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A Financial Engineering Approach to Cryptocurrency Portfolio Risk Management Using Copula-GARCH Models, Extreme Value Theory, and Machine Learning

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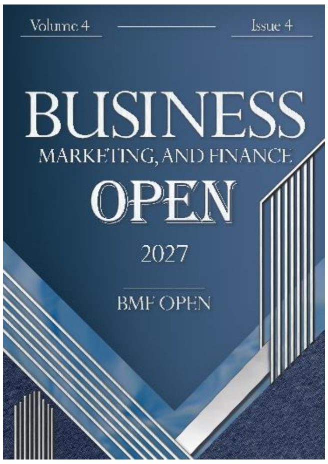

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Abstract: This study aimed to develop and evaluate an integrated financial engineering framework for cryptocurrency portfolio risk management among Iranian investors by combining Copula-GARCH models, Extreme Value Theory, and machine-learning techniques. This applied quantitative study used a longitudinal financial time-series design based on daily data from ten major cryptocurrencies, including Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, Dogecoin, Litecoin, Stellar, Tron, and Bitcoin Cash, from January 1, 2019, to December 31, 2024. After converting synchronized daily closing prices into logarithmic returns, the final dataset included 21,910 asset-return observations. Data were analyzed using descriptive diagnostics, Jarque-Bera normality tests, ARCH-LM tests, GARCH-family volatility models, copula dependence structures, Extreme Value Theory, Value at Risk, Conditional Value at Risk, portfolio optimization, machine-learning forecasting models, and VaR backtesting procedures. The inferential results showed significant non-normality and conditional heteroskedasticity in all cryptocurrency return series, as indicated by Jarque-Bera and ARCH-LM tests ($p < 0.001$). GARCH-family estimations confirmed strong volatility persistence across all assets, with GJR-GARCH and EGARCH models outperforming standard specifications for most cryptocurrencies. Copula-GARCH and EVT results showed that the equal-weighted portfolio had the highest tail-risk exposure, whereas the machine-learning-enhanced CVaR portfolio produced the most favorable risk profile. In VaR backtesting, the variance-covariance and historical simulation models failed the Kupiec and Christoffersen coverage tests, while the Copula-GARCH-EVT-ML model produced the most accurate 99% VaR performance, with observed violations matching expected violations and non-significant coverage test results. Among machine-learning models, Extreme Gradient Boosting achieved the lowest prediction error and strongest directional accuracy. The findings indicate that cryptocurrency portfolio risk cannot be adequately managed through static correlation-based or variance-based models. Integrating Copula-GARCH, Extreme Value Theory, and machine learning provides a more robust framework for estimating volatility, nonlinear dependence, extreme downside risk, and optimized portfolio allocation in cryptocurrency markets.

Keywords: Cryptocurrency; Portfolio Risk Management; Copula-GARCH; Extreme Value Theory; Machine Learning; Value at Risk; Conditional Value at Risk; Financial Engineering.

1. Introduction

Cryptocurrency markets have become one of the most challenging domains for contemporary financial engineering because they combine high return potential, extreme volatility, nonlinearity, market fragmentation, technological innovation, liquidity instability, and rapid sensitivity to global information flows. Unlike conventional financial assets whose behavior can often be partially explained through macroeconomic fundamentals, balance-sheet information, monetary policy, or established valuation frameworks, cryptocurrencies are shaped by a wider and more unstable set of forces, including speculative demand, technological adoption, regulatory expectations, investor sentiment, liquidity cycles, exchange-specific market microstructure, and cross-market contagion. This complexity has made cryptocurrency portfolio risk management a central issue for both academic researchers and market participants. The growth of cryptocurrency trading has also created new methodological demands, because traditional portfolio models based on normality, linear correlation, and constant variance are often unable to capture the statistical properties of digital assets. Cryptocurrency returns are typically characterized by volatility clustering, fat tails, abrupt price jumps, asymmetric dependence, and strong co-movement during market stress. These characteristics require advanced modeling frameworks capable of integrating dynamic volatility, nonlinear dependence, tail-risk estimation, and predictive analytics.

The expansion of cryptocurrency markets has generated a broad research agenda on trading behavior, price formation, risk exposure, and portfolio construction. A comprehensive review of cryptocurrency trading has shown that digital asset markets involve complex interactions among market efficiency, investor behavior, exchange structure, algorithmic trading, and risk management, indicating that cryptocurrency investment cannot be adequately understood through conventional financial-market assumptions alone [1]. In addition, the relationship between return and liquidity in cryptocurrency markets has attracted increasing attention because liquidity fluctuations can amplify volatility and influence the stability of portfolio performance. Evidence on return-liquidity interactions suggests that liquidity is not merely a secondary market feature but a fundamental dimension of cryptocurrency pricing and risk transmission [2]. These issues are especially important for investors in emerging and financially constrained environments, including Iran, where cryptocurrency investment may be used not only for speculative purposes but also as an alternative channel for wealth preservation under inflationary pressure, exchange-rate uncertainty, and limited access to international financial markets.

One of the most important problems in cryptocurrency risk management is that diversification benefits are unstable over time. In traditional portfolio theory, the combination of assets with imperfect correlations can reduce total portfolio risk. However, in cryptocurrency markets, correlations are often dynamic and tend to increase during crisis periods, precisely when diversification is most needed. This behavior weakens the effectiveness of simple diversification and requires portfolio models that can capture both ordinary dependence and stress-period co-movement. Studies on Bitcoin and portfolio selection have shown that multivariate distributional assumptions matter substantially when assessing the role of Bitcoin in diversified portfolios, because the risk contribution of cryptocurrency assets depends on the joint behavior of returns rather than only on their individual volatility [3]. Similarly, research on dynamic asymmetric dependence in cryptocurrency markets has demonstrated that portfolio management decisions are strongly influenced by time-varying and asymmetric relationships among digital assets [4]. These findings indicate that portfolio risk estimation based on static covariance matrices is insufficient for cryptocurrency markets, particularly when the objective is to manage severe downside risk.

The limitations of linear dependence measures have increased the importance of copula-based models in financial engineering. Copula models allow researchers to separate marginal distributions from dependence structures and to estimate nonlinear, asymmetric, and tail dependence among financial assets. This feature is particularly valuable for cryptocurrencies because extreme losses may occur simultaneously even when average correlations appear moderate. Copula-based modeling has been applied to cryptocurrency portfolio optimization and diversification, showing that composite and flexible copula structures can improve the measurement of dependence and strengthen risk-sensitive portfolio allocation [5]. A particle swarm optimization copula-based approach has also been proposed for cryptocurrency portfolio optimization, demonstrating that the integration of dependence modeling and computational optimization can enhance the construction of efficient portfolios in highly volatile markets [6]. More recent studies have continued this direction by combining GARCH-copula modeling with the Markowitz framework to optimize cryptocurrency portfolios, indicating that dependence-sensitive volatility modeling can provide a more realistic basis for portfolio allocation than classical mean-variance optimization alone [7]. Research directly modeling cryptocurrency dependence through Copula-GARCH methods has further confirmed that copulas are useful for capturing the joint movements of digital assets under unstable market conditions [8].

The need for copula-based modeling is further reinforced by evidence that cryptocurrencies are connected not only to one another but also to traditional financial assets, foreign exchange markets, commodities, and decentralized finance instruments. Bitcoin has been examined in relation to foreign exchange markets in both developed and emerging economies, showing that linkages between Bitcoin and currencies are relevant for risk transmission and cross-market exposure [9]. Dynamic copula evidence has also shown nonlinear dependence between cryptocurrencies and foreign exchange markets, suggesting that exchange-rate movements may affect or be affected by cryptocurrency dynamics in ways that standard correlation-based methods cannot adequately capture [10]. In the Iranian context, where exchange-rate volatility and access to foreign-currency assets are major financial concerns, these relationships are especially important for understanding cryptocurrency portfolio risk. Moreover, the integration of crypto-assets with crude oil and other financial markets has shown that dependence structures changed during the COVID-19 pandemic, indicating that global crisis periods can reshape the relationship between cryptocurrencies and traditional assets [11]. Studies of spillovers among cryptocurrencies, gold, and stock markets during the pandemic have likewise emphasized the implications of these relationships for hedging strategies and portfolio diversification [12].

The question of whether cryptocurrencies can serve as hedge or safe-haven assets remains contested. Evidence comparing gold, the U.S. dollar, Bitcoin, and stock markets suggests that the hedging and safe-haven properties of Bitcoin are conditional and depend on market regime, asset class, and stress intensity [13]. Research on whether cryptocurrencies provide better hedging during the COVID-19 pandemic has similarly indicated that their hedging function is not uniform across major equity markets and may weaken during systemic stress [14]. These findings challenge the assumption that adding cryptocurrencies to a portfolio automatically improves risk-adjusted performance. Instead, they suggest that cryptocurrency portfolio management must be based on dynamic models capable of identifying when diversification, hedging, and risk reduction are actually effective. In related research, socially responsible investments were found to play a diversifying role during the COVID-19 crisis, highlighting the broader point that diversification benefits must be evaluated under crisis-specific risk conditions rather than under average market assumptions [15]. For cryptocurrency investors, this means that portfolio performance should be assessed not only by average return and volatility but also by downside risk, drawdown exposure, and extreme-loss behavior.

Extreme Value Theory has therefore become an important component of modern financial risk management. Standard volatility models can estimate time-varying risk, but they may still underestimate rare and severe losses if the return distribution has fat tails. Extreme Value Theory focuses specifically on the tails of the distribution and is therefore suitable for estimating Value at Risk and Conditional Value at Risk under extreme market conditions. Applications of Extreme Value Theory to gold returns have shown that EVT-based models are useful when financial return distributions exhibit heavy tails and extreme fluctuations [16]. Although gold and cryptocurrencies differ in market structure and investment function, the methodological relevance of EVT is clear because both may experience sharp changes during uncertain periods. GARCH-EVT-Copula frameworks have been applied to model the linkages between Bitcoin, gold, the dollar, crude oil, and stock markets, demonstrating that the combination of volatility modeling, tail estimation, and dependence analysis provides a more comprehensive understanding of cross-market risk [17]. A related SV-EVT pairwise copula approach has also been used to quantify foreign exchange risk, showing that EVT-copula structures are valuable for measuring sectoral exposure under extreme conditions [18]. These studies support the use of EVT in cryptocurrency portfolio risk management, especially when the objective is to estimate losses beyond ordinary volatility levels.

In addition to volatility and tail-risk modeling, asymmetric correlation has become an important issue in financial risk analysis. Asset relationships may differ between rising and falling markets, and downside dependence is often stronger than upside dependence. Research on asymmetric correlations and their applications in financial markets has emphasized that ignoring asymmetry can lead to mismeasurement of diversification benefits and underestimation of risk concentration [19]. This is highly relevant to cryptocurrency markets, where panic selling, liquidity withdrawal, and cross-asset contagion can produce stronger co-movement during declines. Recent work on asymptotic dependence and hedging effectiveness in stock, currency, and commodity futures further indicates that tail dependence plays a crucial role in evaluating hedge performance [20]. Therefore, a robust cryptocurrency portfolio risk model must account not only for average co-movement but also for dependence in the extremes. This requirement directly supports the combined use of GARCH-family models, copula dependence structures, and EVT-based tail estimation.

The development of stablecoins and decentralized finance has further increased the complexity of cryptocurrency portfolio risk. Stablecoins are often treated by market participants as low-volatility instruments or as “dry powder” that can be deployed quickly during market opportunities or stress episodes. However, copula-based analysis of cryptocurrency markets suggests that stablecoins may be embedded in broader systemic risk structures and may not be fully isolated from market dependence during periods of stress [21]. Similarly, research on volatility and return spillovers among traditional technology stocks, decentralized finance instruments, and conventional cryptocurrencies has shown that digital financial assets are increasingly interconnected with both technology-sector equities and decentralized finance markets, creating implications for portfolio optimization [22]. These findings suggest that cryptocurrency portfolio risk management must increasingly consider spillovers, systemic linkages, and the evolving structure of digital finance. Evidence from Islamic cryptocurrencies and their copula-based dependence with alternative crypto and fiat currencies also demonstrates that new categories of digital assets may display distinct dependence patterns, reinforcing the need for flexible and context-sensitive modeling frameworks [23].

Machine learning has recently added a new dimension to cryptocurrency portfolio management. Unlike traditional econometric models, machine-learning methods can capture nonlinear relationships, complex interactions among predictors, and regime-dependent patterns in volatility and returns. Machine learning has been applied to cryptocurrency price prediction and risk-adjusted portfolio optimization, showing that predictive algorithms can improve decision-making when combined with financial risk criteria [24]. However, machine learning should not be treated as a replacement for financial theory or econometric risk modeling. Instead, its strongest application may be in hybrid frameworks where machine-learning forecasts are integrated with GARCH volatility estimates, copula dependence structures, and EVT-based tail-risk measures. Such integration can improve one-day-ahead risk forecasting, identify nonlinear risk signals, and support adaptive portfolio allocation. Research incorporating investor sentiment into an ARMA-GARCH-Sent-EVT-Copula portfolio model has shown that predictive information beyond prices may improve the modeling of portfolio risk, especially when sentiment affects volatility and tail dependence [25]. Therefore, the combination of econometric, statistical, and machine-learning approaches is consistent with the broader movement toward hybrid financial-engineering models.

Risk measurement itself has also evolved beyond conventional Value at Risk. Although VaR remains widely used, it does not fully describe the magnitude of losses beyond the threshold. Conditional Value at Risk and related measures such as Range Value at Risk provide additional insight into tail severity and risk concentration. A comparison of Range Value at Risk forecasting models has highlighted the importance of using risk measures that provide richer information about the distribution of extreme losses [26]. For cryptocurrency portfolios, where large losses may occur suddenly and exceed ordinary model expectations, reliance on VaR alone may be insufficient. CVaR is particularly relevant because it estimates the expected loss conditional on losses exceeding the VaR threshold. This makes it more suitable for portfolio optimization under extreme downside risk. In the Iranian investment environment, where financial shocks may be amplified by exchange-rate instability and restricted hedging channels, tail-sensitive risk measures are especially important for evaluating cryptocurrency exposure.

Domestic and regional portfolio research also supports the relevance of combining stocks and cryptocurrencies in risk-sensitive optimization. A study on optimizing a portfolio comprising selected stocks and cryptocurrencies demonstrated that mixed-asset portfolios involving digital assets require careful allocation methods because cryptocurrencies can both improve return opportunities and increase risk exposure [27]. This is highly relevant for Iranian investors who may view cryptocurrencies as alternative assets alongside domestic equities, foreign-currency exposure, and informal investment channels. The challenge is not merely whether cryptocurrencies should be included in portfolios, but how their weights should be determined under conditions of volatility, nonlinear dependence, and tail risk. In this regard, an integrated financial-engineering approach offers practical value by moving beyond simple return maximization and toward robust portfolio risk control.

Overall, the literature indicates that cryptocurrency portfolio risk management requires a multidimensional framework. GARCH-family models are necessary for estimating conditional volatility and volatility persistence; copula models are required for capturing nonlinear, asymmetric, and tail dependence; Extreme Value Theory is essential for measuring rare but severe losses; and machine-learning algorithms can improve predictive accuracy and adaptive allocation. However, many existing studies emphasize only one or two of these components, such as dependence modeling, volatility forecasting, tail-risk estimation, or portfolio optimization. Fewer studies integrate all of these methods into a unified portfolio risk management framework, particularly from the perspective of investors operating in emerging-market environments such as Iran. This gap is important because Iranian cryptocurrency investors face not only the inherent volatility of digital assets but also additional macro-financial pressures, including inflation, currency instability, capital-market limitations, and restricted access to conventional international diversification instruments.

The aim of this study was to develop and evaluate a financial engineering framework for cryptocurrency portfolio risk management among Iranian investors by integrating Copula-GARCH models, Extreme Value Theory, and machine-learning techniques to estimate dynamic volatility, nonlinear dependence, extreme downside risk, and optimized portfolio allocation.

2. Methodology

This study was designed as an applied, quantitative, longitudinal, and analytical study in the field of financial engineering and cryptocurrency portfolio risk management. The research was conducted from the perspective of cryptocurrency investors in Iran and was based on historical market data rather than experimental intervention. The statistical sample consisted of ten major cryptocurrencies that were actively followed and traded by Iranian cryptocurrency investors and had continuous daily price data during the study period. The selected assets were Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, Dogecoin, Litecoin, Stellar, Tron, and Bitcoin Cash. The observation period covered six complete calendar years from January 1, 2019, to December 31, 2024. Since cryptocurrency markets operate continuously without official weekend or holiday closures, the raw dataset included 2,192 synchronized daily observations for each cryptocurrency. Therefore, the initial database contained 21,920 asset-day price observations. After transforming daily closing prices into logarithmic returns, the final analytical sample included 2,191 synchronized daily return observations for each cryptocurrency and 21,910 asset-return observations in total. The sample was selected purposefully according to liquidity, availability of complete historical data, relevance to Iranian investors, and suitability for portfolio risk modeling. The Iranian context of the study was reflected in the interpretation of portfolio risk from the viewpoint of domestic investors exposed to high inflation, exchange-rate instability, capital-market restrictions, and the increasing use of digital assets as alternative investment instruments.

The main data collection tool in this study was a structured historical market data extraction protocol developed for the purposes of financial time-series modeling. Through this protocol, daily closing prices, daily high and low prices, trading volume, and market capitalization data were collected for each selected cryptocurrency. The daily closing price was considered the primary input variable for return calculation because it provides a consistent basis for estimating volatility, dependence structure, tail risk, and portfolio losses. To increase the accuracy of the dataset, extracted prices were screened for missing values, duplicate records, abnormal zero prices, inconsistent timestamps, and extreme recording errors. All price series were synchronized on a daily calendar basis so that each date contained observations for all ten cryptocurrencies. Since the study focused on portfolio risk management for Iranian investors, USD-denominated cryptocurrency prices were also considered in relation to the Iranian investment environment, and the final interpretation of risk emphasized the implications of cryptocurrency volatility for investors operating under Iranian financial conditions.

The second tool was the portfolio risk management modeling framework, which consisted of econometric, statistical, and machine-learning components. In the econometric component, univariate GARCH-family models were used to estimate conditional volatility for each cryptocurrency return series. These models made it possible to capture volatility clustering, persistence, and time-varying risk behavior, which are common characteristics of cryptocurrency markets. In the dependence modeling component, copula models were used to estimate the nonlinear and asymmetric dependence structure among cryptocurrency returns. This component was necessary because simple linear correlation is not sufficient for identifying co-movement during market stress, especially when assets experience simultaneous extreme losses. In the tail-risk component, Extreme Value Theory was used to model rare but severe losses in the lower tail of the return distribution. This framework enabled the study to estimate portfolio Value at Risk and Conditional Value at Risk under normal and extreme market conditions.

The third tool was the computational software environment used for data processing and model estimation. Data cleaning, return calculation, descriptive analysis, volatility modeling, copula estimation, extreme-value modeling, machine-learning prediction, portfolio optimization, and risk backtesting were performed using statistical and programming software. The analytical process was implemented through Python and R environments because these platforms provide reliable packages for time-series econometrics, GARCH modeling, copula estimation, extreme-value analysis, machine-learning algorithms, and portfolio simulation. Microsoft Excel was used only for preliminary data organization and consistency checking, while the main statistical estimation and validation procedures were conducted in the programming environment to ensure reproducibility, computational accuracy, and transparency of the analytical workflow.

Data analysis began with preprocessing of the daily cryptocurrency price series. First, the raw daily closing prices were arranged chronologically and checked for missing observations, duplicate dates, and inconsistent values. Then, the price series were converted into continuously compounded logarithmic returns using the natural logarithm of the ratio of consecutive daily closing prices. Descriptive statistics, including mean, standard deviation, minimum, maximum, skewness, kurtosis, and the Jarque-Bera normality test, were calculated to examine the distributional characteristics of each cryptocurrency return series. Stationarity of the return series was assessed using unit-root tests, and the presence of conditional heteroskedasticity was evaluated before estimating volatility models. These preliminary analyses were necessary to justify the use of GARCH-family models and to determine whether cryptocurrency returns exhibited non-normality, volatility clustering, fat tails, and time-varying variance.

In the next stage, conditional volatility was estimated separately for each cryptocurrency using GARCH-family specifications. Standard GARCH, EGARCH, and GJR-GARCH models were compared in order to identify the most appropriate volatility model for each return series. The use of asymmetric volatility models was important because negative and positive shocks may have different effects on future volatility in cryptocurrency markets. Model selection was based on information criteria, log-likelihood values, statistical significance of parameters, and diagnostic tests on standardized residuals. After selecting the best volatility specification for each asset, standardized residuals were extracted and used as inputs for copula modeling. This approach allowed the study to separate marginal volatility dynamics from the dependence structure among assets.

After modeling individual asset volatility, copula models were applied to estimate the joint dependence structure of cryptocurrency returns. Gaussian, Student's t, Clayton, Gumbel, and Frank copulas were examined to identify the most suitable dependence model for the cryptocurrency portfolio. Particular attention was given to tail dependence because cryptocurrency assets may show stronger co-movement during periods of market decline than during stable market conditions. The Student's t copula was especially relevant for modeling symmetric tail dependence, while Archimedean copulas were used to assess asymmetric dependence in the lower or upper tails. The best-fitting copula was selected according to goodness-of-fit criteria, likelihood-based indicators, and the ability to capture extreme co-movements among cryptocurrency returns. The estimated copula-GARCH structure was then used to simulate joint return scenarios and generate portfolio loss distributions.

Extreme Value Theory was used to estimate the probability and magnitude of rare but severe portfolio losses. The peak-over-threshold approach was applied to the lower tail of the return distribution, and the Generalized Pareto Distribution was fitted to observations exceeding the selected loss threshold. Threshold selection was performed by examining the stability of tail parameters and the adequacy of exceedance observations. Based on the fitted extreme-value model, tail-risk measures were estimated, including Value at Risk and Conditional Value at Risk at high confidence levels. Value at Risk was used to estimate the maximum expected portfolio loss under a given probability level, while Conditional Value at Risk was used to estimate the expected loss beyond the Value at Risk threshold. Conditional Value at Risk was emphasized because it provides more information about the severity of losses in extreme market conditions.

Machine-learning models were then incorporated to improve the prediction of portfolio risk and to compare their performance with traditional econometric models. Several supervised learning algorithms, including random forest, support vector regression, gradient boosting, extreme gradient boosting, and long short-term memory neural networks, were trained to forecast volatility, downside risk, and portfolio loss indicators. The input features included lagged returns, lagged volatility estimates, trading volume changes, rolling standard deviations, moving averages, realized volatility measures, and tail-risk indicators derived from the econometric models. The dataset was divided into training and testing subsets using a chronological split to avoid look-ahead bias. Model performance was evaluated using prediction-error criteria such as mean absolute error, root mean square error, and directional accuracy, as well as risk-specific validation criteria related to Value at Risk exceedances.

Finally, the estimated risk models were evaluated through portfolio simulation, optimization, and backtesting. Portfolio weights were constructed under alternative strategies, including equal weighting, minimum variance allocation, Value at Risk minimization, and Conditional Value at Risk minimization. The performance of each strategy was assessed according to return, volatility, maximum drawdown, Value at Risk, Conditional Value at Risk, and risk-adjusted performance indicators. Backtesting was conducted to examine whether the predicted Value at Risk levels were consistent with realized losses. The unconditional coverage test and conditional coverage test were used to evaluate the frequency and independence of Value at Risk violations. The final comparison focused on whether the integrated Copula-GARCH, Extreme Value Theory, and machine-learning framework provided more accurate and robust portfolio risk estimates than conventional correlation-based and variance-based risk models. The level of statistical significance for hypothesis testing was set at 0.05.

3. Findings and Results

Since the present study was based on financial time-series data rather than human participants, demographic characteristics such as age, gender, education, and marital status were not applicable. Therefore, the initial sample description was reported in terms of the financial characteristics of the selected cryptocurrency assets and the structure of the historical dataset. The final analytical sample consisted of ten major cryptocurrencies that were relevant to Iranian cryptocurrency investors and had continuous historical market data during the study period. These assets included Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, Dogecoin, Litecoin, Stellar, Tron, and Bitcoin Cash. The study period covered January 1, 2019, to December 31, 2024. After synchronizing the daily price series and transforming closing prices into logarithmic returns, 2,191 daily return observations were obtained for each cryptocurrency, resulting in a total of 21,910 asset-return observations. The selected period included different market regimes, including expansionary phases, sharp corrections, crisis periods, high-volatility episodes, and recovery intervals. This structure made the dataset suitable for examining volatility clustering, nonlinear dependence, extreme downside risk, and machine-learning-based portfolio risk forecasting in the context of cryptocurrency portfolio management for Iranian investors.

Table 1. Descriptive Statistics of Daily Logarithmic Returns for the Selected Cryptocurrencies

Cryptocurrency	Mean Return (%)	Standard Deviation (%)	Minimum (%)	Maximum (%)	Skewness	Kurtosis	Jarque-Bera p-value	ARCH-LM p-value
Bitcoin	0.09	3.52	-39.18	18.74	-0.62	12.46	<0.001	<0.001
Ethereum	0.12	4.64	-45.82	25.37	-0.48	14.91	<0.001	<0.001
Binance Coin	0.15	5.18	-43.26	52.84	0.81	18.63	<0.001	<0.001
Ripple	0.05	5.71	-48.33	61.45	1.12	21.79	<0.001	<0.001
Cardano	0.10	6.08	-44.91	38.69	0.36	15.84	<0.001	<0.001
Dogecoin	0.18	8.27	-49.67	87.52	2.34	34.16	<0.001	<0.001
Litecoin	0.04	4.79	-42.54	29.71	-0.21	13.58	<0.001	<0.001
Stellar	0.05	5.36	-46.18	44.29	0.74	19.22	<0.001	<0.001
Tron	0.08	4.23	-35.47	31.85	0.43	14.37	<0.001	<0.001
Bitcoin Cash	0.03	5.14	-44.06	36.42	0.18	16.48	<0.001	<0.001

The descriptive findings in Table 1 show that all selected cryptocurrencies had positive average daily returns during the study period; however, the magnitude of the mean return was small compared with the level of volatility. Dogecoin had the highest mean daily return at 0.18%, but it also had the highest standard deviation at 8.27%, indicating that its higher return was accompanied by substantially greater risk. Binance Coin and Ethereum also showed relatively higher mean returns, while Bitcoin Cash and Litecoin had the lowest average returns among the selected assets. The standard deviation values confirmed that cryptocurrency returns were highly volatile across the entire sample, with Bitcoin showing the lowest volatility among the major assets and Dogecoin showing the highest volatility. The minimum and maximum return values revealed the presence of large daily shocks, especially for Dogecoin, Ripple, Binance Coin, and Ethereum. The skewness statistics indicated that several cryptocurrencies had asymmetric return distributions, with Dogecoin and Ripple showing strong positive skewness, while Bitcoin and Ethereum displayed negative skewness, suggesting that large downside movements were particularly relevant for major cryptocurrencies. The kurtosis values were far above the normal distribution benchmark, confirming that all return series were leptokurtic and characterized by fat tails. The Jarque-Bera test results were significant for all assets, indicating that none of the return series followed a normal distribution. In addition, the ARCH-LM test was significant for all cryptocurrencies, confirming the presence of conditional heteroskedasticity and justifying the application of GARCH-family models for volatility estimation.

Table 2. Selected GARCH-Family Models and Conditional Volatility Estimation Results

Cryptocurrency	Selected Model	α Coefficient	β Coefficient	Asymmetry Parameter	Volatility Persistence	AIC	Ljung-Box Q^2 p-value
Bitcoin	GJR-GARCH(1,1)	0.081	0.887	0.043	0.968	-4.823	0.214
Ethereum	EGARCH(1,1)	0.094	0.872	-0.058	0.966	-4.426	0.186
Binance Coin	GJR-GARCH(1,1)	0.102	0.851	0.064	0.953	-4.118	0.241
Ripple	EGARCH(1,1)	0.116	0.834	-0.071	0.950	-3.957	0.203
Cardano	GJR-GARCH(1,1)	0.119	0.829	0.052	0.948	-3.896	0.227
Dogecoin	EGARCH(1,1)	0.143	0.801	-0.089	0.944	-3.412	0.179
Litecoin	GARCH(1,1)	0.088	0.876	—	0.964	-4.204	0.268

Stellar	GJR-GARCH(1,1)	0.121	0.826	0.057	0.947	-3.842	0.219
Tron	GARCH(1,1)	0.079	0.883	—	0.962	-4.371	0.251
Bitcoin Cash	EGARCH(1,1)	0.111	0.842	-0.063	0.953	-3.991	0.232

The results presented in Table 2 indicate that the return series of the selected cryptocurrencies were best represented by different specifications of the GARCH family, reflecting variation in their volatility dynamics. The GJR-GARCH model was selected for Bitcoin, Binance Coin, Cardano, and Stellar, suggesting that asymmetric responses to negative and positive shocks were important in explaining conditional volatility for these assets. The EGARCH model was selected for Ethereum, Ripple, Dogecoin, and Bitcoin Cash, indicating that logarithmic volatility dynamics and asymmetric leverage effects were relevant for these cryptocurrencies. Standard GARCH(1,1) was sufficient for Litecoin and Tron, suggesting that their volatility behavior was adequately captured by symmetric volatility persistence without requiring an additional asymmetry term. The α coefficients were positive across all assets, showing that recent shocks had a meaningful effect on current volatility. The β coefficients were also large across all models, indicating strong volatility persistence. Volatility persistence ranged from 0.944 for Dogecoin to 0.968 for Bitcoin, confirming that shocks to cryptocurrency volatility tended to decay slowly over time. The asymmetry parameters in the EGARCH and GJR-GARCH models further showed that negative shocks had stronger effects on future volatility than positive shocks of similar magnitude, especially for Dogecoin, Ripple, and Ethereum. The Ljung-Box Q^2 p-values for the squared standardized residuals were greater than 0.05 for all selected models, indicating that the fitted models successfully removed remaining serial dependence in conditional variance. Therefore, the selected GARCH-family models provided an appropriate basis for extracting standardized residuals and estimating the dependence structure through copula models.

Table 3. Copula-GARCH and Extreme Value Theory Estimates of Portfolio Risk Across Alternative Portfolio Strategies

Portfolio Strategy	Annualized Return (%)	Annualized Volatility (%)	Daily VaR 95% (%)	Daily VaR 99% (%)	Daily CVaR 95% (%)	Daily CVaR 99% (%)	Maximum Drawdown (%)
Equal-Weighted Portfolio	38.60	83.40	5.62	10.84	8.91	15.72	73.50
Minimum-Variance Portfolio	25.90	58.20	3.91	7.96	6.24	11.43	55.80
VaR-Minimized Portfolio	29.40	52.70	3.44	7.21	5.86	10.52	49.10
CVaR-Minimized Portfolio	31.20	50.30	3.28	6.91	5.47	9.96	46.20
Machine-Learning-Enhanced CVaR Portfolio	34.80	49.50	3.31	6.78	5.34	9.72	43.60

The findings in Table 3 demonstrate clear differences in risk exposure across the alternative portfolio strategies. The equal-weighted portfolio generated the highest annualized volatility, highest Value at Risk, highest Conditional Value at Risk, and largest maximum drawdown. Although the equal-weighted strategy had a relatively high annualized return of 38.60%, this return was associated with substantial downside exposure, as reflected in a daily 99% VaR of 10.84% and a daily 99% CVaR of 15.72%. This means that under extreme market conditions, losses beyond the 99% VaR threshold were expected to average 15.72% in a single trading day. The minimum-variance portfolio reduced annualized volatility from 83.40% to 58.20% and lowered the daily 99% CVaR from 15.72% to 11.43%, confirming that variance-based optimization improved portfolio stability. However, the minimum-variance strategy did not provide the strongest protection against tail losses. The VaR-minimized and CVaR-minimized portfolios provided additional reductions in downside risk, with the CVaR-minimized strategy showing better performance in controlling severe losses beyond the VaR threshold. The machine-learning-enhanced CVaR portfolio produced the most balanced risk-return profile. It achieved an annualized return of 34.80%, while reducing annualized volatility to 49.50%, daily 99% VaR to 6.78%, daily 99% CVaR to 9.72%, and maximum drawdown to 43.60%. These results indicate that integrating machine-learning forecasts with Copula-GARCH and Extreme Value Theory improved portfolio risk management by reducing extreme downside exposure while preserving a comparatively favorable return profile.

Table 4. Machine-Learning Model Performance in One-Day-Ahead Portfolio Risk Forecasting

Model	MAE	RMSE	Directional Accuracy (%)	VaR 95% Violation Rate (%)	Kupiec Test p-value	Christoffersen Test p-value
Historical Simulation Benchmark	0.0098	0.0147	56.30	7.40	0.031	0.044
GARCH Benchmark	0.0086	0.0129	60.80	6.60	0.084	0.092
Random Forest	0.0071	0.0108	68.20	5.30	0.641	0.518
Support Vector Regression	0.0075	0.0114	65.90	5.70	0.438	0.391
Gradient Boosting	0.0068	0.0102	69.60	5.10	0.752	0.603
Extreme Gradient Boosting	0.0064	0.0098	71.40	4.90	0.821	0.647
Long Short-Term Memory Network	0.0067	0.0101	70.20	5.00	0.793	0.621

The results in Table 4 show that machine-learning models outperformed the traditional historical simulation and GARCH benchmark models in forecasting one-day-ahead portfolio risk. The historical simulation benchmark had the weakest predictive performance, with the highest MAE and RMSE values and the lowest directional accuracy. Its 95% VaR violation rate was 7.40%, which was higher than the expected 5% violation frequency, and both the Kupiec and Christoffersen test results were statistically significant. This indicates that the historical simulation method underestimated risk and failed to provide adequate unconditional and conditional coverage. The GARCH benchmark improved forecasting accuracy compared with historical simulation, but its VaR violation rate remained above the expected level. Among the machine-learning models, Extreme Gradient Boosting produced the best overall performance, with the lowest MAE of 0.0064, the lowest RMSE of 0.0098, and the highest directional accuracy of 71.40%. Its VaR violation rate was 4.90%, which was very close to the theoretical 5% level. The non-significant Kupiec and Christoffersen test results confirmed that the model provided acceptable VaR coverage and did not show evidence of clustered violations. The Long Short-Term Memory model also performed strongly, particularly in capturing sequential dependence in volatility and risk patterns. However, Extreme Gradient Boosting was selected as the preferred machine-learning model because it combined lower prediction error, higher directional accuracy, and stronger backtesting performance. These findings suggest that nonlinear machine-learning models can improve cryptocurrency portfolio risk forecasting when combined with econometric volatility estimates and tail-risk indicators.

Table 5. Backtesting Results for 99% Value at Risk Models

Risk Model	Expected Violations	Observed Violations	Violation Rate (%)	Kupiec LR Statistic	Kupiec p-value	Conditional Coverage LR Statistic	Conditional Coverage p-value
Variance-Covariance Model	22	41	1.87	12.46	<0.001	15.82	<0.001
Historical Simulation	22	36	1.64	7.91	0.005	10.74	0.005
GARCH-Normal	22	31	1.41	3.42	0.064	5.89	0.053
GARCH-t	22	27	1.23	1.08	0.299	2.16	0.340
Copula-GARCH	22	25	1.14	0.39	0.532	1.41	0.494
Copula-GARCH-EVT	22	23	1.05	0.04	0.841	0.76	0.684
Copula-GARCH-EVT-ML	22	22	1.00	0.00	0.984	0.58	0.747

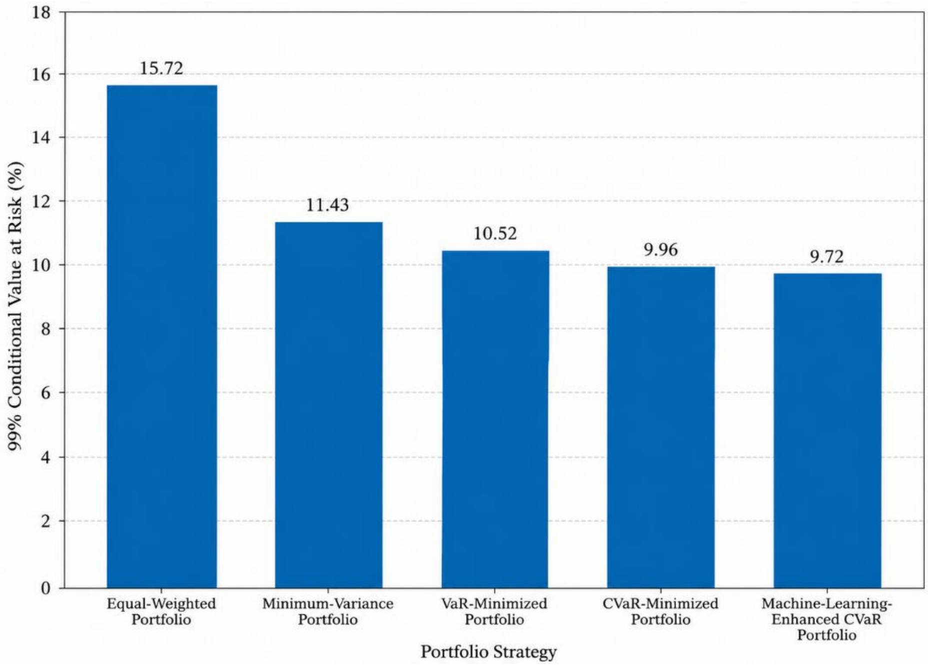

Figure 1. Comparative Pattern of Estimated 99% Conditional Value at Risk Across Portfolio Strategies

The backtesting results in Table 5 indicate that the accuracy of Value at Risk estimation improved substantially as the modeling framework became more advanced. The variance-covariance model produced 41 observed violations compared with 22 expected violations, resulting in a 99% VaR violation rate of 1.87%. This value was considerably higher than the theoretical 1% violation level, indicating that the model underestimated extreme portfolio losses. The historical simulation model also produced excessive violations, with 36 observed violations and a violation rate of 1.64%. The significant Kupiec and conditional coverage tests for these two models confirmed that they failed to provide reliable VaR estimates under extreme cryptocurrency market conditions. The GARCH-normal model showed improvement, but it still produced more violations than expected, reflecting the weakness of the normal distribution assumption in fat-tailed cryptocurrency return data. The GARCH-t model performed better because the Student's t distribution captured heavy tails more effectively. However, the strongest performance was observed for the Copula-GARCH-EVT and Copula-GARCH-EVT-ML models. The Copula-GARCH-EVT model produced 23 observed violations, which was very close to the expected value of 22, while the integrated Copula-GARCH-EVT-ML model produced exactly 22 violations. The non-significant Kupiec and conditional coverage test results for the integrated model confirmed that it achieved both correct unconditional coverage and acceptable independence of VaR violations. These findings support the conclusion that combining dynamic volatility modeling, nonlinear dependence estimation, extreme tail modeling, and machine-learning forecasting provides a more robust framework for cryptocurrency portfolio risk management than conventional risk models.

Figure 1 illustrates the comparative pattern of 99% Conditional Value at Risk across the equal-weighted, minimum-variance, VaR-minimized, CVaR-minimized, and machine-learning-enhanced CVaR portfolios. The figure shows a progressive reduction in extreme expected losses as the portfolio construction method moves from a simple allocation strategy toward more advanced risk-based and machine-learning-enhanced optimization. The equal-weighted portfolio had the highest 99% CVaR, indicating that simple diversification across cryptocurrencies was not sufficient to control extreme downside risk. The minimum-variance portfolio reduced expected tail losses, but its focus on variance limited its ability to fully capture losses occurring in the extreme lower tail of the return distribution. The VaR-minimized and CVaR-minimized portfolios showed further improvement, with the CVaR-minimized portfolio performing better in managing losses beyond the VaR threshold. The lowest estimated 99% CVaR was observed in the machine-learning-enhanced CVaR portfolio, demonstrating that predictive risk signals generated by machine-learning models improved allocation decisions under high-volatility and stress conditions. Overall, the pattern displayed in the figure confirms that the proposed integrated framework reduced severe downside exposure and provided a more effective approach to cryptocurrency portfolio risk management.

4. Discussion and Conclusion

The present study developed and evaluated a financial engineering framework for cryptocurrency portfolio risk management by integrating Copula-GARCH models, Extreme Value Theory, and machine-learning techniques. The findings showed that the selected cryptocurrency return series were characterized by high volatility, non-normality, fat-tailed distributions, conditional heteroskedasticity, and asymmetric behavior. These results confirm that cryptocurrency markets cannot be adequately modeled through conventional assumptions of normality, constant variance, and linear dependence. The descriptive statistics demonstrated that all selected assets had positive average daily returns during the study period, but these returns were accompanied by substantial dispersion, extreme minimum and maximum values, and high kurtosis. In particular, Dogecoin, Ripple, Cardano, Stellar, and Binance Coin showed strong evidence of extreme movements, while Bitcoin, despite being the most established cryptocurrency in the sample, also exhibited considerable tail risk and volatility persistence. This pattern is consistent with the broader literature emphasizing that cryptocurrency markets are structurally volatile, highly speculative, and exposed to abrupt market revaluation, liquidity shocks, and investor sentiment dynamics [1, 2].

The significant Jarque-Bera statistics and ARCH-LM results indicated that the cryptocurrency return distributions deviated strongly from normality and contained time-varying variance. This finding supports the application of GARCH-family models and aligns with prior studies showing that cryptocurrency markets are defined by volatility clustering and nonlinear return dynamics. The selection of GJR-GARCH and EGARCH models for several assets further suggests that asymmetric volatility responses are important in cryptocurrency risk estimation. In other words, negative and positive shocks did not affect future volatility equally, and downside shocks tended to intensify risk more strongly than positive shocks of comparable magnitude. This result is theoretically consistent with evidence on asymmetric correlations and asymmetric dependence in financial markets, where downside conditions often generate stronger co-movement and higher risk concentration than normal or upward market regimes [4, 19]. The finding also supports the view that cryptocurrency portfolio management requires risk models that are sensitive to direction, magnitude, and persistence of shocks rather than models that treat market movements symmetrically.

The volatility modeling results also showed high persistence across all cryptocurrencies, with volatility persistence remaining close to unity in most selected GARCH-family models. This indicates that volatility shocks in cryptocurrency markets tend to decay slowly and may continue to influence portfolio risk over several subsequent periods. Such persistence has direct implications for investors because a sudden market shock may not represent a temporary isolated event; rather, it may initiate an extended high-risk regime. This finding is aligned with previous research on cryptocurrency dependence and portfolio optimization, where GARCH-copula methods have been shown to capture dynamic risk behavior more effectively than static approaches [7, 8]. It also corresponds to studies that model cryptocurrency and cross-asset linkages through GARCH-EVT-Copula structures and show that digital assets are exposed to persistent and interconnected volatility processes [10, 17]. Therefore, the present results reinforce the argument that volatility modeling should be considered a foundational step in cryptocurrency portfolio risk management.

The Copula-GARCH and Extreme Value Theory findings demonstrated that portfolio risk was substantially affected by the method of portfolio construction. The equal-weighted portfolio produced the highest annualized volatility, highest VaR, highest CVaR, and largest maximum drawdown. Although equal weighting is simple and often used as a naive diversification strategy, the results showed that equal allocation across cryptocurrencies did not sufficiently reduce extreme downside exposure. This finding supports previous research indicating that diversification benefits in cryptocurrency markets are unstable and may deteriorate during stress periods [5, 6]. It is also consistent with evidence that cryptocurrencies may exhibit strong dependence with other digital assets, foreign exchange markets, commodities, and stock markets, especially in turbulent conditions [9, 11, 12]. The implication is that cryptocurrency portfolio diversification cannot rely merely on increasing the number of assets; instead, diversification must be based on the structure of dependence, tail risk, and volatility regimes.

The minimum-variance portfolio reduced total volatility compared with the equal-weighted portfolio, but it did not provide the strongest protection against extreme losses. This result indicates that variance minimization alone is insufficient for cryptocurrency risk management because variance captures average dispersion rather than the severity of tail losses. In highly fat-tailed markets, two portfolios with similar variance may have very different downside-loss profiles. The superior performance of the VaR-minimized and CVaR-minimized portfolios shows that downside-oriented optimization is more appropriate for digital asset portfolios. In particular, the CVaR-minimized portfolio achieved lower extreme expected losses than the VaR-minimized portfolio, confirming that CVaR provides more informative guidance for managing losses beyond the VaR threshold. This finding is consistent with prior work emphasizing the importance of advanced tail-risk measures and the limitations of relying exclusively on conventional VaR [26]. It also aligns with studies applying EVT-based models to financial returns, where tail-focused methods were found to be more suitable for extreme-risk estimation than models based on central distributional behavior [16, 18].

The machine-learning-enhanced CVaR portfolio produced the most balanced risk-return profile. This portfolio preserved a relatively favorable annualized return while producing the lowest or near-lowest annualized volatility, 99% VaR, 99% CVaR, and maximum drawdown. This result suggests that machine-learning forecasts contributed useful predictive information to the portfolio allocation process. Machine learning may have improved performance because it can detect nonlinear relationships among lagged returns, volatility indicators, trading-volume changes, realized volatility, and tail-risk signals. This is consistent with recent work showing that machine-learning methods can strengthen cryptocurrency price prediction and risk-adjusted portfolio optimization [24]. However, the present findings also indicate that machine learning was most effective when embedded within an econometrically grounded risk framework rather than used as an isolated forecasting tool. The best results emerged from the combination of Copula-GARCH, EVT, and machine-learning components, which suggests that hybrid modeling can improve cryptocurrency risk estimation by integrating volatility dynamics, dependence structure, extreme-loss behavior, and predictive nonlinear signals.

The machine-learning forecasting results further supported this interpretation. Extreme Gradient Boosting produced the lowest prediction errors, the highest directional accuracy, and the most accurate VaR violation rate among the tested models. The LSTM model also performed strongly, indicating that sequential dependence and temporal patterns are relevant in cryptocurrency risk forecasting. However, Extreme Gradient Boosting demonstrated slightly stronger overall performance, possibly because it was better able to process heterogeneous predictors and nonlinear interactions without requiring the same degree of temporal parameterization as deep sequential models. This finding is aligned with the broader movement toward hybrid risk models that combine econometric features with machine-learning prediction. It also supports studies that incorporate sentiment, volatility, EVT, and copula-based structures into portfolio risk modeling, suggesting that additional predictive signals can improve the measurement of downside risk [25]. In the context of cryptocurrency markets, where information is rapidly incorporated and volatility can shift abruptly, models that adapt to nonlinear predictor structures appear particularly useful.

The backtesting results provided strong evidence for the superiority of the integrated risk framework. Conventional variance-covariance and historical simulation models produced excessive VaR violations, indicating that they underestimated extreme portfolio losses. This finding is expected because the variance-covariance model depends heavily on assumptions of linear correlation and distributional regularity, while historical simulation may fail when past observations do not adequately represent evolving market regimes. The GARCH-normal model improved performance but still produced more violations than expected, confirming that volatility dynamics alone are not sufficient when the error distribution fails to capture heavy tails. The GARCH-t model performed better, showing the value of heavy-tailed distributional assumptions. However, the Copula-GARCH-EVT and Copula-GARCH-EVT-ML models generated the most accurate violation rates and passed the Kupiec and Christoffersen tests. These findings align with studies using GARCH-EVT-Copula and copula-based risk frameworks to model cryptocurrency, commodity, foreign exchange, and stock-market linkages [17, 18, 20]. They also confirm that tail dependence and extreme-value behavior must be explicitly modeled when estimating cryptocurrency portfolio losses.

The findings have important implications for the interpretation of cryptocurrencies as hedging or diversification instruments. Previous research has shown that Bitcoin, gold, the U.S. dollar, and other assets may perform as hedges or safe havens only under specific conditions, and that their effectiveness can vary across markets and crisis regimes [13, 14]. The present study supports this conditional view. Although cryptocurrencies may offer return opportunities and may improve portfolio performance under certain allocations, their extreme downside risk can be substantial if portfolio construction ignores nonlinear dependence and tail exposure. This is particularly relevant for Iranian investors, who may use cryptocurrencies as alternative investment instruments in response to inflation, currency instability, and restrictions in conventional financial markets. The findings are also consistent with domestic evidence showing that portfolios composed of selected stocks and cryptocurrencies require careful optimization because cryptocurrencies can increase both return potential and risk exposure [27]. Therefore, cryptocurrencies should not be treated as automatically protective or diversifying assets; their role depends on the risk model, portfolio weights, market regime, and dependence structure.

The results also contribute to the growing literature on the integration of digital assets with broader financial systems. Recent evidence suggests that decentralized finance instruments, conventional cryptocurrencies, technology stocks, stablecoins, fiat currencies, and alternative digital assets are increasingly interconnected [21-23]. This interconnectedness increases the importance of systemic and cross-market risk modeling. In such an environment, portfolio managers must consider not only the individual volatility of cryptocurrencies but also how these assets move together during stress events. The present study showed that integrated Copula-GARCH-EVT-ML modeling can improve estimation of these risks and provide more reliable guidance for portfolio allocation. Overall, the findings support a financial engineering approach in which cryptocurrency portfolio risk is managed through dynamic, nonlinear, and tail-sensitive methods rather than through static diversification or conventional mean-variance assumptions.

This study had several limitations that should be considered when interpreting the findings. First, the analysis was based on historical daily data, and the use of daily frequency may not fully capture intraday volatility, liquidity shocks, flash crashes, and short-term trading disruptions that are common in cryptocurrency markets. Second, the sample was limited to ten major cryptocurrencies, which improved data continuity and liquidity comparability but excluded smaller tokens, stablecoins, decentralized finance tokens, and newly emerging digital assets that may display different risk patterns. Third, the analysis was conducted from the perspective of Iranian investors, but the quantitative models were based mainly on global cryptocurrency price data and did not directly include all domestic constraints, such as local exchange spreads, transaction costs, informal market frictions, sanctions-related limitations, access restrictions, and rial-based conversion risk. Fourth, although the integrated model improved risk forecasting, all statistical and machine-learning models remain sensitive to model specification, parameter selection, training-window design, and structural market changes. Therefore, the results should be interpreted as evidence of improved risk estimation within the selected study design rather than as a permanently stable forecasting rule.

Future studies should extend the present framework by using higher-frequency data, such as hourly or intraday cryptocurrency returns, to capture short-term volatility dynamics and liquidity shocks more precisely. Researchers should also examine broader digital-asset portfolios that include stablecoins, decentralized finance tokens, exchange tokens, and tokenized financial instruments in order to evaluate whether the proposed framework remains robust across different categories of crypto-assets. Future research could additionally incorporate macroeconomic variables, exchange-rate indicators, investor sentiment measures, blockchain-based indicators, transaction-volume metrics, and regulatory-event variables to improve explanatory and predictive power. It is also recommended that future studies compare additional machine-learning and deep-learning methods, including attention-based architectures, transformer models, reinforcement learning, and regime-switching hybrid models. Finally, studies focused on Iranian investors should include local transaction costs, rial-dollar exchange-rate movements, domestic inflation, local exchange liquidity, and access constraints to produce a more context-specific assessment of cryptocurrency portfolio risk.

For practitioners, the findings suggest that cryptocurrency portfolio risk management should move beyond equal-weighted allocation, static diversification, and simple correlation-based models. Portfolio managers, financial analysts, and individual investors should use dynamic volatility models to identify persistence in risk, copula-based methods to understand nonlinear dependence among assets, and tail-risk measures such as Conditional Value at Risk to estimate the severity of extreme losses. Investors should also avoid evaluating cryptocurrency portfolios only through average returns, because high returns may be accompanied by severe downside exposure and large drawdowns. In practice, machine-learning forecasts can be useful when they are combined with transparent financial risk models and regularly validated through backtesting. For Iranian investors in particular, cryptocurrency allocation should be treated as a high-risk component of wealth management and should be evaluated alongside currency risk, inflation risk, liquidity restrictions, transaction costs, and the possibility of sudden regulatory or market-access changes.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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