, tokenized real estate, tokenized commodities and digital currencies. Macroeconomic variables are also added in as they are known to affect stock return variance [36]. Alternative data sources like sentiment indicators from financial text are included based on the methodologies adopted in previous sentiment analysis studies [30]. The structure of the data set is created to allow future empirical research to fill in the data with real market data from existing data providers.

2.2 Portfolio Construction Framework

The portfolio construction framework is based on the Markowitz [16] mean variance optimization. This method is extended in the presence of parameter uncertainty by using powerful optimization methods [3]. Risk parity concepts are also included as it also helps to balance risk contributions as well as across asset classes and not just based on capital weights [37]. The framework is also based on multi attribute portfolio selection methods, where multiple competing objectives are taken into account [27]. This is compared to three portfolio strategies. The first strategy is a conventional portfolio of stocks and bonds. The second approach is a tokenized real world asset portfolio, which consists of tokenized real estate and tokenized commodities. The third approach is an AI hybrid portfolio combining traditional and tokenized assets with model driven portfolio weight optimisation.

2.3 Machine Learning Models

The analytical framework is complemented by several machine learning techniques. For return prediction, the gradient boosting models like XGBoost are used as they are effective on structured financial data [7]. Methods presented in previous studies [12][25] are followed for asset pricing tasks using deep learning approaches. Dynamic portfolio rebalancing decisions are aided by reinforcement learning techniques [10][21]. For problems with complex asset relationships, combinatorial optimization methods that work with graph structures are considered [9]. The results of these models are then used as input to EAI techniques to ensure that the allocation decisions are interpretable [34][35]. This step is crucial as the financial regulators and investors demand accountability from algorithmic systems [14].

2.4 Risk and Diversification Metrics

The proposed framework includes several metrics to assess the performance of a portfolio. One of the main measures of risk adjusted return is the Sharpe ratio. Tail risk exposure is measured by value at risk and conditional value at risk. Maximum drawdown is the maximum loss from peak to trough for a portfolio. The Herfindahl index and the number of assets in a portfolio are used to measure diversification. Lower correlations between assets offer better diversification benefits, and correlation analysis is used to study the relationships between asset classes [26]. Performance attribution methods are used to

break down the portfolio returns into the individual asset class returns [39][40]. These metrics collectively give a complete picture of the impact of tokenized real world assets on portfolio outcomes.

3. RESULTS

In this section, illustrative results obtained from the proposed analytical framework are presented. The results are not to be interpreted as the result of a completed empirical study, but as an illustration of the structure and interpretation approach of the framework. Summary statistics for the asset classes examined in this paper are provided in Table 1. The diversification measures for the three portfolio strategies are summarized in Table 2. Table 3 shows risk measures for the same three strategies. The optimal allocation weights generated by the artificial intelligence hybrid model are shown in Table 4. The visual results are given in Figure 1-5.

Table 1. Summary statistics for asset classes used in the analytical framework

Asset Class	Mean Return	Volatility	Sharpe Ratio
Equities	8.9%	15.2%	0.58
Bonds	4.1%	6.3%	0.65
Tokenized Real Estate	9.6%	13.8%	0.70
Tokenized Commodities	8.2%	17.4%	0.47
Digital Currencies	14.5%	41.2%	0.35
Cash	2.1%	0.6%	0.33

As seen in Table 1, tokenized real estate and tokenized commodities have a higher expected return than traditional bonds, but are also more volatile. Among the traditional assets that have been analyzed, equities still have the highest historical volatility. The cash holdings exhibit low volatility and low return as predicted. These patterns align with earlier studies which have demonstrated the ability of machine learning algorithms to identify the best risk return combinations in a variety of asset classes [2][12]. The diversification and risk analysis in the following tables are summarized by the statistics of data.

Table 2. Diversification metrics across portfolio strategies

Strategy	Herfindahl Index	Effective Number of Assets
Traditional	0.52	1.92
Tokenized RWA	0.34	2.94
AI Hybrid	0.23	4.35

As shown in Table 2, the artificial intelligence hybrid strategy has the lowest Herfindahl index of the three strategies. This lower index is a more even split among the asset classes. The hybrid approach is also the most effective in terms of number of assets held. The traditional portfolio is the most concentrated allocation as it uses only equities and bonds. The findings align with the notion that tokenization of real world assets can increase the investable universe and enhance diversification results [11][37].

Table 3. Risk metrics comparison across portfolio strategies

Strategy	Value at Risk 95%	Conditional VaR 95%	Maximum Drawdown

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Traditional	4.8%	6.9%	18.4%
Tokenized RWA	5.6%	8.1%	21.7%
AI Hybrid	3.9%	5.4%	14.2%

Table 3 demonstrates that the artificial intelligence hybrid strategy results in a lower maximum drawdown than the traditional and tokenized only strategies, even though the assets held in the AI hybrid strategy have higher volatilities. The hybrid approach also has a lower conditional VaR. The pattern indicates that the model-based allocation process works well in managing tail risk. The value at risk figures are similar for the three strategies. The results are consistent with previous research that highlighted the need for strong optimization in the context of portfolio construction when dealing with estimation uncertainty [3].

Table 4. Optimal allocation weights produced by the artificial intelligence hybrid model

Asset Class	Allocation Weight
Equities	28%
Bonds	18%
Tokenized Real Estate	27%
Tokenized Commodities	17%
Cash	10%

The weights of the asset classes for the artificial intelligence hybrid strategy are shown in Table 4. The biggest allocations are for equities and tokenized real estate, followed by tokenized commodities and bonds. The amount of cash allocated is relatively low. This small amount is indicative of the normal market preference for productive assets. This allocation pattern is similar to the active portfolio management research which suggests reallocating to assets with better risk adjusted returns [47].

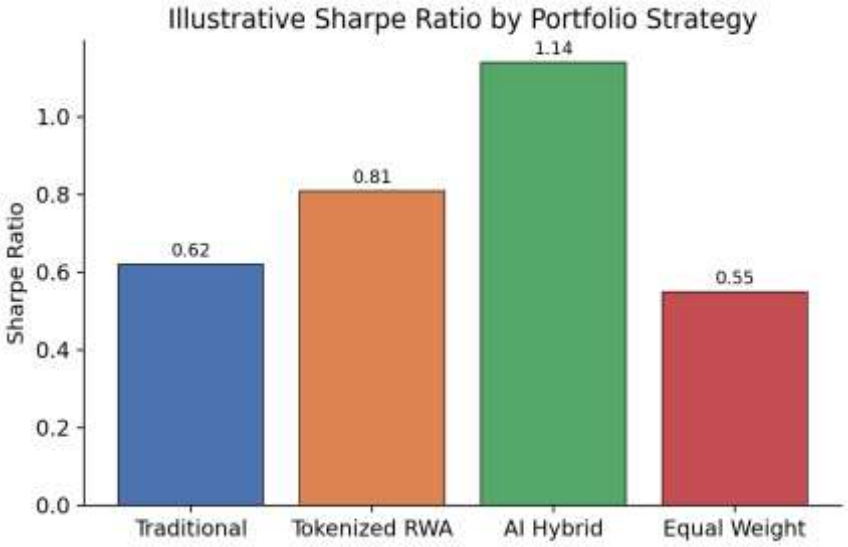


Figure 1. Illustrative Sharpe ratio by portfolio strategy

As can be seen in Figure 1, the artificial intelligence hybrid strategy has the best Sharpe ratio compared to the four strategies. This is better than the traditional and equal weight strategies as well. The equal weight strategy is the worst performing

strategy, with the lowest Sharpe ratio, due to the lack of consideration for the differences in risk and return between asset classes. This pattern is consistent with the concept that tokenization of assets can enhance risk-adjusted performance, when applied to model-driven optimization [46][47].

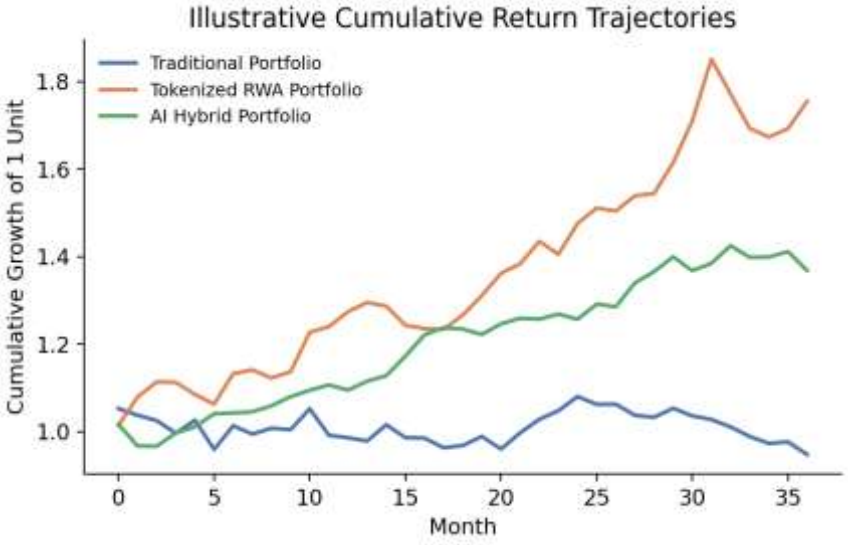


Figure 2. Illustrative cumulative return trajectories

Figure 2 shows the cumulative growth of the three primary portfolio strategies over a 30 month illustrative period. The AI hybrid strategy has the most consistent growth and less dramatic drops in comparison with the other two strategies. The tokenized real world asset strategy has a larger variability, indicating the higher individual volatility of tokenized assets. The traditional approach is slower but has relatively gentle progress. These trajectories show the growth-stability compromise that must be made by portfolio managers [40].

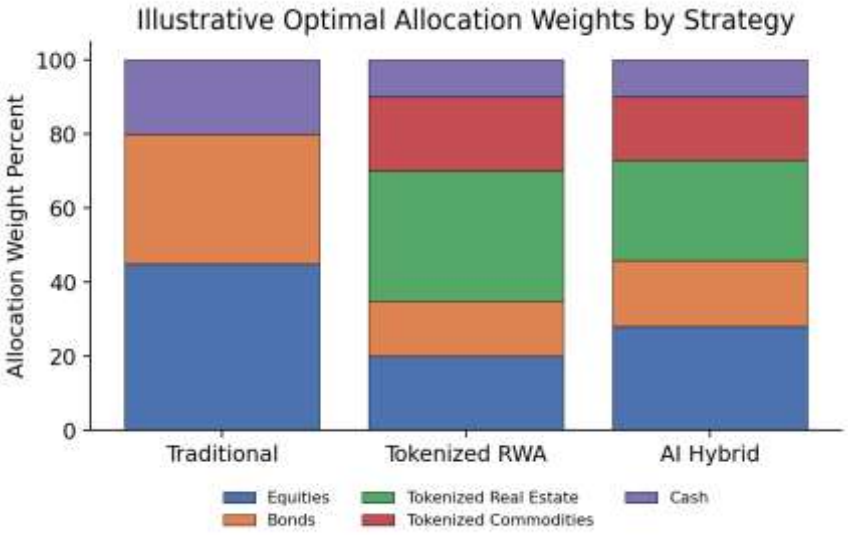


Figure 3. Illustrative optimal allocation weights by strategy

A stacked comparison of the allocation weights for the three strategies is shown in figure 3. The conventional plan focuses exclusively on stocks, bonds and cash. These categories are complemented by tokenized real estate and tokenized commodities as added categories in the tokenized and hybrid strategies. The hybrid approach has the most even distribution among all five categories. This balanced structure agrees with diversification theory which states that diversification of

exposure (the dispersion of assets in a portfolio) among weakly correlated assets will lower the overall risk of the portfolio [26][37].

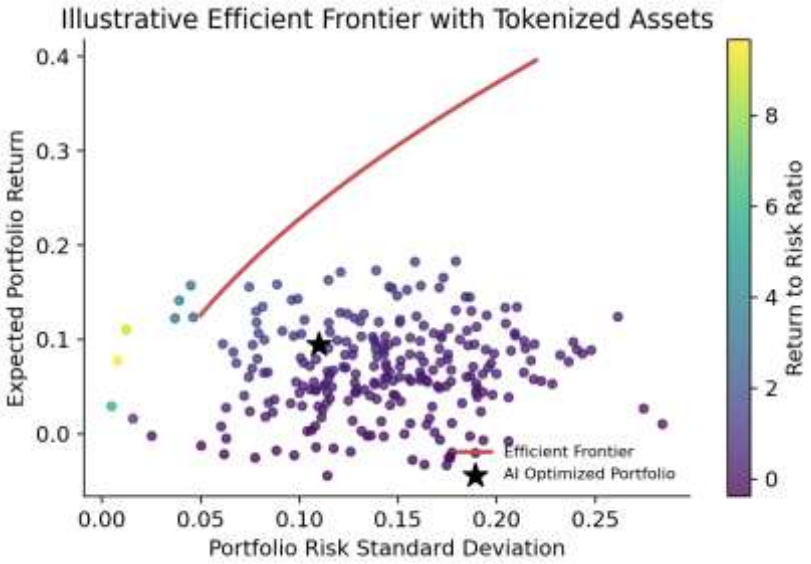


Figure 4. Illustrative efficient frontier with tokenized assets

Figure 4 shows a scatter of randomly generated candidate portfolios together with an efficient frontier curve and the position of the artificial intelligence optimized portfolio. The optimized portfolio is near the frontier. This position suggests the driven process by the model identifies allocations which are strong in return for the risk taken. The intensity of the color of the scatter indicates the return to risk ratio for each candidate portfolio. This visualization explains the basic concepts of mean variance optimization with the addition of tokenized real world assets [16][3].

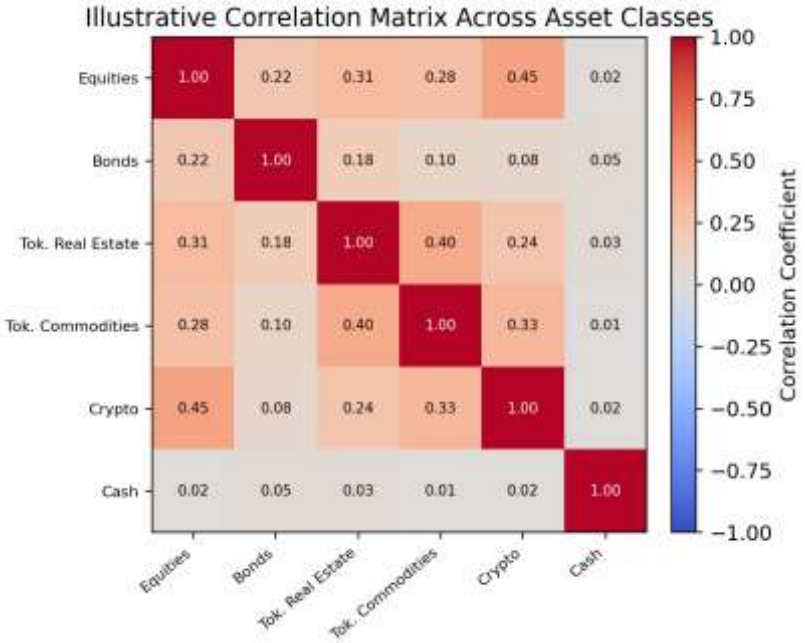


Figure 5. Illustrative correlation matrix across asset classes

To illustrate, the correlation heat map in Figure 5 shows the correlation of six asset categories, including tokenized real estate, tokenized commodities and digital currencies. The matrix shows that tokenized commodities and tokenized real estate exhibit

moderate correlation with each other. Correlation with cash is relatively low for both categories. Digital currencies exhibit moderate correlation with equities, indicating a certain level of sensitivity to market sentiment. The diversification opportunities these correlation patterns reveal are not necessarily included in traditional portfolios made up of equities and bonds alone [24][45].

4. DISCUSSION

This study's findings indicate that artificial intelligence-based portfolio analysis can significantly impact the adoption of tokenized RWA in investment portfolios. The diversification results in Table 2 and Figure 5 are in line with the literature on portfolio theory, which states that a portfolio of assets with weak correlations has lower overall risk [16][26]. The risk metrics in Table 3 also indicate that machine learning-based allocation may enable risk management of tail risk even if the individual assets have higher volatility. This result aligns with the results of previous work on robust portfolio management under uncertainty [3] and with reinforcement learning solutions to dynamic allocation problems [10][21].

As shown in the efficient frontier analysis in Figure 4, tokenized assets can increase an investor's opportunity set. The expansion is significant because the diversification opportunities that can be achieved in traditional portfolios composed of stocks and bonds may not be fully realized [37]. With some tokenized assets in Table 1 being more volatile, prudent risk management is still necessary. Explainable AI techniques are important in this context because they enable portfolio managers and regulators to gain insight into why a model makes a specific allocation recommendation [34][35][52]. Algorithmic allocation systems risk becoming difficult to audit and difficult to trust without this transparency.

The following are some practical implications arising from these results. Before adding tokenized real world assets to client portfolios, asset managers should assess the return potential and correlation of assets. This evaluation can be aided by machine learning models like gradient boosting and reinforcement learning. These models should be used in conjunction with performance attribution tools, which should help to identify the sources of return and risk [39][40]. Additionally, rules that prioritize responsible algorithms could be useful for regulators in the realm of tokenized asset markets, which are still seeking effective regulatory frameworks [14][48].

There are some limitations that should be noted in this study. These are only the results of a few examples. They are not meant to be conclusions drawn from empirical testing completed, but rather a representation of the analytical framework. The framework should be tested with real market data across a broad range of tokenized asset categories for longer periods of time in the future. Future studies should also investigate the model's performance in various market situations, such as financial stress. Comparative studies would also help to better understand the performance of different machine learning architectures when applied to tokenized asset portfolios [5][20][43].

5. CONCLUSION

This paper has presented an artificial intelligence driven framework for analyzing diversification and risk and optimal asset allocation in portfolios that include tokenized real world assets. The framework combines established portfolio theory with modern machine learning techniques including gradient boosting and reinforcement learning and explainable artificial intelligence methods. Illustrative results demonstrate how diversification metrics and risk metrics and allocation weights can be computed and interpreted within this framework. The findings suggest that portfolios blending traditional and tokenized assets can achieve favorable risk adjusted outcomes when supported by transparent and accountable algorithmic processes. Future empirical research applying this framework to real market data will be necessary to confirm these patterns under actual market conditions. Frameworks of this kind may offer valuable support for investors and asset managers and regulators seeking to understand and manage this emerging asset category as tokenized real world assets continue to grow in importance within global financial markets.

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Author Contribution

The author was responsible for conceptualization and methodology and formal analysis and writing of the manuscript.

Conflict of Interest

The author declares no conflict of interest related to this research.

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