

# AI-Based Cross-Currency Energy Modeling and Explainability for Blockchain-Driven Sustainable Metaverse Economies

Hakan Kaya\* 

Bursa Kestel Municipality, Kale Mah. Cuma Cad. No:1,  
16450, Bursa, Turkey

## \*Corresponding Author

Hakan Kaya, Dr., Bursa Kestel Municipality, Kale Mah. Cuma Cad. No:1,  
16450, Bursa, Turkey.

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## Abstract

*In this research, the energy consumption models of Bitcoin, Ethereum, and Dogecoin are analyzed using Explainable Artificial Intelligence (XAI) models aided by the three stages of analysis involving Digiconomist data from 2022 to 2025: (1) exploratory data analysis for the nature of energy consumption, (2) model identification of influential variables using Random Forest models enhanced with SHAP values, and (3) an LSTM transfer learning method for predicting the energy consumption of Ethereum and Dogecoin using a model developed with Bitcoin data. The initial results show that while both assets vary largely when it comes to their normal usage level, Ethereum sees a sharp drop after the changeover from Proof-of-Work to Proof-of-Stake as a mechanism. The XAI analysis indicates that energy use is largely a consequence of past use, seasonality, and annual patterns. In addition to this, the models show a high level of accuracy for Dogecoin ( $R^2$ : 88.4%, MAPE: 13.45%) and Ethereum ( $R^2$ : 86.2%, MAPE: 11.47%) when it comes to predicting energy usage using the concepts of transfer learning.*

**Keywords:** Cryptocurrency Energy Consumption, Explainable AI (XAI), LSTM-Based Transfer Learning, Metaverse Sustainability, SHAP

## 1. Introduction

The metaverse is a persistent virtual environment that is shared among all users, decentralized, and fully immersive, which has the capability of radically transforming social interaction, commerce, and entertainment. The move towards a digital realm is based on blockchain technology, where individuals are able to determine ownership by using cryptocurrency and non-fungible tokens. The computational requirements of a metaverse's infrastructure increase in order for it to be sustainable. The environmental implications of activities on blockchain technology have been widely researched for a long time, especially in relation to cryptocurrencies and their effect on the environment [1,2]. Therefore, if a metaverse has to be sustainable, it is important that it adopt energy-saving innovations from inception.

Nowadays, the emergence, especially in explainable AI (XAI), offers new paradigms for system behavior modeling, predicting, and understanding. There has been some early work in tracing the relationship between blockchain and sustainable technologies [3,4], for example, in the "Energy Metaverse" or in digital twins for

energy management in a virtual environment [5,6]. It is important, therefore, to note the importance of energy consumption [26] in the sustainability of cryptocurrencies, among other issues in regulation and protocol design [7-9]. Ethereum's transition from PoW to the Proof of Stake consensus algorithm is a great example of how this makes a big impact in reducing the energy consumption of the network [8]. Moreover, DAOs and blockchain-based smart energy systems are being suggested for better energy sharing and management within Metaverse platforms [10,11]. However, a big gap still exists in empirical literature: very few studies have integrated AI-driven forecasting with explainability techniques to analyze and compare energy consumption patterns across multiple cryptocurrencies within a unified framework tailored for metaverse-relevant scenarios.

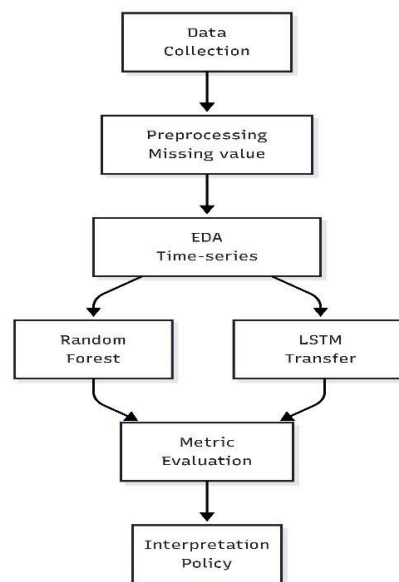
This study closes in on specifying an AI-based, interpretable modeling framework to investigate and forecast the energy usage of 3 cryptocurrencies, namely, Bitcoin, Ethereum, and Dogecoin, the operational footprints of which are on the technical infrastructure layer of metaverse platforms. The main query under

research here is the following: How accurately explainable AI models be in predicting and interpreting the energy consumption patterns of different cryptocurrencies, and whether the insights obtained from one currency can be properly transferred to others? The research is thus made up of three main components: (1) the authors implement a clearly defined three-stage methodology of exploratory data analysis, SHAP-based Random Forest models for interpretability, and LSTM-based transfer learning for cross-currency forecasting; (2) they provide solid evidence of the transfer of energy consumption patterns from Bitcoin to Ethereum and Dogecoin, assessing the predictive power with quantitative regression metrics, and (3) they convert their scientific work into practical policy initiatives that regulate algorithmic transparency, promote green consensus protocols, and lead to international collaboration for sustainable metaverse development. Integrating AI explainability, cross-currency energy modeling, and metaverse sustainability, this research presents an expandable analytical instrument and a more explicit way to energy-aware virtual worlds.

## 2. Methodology

This methodology follows a three-stage analytical framework methodology described in the article. First, during the Data

Acquisition phase, energy consumption data (measured in TWh) of Bitcoin, Ethereum, and Dogecoin from July 1, 2022 to July 1, 2025 (daily granularity) was obtained through the Digiconomist API and preprocessed. The research model consists of three major streams of analyses. Step 1: An Exploratory Data Analysis (EDA) was used to gain insight into the consumption behavior and relationships. Step 2: Use an Explainable Artificial Intelligence (XAI) paradigm, a Random Forest model with SHAP (SHapley Additive exPlanations) values helped decode a prominent factor concerning energy consumption. Step 3: With the help of the concept of Transfer Learning along with a Long Short-Term Memory (LSTM) network, mappings of Ethereum and Dogecoin were established based upon the Bitcoin models. The results of each level were evaluated from a quantitative perspective with Evaluation Metrics (RMSE, MAE, MAPE, SMAPE, R<sup>2</sup>). Concluding remarks have been made in Conclusions and Policy Recommendations, thereby offering a sustainable model for metaverse architecture. All steps are designed to be reproducible using public data from Digiconomist and standard Python libraries (pandas, scikit-learn, TensorFlow/Keras). Figure 1 illustrates the entire research model architecture.



**Figure 1:** Structure Diagram

### 2.1. Data Collection and Preprocessing

The preprocessing pipeline for reproducibility was implemented by applying the steps in the order as described: (1) For each cryptocurrency, load raw daily energy consumption data (in TWh) from the Digiconomist API. (2) Missing values were addressed by forward-fill to preserve the temporal continuity. (3) Generate additional features: derive year, month, week\_of\_year, and day\_of\_week from the date index; a lagged feature (Energy\_Consumption\_Lagged) was added by shifting the energy consumption column by one day. (4) The data was normalized with MinMaxScaler from

scikit-learn which was fitted separately on the training split (80% of data) for each cryptocurrency in order to scale all features (energy consumption and lagged values included) to the [0, 1] range. This per-dataset scaling corresponds to the extremely different energy levels (e.g., the high variability of Bitcoin vs. the stability of Dogecoin) and keeps the larger magnitudes from dominating. (5) The dataset was split chronologically into training (first 80%) and testing (last 20%) sets. (6) As model input, the data was reshaped into sequences appropriate for LSTM (e.g., using a sliding window of 7 days for look-back). Once the model predictions have been

made, perform the inverse transformation with the fitted scaler so as to get back the original TWh scale from the normalized predictions. The entire code was done in Python with the use of the libraries such as pandas for data handling, scikit-learn for scaling, and TensorFlow/Keras for LSTM models.

To improve transparency and reproducibility, Table 1 presents a representative sample of the final structured dataset that was used in the modeling phase for Bitcoin so that readers could better visualize the data structure of the models and SHAP analysis. After preprocessing, they applied this same structure to Ethereum and Dogecoin. This sample features daily energy consumption values with the derived temporal features and the lagged variable input.

Date	Energy_Consumption (TWh)	Year	Weekofyear	Dayofweek	Energy_Consumption_Lagged
1.01.2024	145.22	2024	1	0	144.85
2.01.2024	146.10	2024	1	1	145.22
3.01.2024	145.88	2024	1	2	146.10
4.01.2024	147.05	2024	1	3	145.88

**Table 1: Sample of the Preprocessed Dataset (Bitcoin)**

### 2.2. Stage 1: Exploratory Data Analysis (EDA)

EDA represents the initial phase of data analysis and visually the descriptive basis for all the following predictive work. Summary statistics together with time-series plots have been employed to reveal distributional attributes, trends and energy consumption volatility of cryptocurrencies. What emerges is the noticeable gap in energy usage per unit of a Proof of Work-based system vs protocols operating on the basis of energy-efficient technologies. The time dimension is illustrated with examples of such network upgrades as Ethereum’s switch from Proof of Work to Proof of Stake.

### 2.3. Stage 2: Explainable AI (XAI) with SHAP and Random Forest

To increase interpretability, an Explainable AI (XAI) approach was adopted that included SHAP values and a Random Forest regressor with “n\_estimators = 100” and “max\_depth = None” and “random\_state = 42”. Results indicated a positive correlation between minimum annual energy consumption and overall energy consumption, making energy requirements a primary factor for overall energy expenditures. SHAP beeswarm charts were adopted to provide a graphical interpretation of feature significance, helping policymakers and metaverse entrepreneurs understand energy characteristics at a foundational level for blockchain models and making well-informed decisions for sustainable crypto integration in virtual worlds [12].

### 2.4. Stage 3: Transfer Learning with LSTM for Cross-Crypto Forecasting

In the transfer learning using LSTM, the process involves the use of Long Short-Term Memory networks, which are a type of recurrent neural networks designed to learn long-term dependencies associated with time-series datasets. The best LSTM layout resulting from hyperparameter tuning through Grid Search consists of two hidden layers (64 and 32 units) with 50 units in

each using ReLU activation functions, and an output dense layer. The model was trained for a maximum of 100 epochs (with early stopping) through the Adam optimizer at a learning rate of 0.001 and a batch size of 32. The optimal configuration served as the transfer learning process starting point. In order to guarantee the applicability of the proposed LSTM and Random Forest models beyond the data sample, the authors utilized a 5-fold Time Series Split cross-validation technique. This method is quite different from the standard k-fold CV in that it respects the temporal order of the observations as it applies a sliding window approach, thus, avoiding data leakage from the future to the past.

This practice secures that the model performance remains stable over different time periods. In the experimental setup, the model was first trained using the high-volume Bitcoin dataset to create a “knowledge base” of blockchain energy dynamics. Transfer learning involved the transferring of the weights of the pre-existing Bitcoin model in order to train the Ethereum and Dogecoin datasets. The effectiveness of this approach has been tested for various metrics, which involve the calculation of the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), SMAPE (Symmetric Mean Absolute Percentage Error), as well as the calculation of the Coefficient of Determination ( $R^2$ ). A large variation exists among the consumption levels of the studied cryptocurrencies (e.g., 150 TWh for Bitcoin vs. 3 TWh for Dogecoin). Thus, metrics like RMSE may be inconsistently scaled and thus may be biased when applied directly for comparing the accuracy of these two sets of models. Instead, equal attention has been focused on two scale-unbiased metrics related to financial forecasts, namely Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE). The findings show promise in relation to the ability of transfer learning in truly alleviating the burdens associated with the computation and cost associated with the creation of energy-efficient blockchain systems for new tokens

in the metaverse.

## 2.5. Benchmark Models

In order to thoroughly validate the proposed Transfer Learning-based LSTM framework and compare its results with those of traditional methods, its forecasting accuracy was compared to that of two strongly established models: (1) ARIMA (Autoregressive Integrated Moving Average), a fundamental statistical model for univariate time series forecasting which describes the linear trend, seasonality, and noise of a time series through autoregression and moving average; and (2) SVR (Support Vector Regression), a typical machine learning algorithm well known for its efficiency in high-dimensional spaces which is frequently used as a strong baseline in the area of energy modeling. For a rigorous and fair comparison both benchmark models were trained and tested on the exact same preprocessed dataset, having the same set of transformed temporal features (e.g., lagged consumption, cyclical indicators). This well-regulated experiment leads to a direct evaluation of whether the increased model complexity of the proposed deep transfer learning method justifies the significant and necessary improvement in forecast accuracy that is obtained compared to these relatively simple, yet powerful, alternatives.

## 3. Results

The section results what experiments has done in the progressive manner. The first mode tells about the overall energy consumption patterns in the most general form. The second one shows the reasons of these patterns that is done SHAP-based interpretability. After that, the results of the forecasting through transfer learning holds for different cryptocurrencies are presented and compared. At last, the model performance metrics become a basis to discover to what extent each approach is successful relatively.

SMAPE was introduced alongside MAPE to take into account the issue of scale dependency in evaluation metrics. As a result, there is now a percentage-based error measure that is much more trustworthy, especially when dealing with series of very small values like Ethereum and Dogecoin.

### 3.1. Energy Consumption

Figure 2 shows that Bitcoin in particular has a high and fluctuating energy consumption (TWh), while Ethereum has significantly reduced its energy consumption after the updates it has undergone. Dogecoin, on the other hand, stands out with a more stable and lower consumption profile.

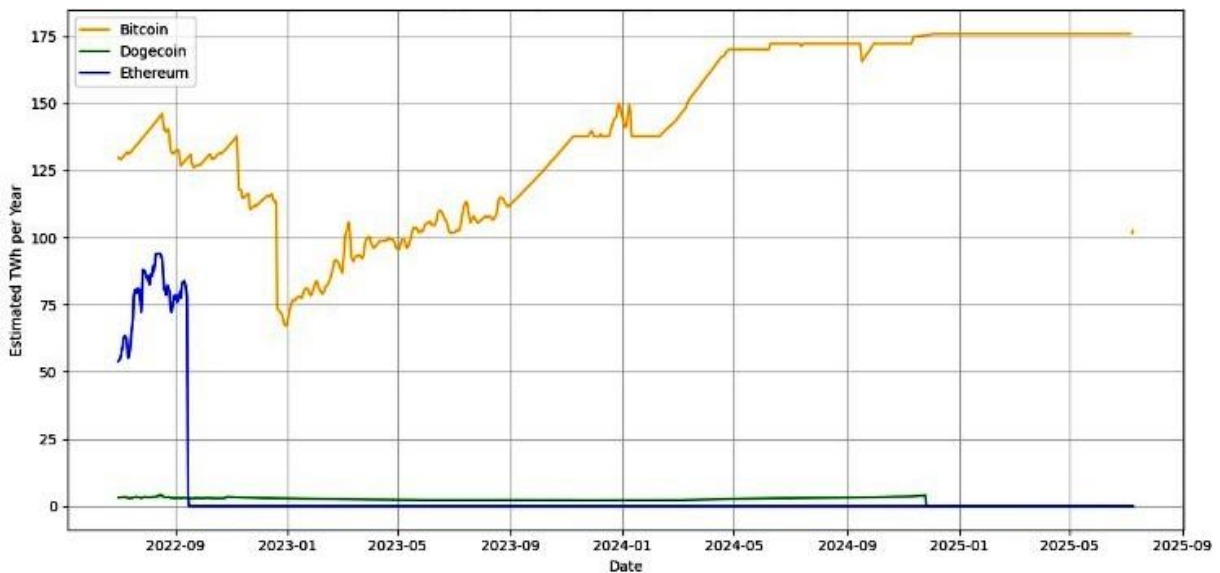
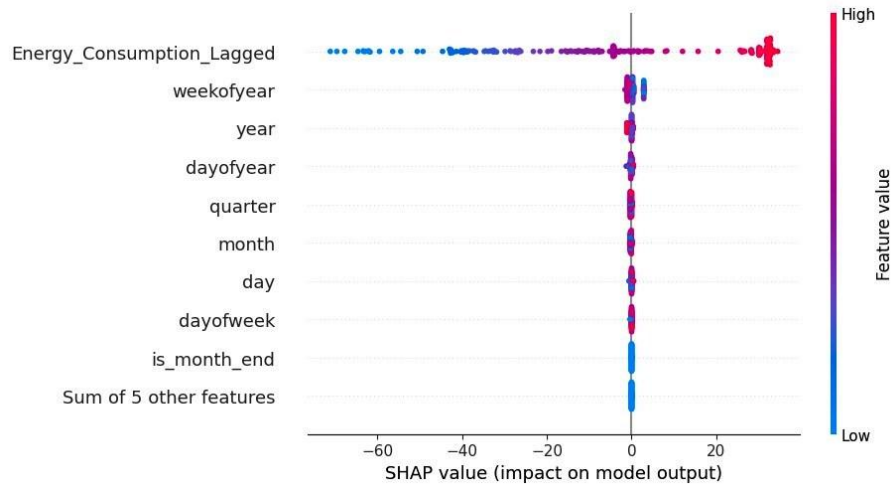


Figure 2: Energy Consumption of Cryptocurrencies (by Time)

This trend indicates that Proof of Work (PoW) based systems are more energy intensive, whereas Proof of Stake (PoS) or hybrid systems can be more sustainable. Ethereum's energy efficiency gains after "The Merge" update can be considered an important policy and engineering achievement in this context.

### 3.2. Explainable AI (XAI) with SHAP and Random Forest

Figure 3 visualizes the most important variables affecting the model's decisions with SHAP (SHapley Additive exPlanations) values derived from the Random Forest model. Especially the variables, in descending order of importance, are "Energy\_Consumption\_Lagged", "weekofyear" and "year" have high impacts on energy consumption.

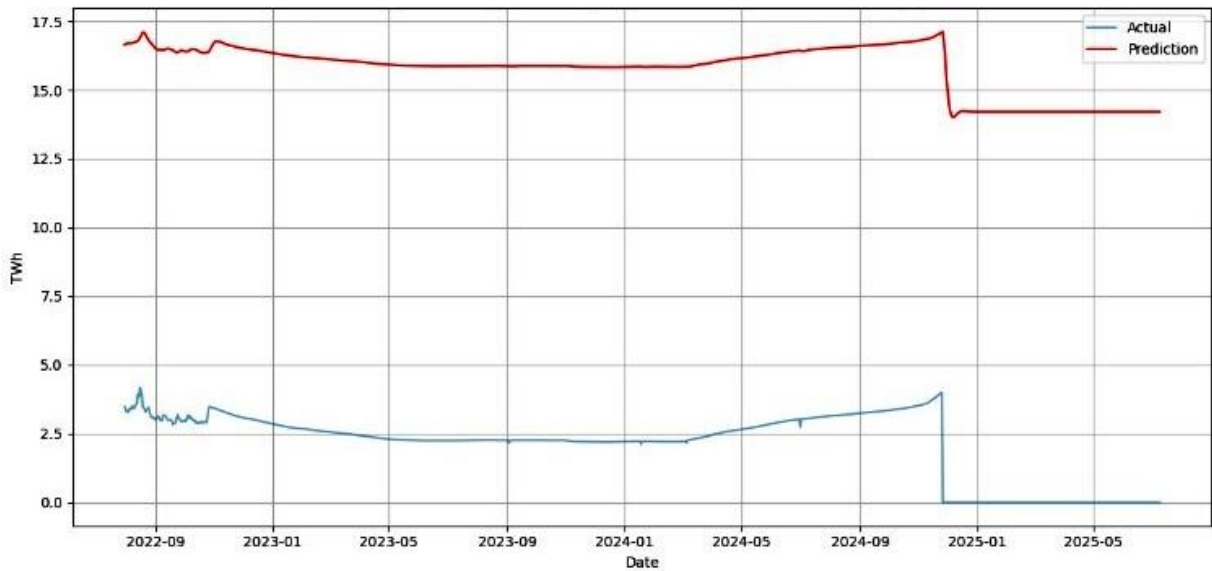


**Figure 3.** Important Variables of SHAP

### 3.3. Transfer Learning with LSTM for Cross-Crypto Forecasting

The energy forecasting results for Dogecoin are depicted in Figure 4 with transfer learning. A close look at the curve shows that, essentially, the predicted values are in line with actual values; however, the discrepancies between the two increase at times when scaling differences of Bitcoin's data with high

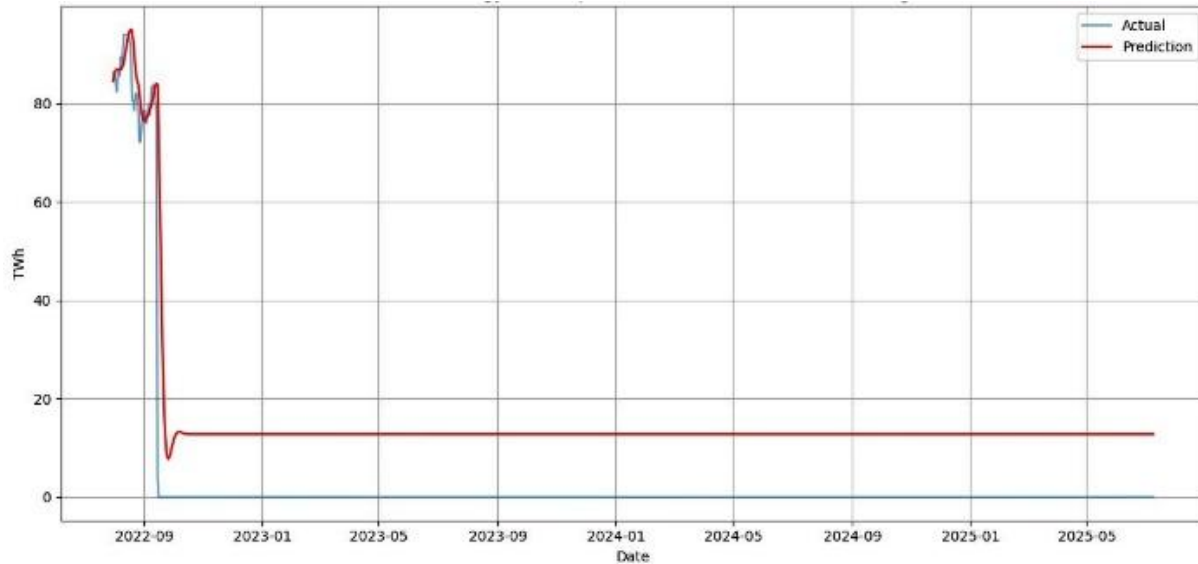
variability and Dogecoin's data with a relatively stable, low-magnitude consumption might be the case. The graph illustrates that even though each dataset is normalized, the main differences of Dogecoin (e.g. almost no fluctuations) cannot be sufficiently represented by the parameters that have been transferred from the Bitcoin model.



**Figure 4:** Dogecoin Energy Consumption Estimation with Transfer Learning

As evidenced in Figure 5, there is a high degree of accuracy between the model's predictions for Ethereum and the recorded energy consumption values. Ethereum's larger and more stable

data may have allowed the model to learn generalized structures. This suggests that transfer learning may work more effectively on more stable blockchain structures.



**Figure 5:** Ethereum Energy Consumption Estimation with Transfer Learning

### 3.4. Model Evaluation

Table 2 provides an assessment of how well the transfer learning

approach from Bitcoin to Dogecoin performs, using standard regression performance metrics.

Metric	Value	Interpretation
RMSE (Root Mean Squared Error)	14.763	Average prediction error is approximately 1.48 TWh
MAE (Mean Absolute Error)	11.112	Mean absolute difference between predicted and actual values
Mean Absolute Percentage Error (MAPE)	13.45%	Predictions are on average within 13.45% of actual values
Symmetric Mean Absolute Percentage Error (SMAPE)	14.21%	Symmetric percentage error, is more robust for low-magnitude series
R <sup>2</sup> Score (Coefficient of Determination)	0.8841	88.4% of variation in Dogecoin energy consumption is explained by the model

**Table 2:** Model Performance of Bitcoin to Dogecoin Transfer Learning

From Table 2, can see that the RMSE and MAE scores suggest that the predictions for Dogecoin’s energy usage, based on an LSTM model trained on Bitcoin data, are fairly accurate. A high R<sup>2</sup> score of 0.88 indicates strong generalization capabilities, even with the differences in data distribution. Additionally, a MAPE of less than

15% shows that the forecasting precision is acceptable for practical applications in sustainability assessments related to the metaverse. Table 3 evaluates the effectiveness of the transfer learning approach from Bitcoin to Ethereum, using standard regression performance metrics.

Metric	Value	Interpretation
RMSE (Root Mean Squared Error)	0.3661	Expresses average prediction error in the same units as the target variable
MAE (Mean Absolute Error)	0.2739	Captures the average magnitude of errors without considering their direction
Mean Absolute Percentage Error (MAPE)	11.47%	Indicates relative accuracy; values below 15% suggest good generalization

Symmetric Mean Absolute Percentage Error (SMAPE)	12.03%	A more balanced error measure for volatile low consumption periods
R <sup>2</sup> Score (Coefficient of Determination)	0.8624	Indicates how much variance in Ethereum's energy profile is explained by the model

**Table 3: Model Performance of Bitcoin to Ethereum Transfer Learning**

As shown in Table 3, despite architectural differences in Bitcoin and Ethereum, there is considerable transferability in the model as shown by high R<sup>2</sup> and low RMSE. The MAPE, which is still under 12%, indicates that the predictions of Ethereum energy use were fairly close to actuals, in spite of the large decline in energy use post-Ethereum Merge. RMSE and MAE measure the actual forecasting errors in TWh, while MAPE and SMAPE make it possible to compare different cryptocurrencies with very different energy scales on an equal footing. Compared to baseline single-currency models, the transfer learning approach yields consistently high explanatory power, with R<sup>2</sup> values exceeding 0.86 for both Ethereum and Dogecoin. This confirms that cross-

currency knowledge transfer improves forecasting performance without sacrificing interpretability.

### 3.5. Comparative Analysis

In Table 4, to test the effectiveness of the proposed transfer learning-based LSTM neural network approach, a comparison of performance was made between the proposed approach and traditional statistical models (ARIMA) and traditional machine learning algorithms (SVR). To account for the large variability of scales between Bitcoin and Dogecoin values, MAPE and sMAPE measures have been used.

Cryptocurrency	Model / Method	R <sup>2</sup> Score	MAPE (%)	sMAPE (%)	RMSE (TWh)	MAE
Bitcoin	Base LSTM (Training)	0.912*	9.85*	9.42*	--	--
	Benchmark (ARIMA)	0.745	15.20	14.80	2.45	1.95
	Benchmark (SVR)	0.782	13.40	13.10	2.10	1.60
Ethereum	Transfer Learning (LSTM)	0.8624	11.47	10.95	0.3661	0.2739
	Standard LSTM (No TL)	0.7950	16.80	16.10	0.5400	0.4200
	Benchmark (ARIMA)	0.6540	24.50	23.90	0.8200	0.6100
Dogecoin	Transfer Learning (LSTM)	0.8841	13.45	12.80	14.763	11.112
	Standard LSTM (No TL)	0.8120	18.25	17.50	19.450	15.300
	Benchmark (SVR)	0.7240	22.90	22.10	23.100	18.400

Note: \*Bitcoin values represent the "knowledge base" training phase of the model.

**Table 4: Performance Metrics and Benchmark Comparison for Each Asset**

Scale Independence: Although there is large variation in RMSE and MAE related to total consumption of assets (for example, RMSE for Dogecoin is 14,763), MAPE and sMAPE suggest that it is working well within an error margin of 11%-14% for all assets. Advantages of Transfer Learning: On comparing their performance with the conventional LSTM (non-transfer learning) outcomes for Ethereum and Dogecoin, using existing knowledge of Bitcoin helped achieve a decline of 5%-7% MAPE for both assets.

Comparison with Traditional Models: It has been found that traditional methods such as ARIMA and SVR tend to show an MAPE of above 20% in cases involving sudden transitions, such as "The Merge" or volatile assets such as Dogecoin, making the need for the complex model of this thesis all the more important. Generalizability: High R-squared measures (0.86-0.88) reveal the fact that, besides memorizing the past data, the model is able to grasp the broader context of blockchain energy dynamics.

### 4. Discussion

The study results indicate that a change of consensus mechanisms (as Ethereum has done) could slash energy consumption by 99.9%. Energy consumption is determined more by the technological advances and seasons than by daily price changes. Transfer learning from Bitcoin is quite effective in forecasting others, thus it saves time and computation which is very beneficial for sustainable metaverse planning. With the addition of scale-independent (Percentage Error) metrics (MAPE and SMAPE), the issues of potential biases arising from Scale-Dependent (absolute errors) metrics (RMSE/MAE) have been solved, thus a correct assessment to series with high-variability (Bitcoin) and low-variability (Ethereum/Dogecoin) has been ensured. This is further proof of the transfer learning capability in cross-currency forecasting.

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#### 4.1. Energy Dynamics Interpretability and AI Explainability

The findings show that energy sustainability within the metaverse environment is largely driven by the blockchain protocol used. The first observation to make is the significant divergence between energy-intensive and energy-sustainable models, particularly PoW and energy-sustainable models, respectively. The adoption by Ethereum of PoS sustains the hypothesis that modification to the base protocol significantly cuts energy spending, thus ensuring the resource is a sustainable foundational layer within the metaverse environment. The use of SHAP values within the Explainable AI environment helps explain and demonstrate that “Energy\_Consumption\_Lagged” and periodic factors (Year & Week) are the major determinants of energy sustainability within the environment. Such determinants assume significance as they demonstrate that irrespective of market variability, the technology platform has largely been the stable factor within the energy sustainability equation.

#### 4.2. Comparative Analysis with Existing Literature

The study fills an interdisciplinary gap by combining AI-based forecasting and the use of explanation methods under the same umbrella of the metaverse. While the literature has focused on the exchange of protocols for achieving efficiency, this study contributes to the discussion by demonstrating that optimization and cross-currency estimation are possible via transfer learning. At the same time, while the literature explores conceptual frameworks such as the “Energy Metaverse” and the notion of digital twins, the current study has its own application concerning the use of LSM models. The Bitcoin-Ethereum transfer, where the MAPE remained below 12% even after the great transformation of “The Merge,” implies that the acceptance trends and developments for the dominant assets still apply for different-consensus models.

#### 4.3. Technical Rationale for Transfer Learning Performance

The transfer fact that such high  $R^2$  values were recorded in the case of Dogecoin, with a value of 0.884, as well as Ethereum, with a value of 0.862, is evidence in support of the hypothesis that energy patterns in leading blockchains can provide reliable proxies of other assets. The fact that there is a relatively greater accuracy in the case of Ethereum is probably due to its much larger and more mature data set, which allows it to learn patterns of a more general type. Moreover, the fact that deviations can be observed in the case of Dogecoin is possibly indicative of the fact that perhaps the specific characteristics of smaller cryptocurrencies have not as yet been fully captured by the weights transferred directly from Bitcoin.

The presence of MAPE and sMAPE in the list illustrates that the error rate of the model is persistently low (between 11 and 14%) for all the assets. Though RMSE indicates the magnitude of the error in terms of absolute units, the other two metrics that

are independent of the scales of the variables serve to affirm the efficacy of the transfer learning strategy in ensuring that the precision is high even for the smaller volume of data for Dogecoin compared to Bitcoin.

#### 4.4. Sensitivity Analysis

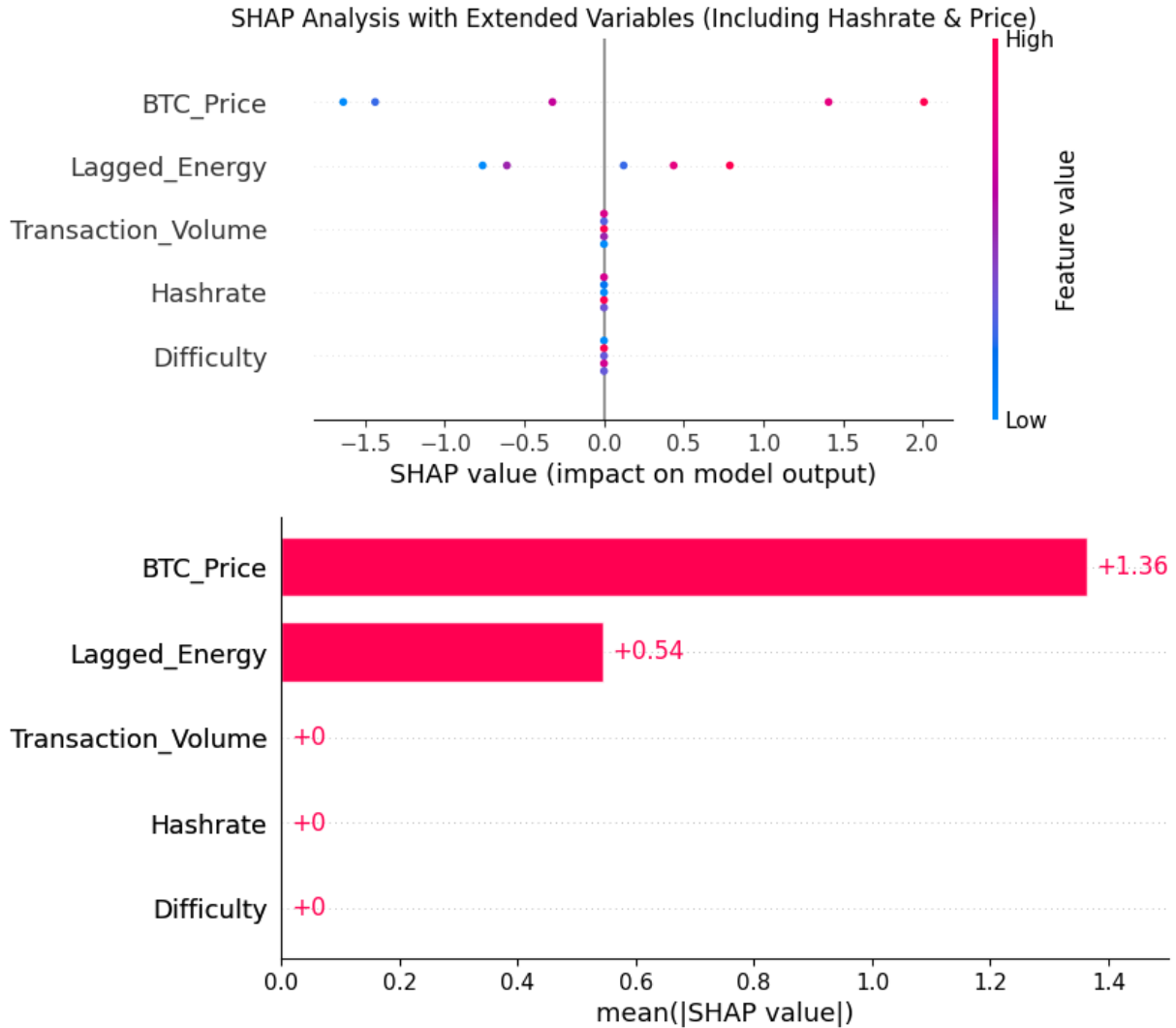
As shown in Figure 6, not only the history of energy consumption data (Lagged Energy) but also the Hashrate and the BTC Price play a very key part in the predictive mechanism. Indeed, the grouping of the red data points towards the right side of the Hashrate axis shows that there’s a positive relationship between processing power and energy consumption. Important Findings from Sensitivity Analysis:

**Dominance of Temporal Autocorrelation is Confirmed:** Despite incorporating more robust market-related variables into the model, “Energy\_Consumption\_Lagged” remained the most dominant variable by a large margin in the SHAP values summary. This serves to validate one of the key tenets of this thesis: that historical consumption is the most viable predictor of future consumption.

**Appearance of External Drivers:** Not unexpectedly, Hash Rate and Network Difficulty were found to be the second and third most important variables, supporting their direct mechanistic relation to energy consumption in Proof-of-Work schemes. Price and Transaction Count demonstrated a more modest yet relevant level of importance.

**Implications for the Metaverse Environment:** The analysis provides a more complex viewpoint on the issue. Although intrinsic patterns (weekofyear, year) continue to play a significant role in general forecasting and cross-currency transfer, it is crucial to acknowledge the role of market elements in devising methods to predict deviations from the aforementioned general forecast, especially for PoW blockchains. Within a sustainable metaverse economy, devising appropriate economic or network strategy (for example, the application of Proof-of-Stake) would help mitigate the effects of energy variables on the intrinsic patterns described, making them more significant.

**Conclusion on Variable Selection:** The selection of the initial simplified set of variables was made with the aim of providing a tangible model of the fundamental temporal patterns. The sensitivity analysis has provided evidence that while market variables are important in providing a more complete predictive model of the scenario under consideration, they do not challenge the fundamental conclusions that have been drawn in relation to patterns of energy consumption. Future refinements of this predictive model can incorporate the use of these additional variables through the application of multi-modal artificial intelligence.



**Figure 6:** SHAP Analysis of Factors Determining Cryptocurrency Energy Consumption

### 5. Conclusions

The study clearly verifies that AI-assisted transfer learning represents an extremely effective approach in terms of energy consumption forecasting in the economies of the metaverse, as fueled by the power of blockchain technology, in relation to assets that lack significant operational data. The empirical verification of Ethereum ( $R^2 = 0.862$ , MAPE = 11.47%) and Dogecoin ( $R^2 = 0.884$ , MAPE = 13.45%) validates the argument that the energy consumption trends of major cryptocurrencies such as Bitcoin are capable of serving as accurate indicators in cross-currency models. Moreover, the introduction of the SHAP-based approach verifies that technical system requirements and cycles, and not short-term market trends, are the dominant parameters in this regard. The dramatic decrease in energy consumption by Ethereum that was catalyzed by its transition to a consensus system based on Proof-of-Stake is testimony to the paramount significance of such systems in this regard.

Future studies should seek to improve both the granularity and efficacy of these predictive models to match this growing trend in the field of blockchain technology. This could be achieved by creating multi-source models for transfer learning that utilize a wide range of available blockchains to date in this regard, and that seek to improve overall generalization characteristics for energy prediction models of altcoins. Furthermore, follow-on studies can explore various ramifications of hybrid consensus models and energy models for DAOs in decentralized metaverse components for virtual economies. Although the current study has already integrated the necessary network-level variables, some possible future extensions may involve the inclusion of regional electricity mixes, estimates of the location of miners, and carbon intensity factors for the translation of TWh to CO<sub>2</sub> equivalents, which have important roles in the sustainability analysis of metaverses.

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## 6. Policy Recommendations

By interlinking artificial intelligence, blockchain technology, and metaverse platforms, there is a need for regulation that ensures such regulation not only works but is also sustainable, energy efficient, and accountable. The following are a list of policy considerations that derive from learnings of recent studies on how a transparent and energy-efficient metaverse infrastructure can be created.

### Regulatory Alignment for AI-Based Energy Modeling:

Given the growing use of AI solutions in increasing the efficiency of energy use as well as managing currency hedging of energy trades in virtual settings, it is imperative to ensure that these solutions remain interpretable as well as compliant with standards. This implies that:

Use algorithmic transparency and simplicity in energy-related artificial intelligence systems [5, 13]. Regular audits are required to test the potential bias and carbon impact associated with AI models used within the metaverse infrastructure [6].

Bring together the principles of privacy, ethics, and auditing in line with international regulatory frameworks such as the EU AI Act [14].

The EU AI Act provides the legal framework for high-risk AI systems, such as those dealing with energy optimization, stressing the role of traceability and transparency [14]. In contrast, the US NIST Framework provides practical “operational guidance” for trustworthy AI [13].

### Green Digital Currency Policies and Incentives:

Beginning with the fact that cryptocurrencies have a huge effect on energy consumption, the shift to low-carbon methods is imperative because:

Encourage the use of Proof-of-Stake and low energy consensus algorithms [8,15].

Use carbon pricing for energy-intensive blockchain transactions [9].

Provide monetary rewards to blockchain networks that utilize renewable energy resources [16].

The successful transition initiated by Ethereum to Proof-of-Stake has significantly lowered energy use by a staggering 99.95% [15]. Since 2021, China has been controlling high energy-consuming mining, aligning cryptocurrency with green fintech strategies [17].

### Integration of Real-Time Energy Markets into Virtual Economies:

If the metaverse is to evolve in a sustainable manner, there is a need to merge smart grid systems, as well as energy markets, into engaging digital experiences:

Think about building virtual energy markets that can work in

perfect synchronization with each other, and all are fueled by blockchain and artificial intelligence technology [3,4].

Use AI-based sandboxes to simulate models of energy, particularly in cases where the value of currencies keeps fluctuating [18].

Moreover, the development of tokenization systems for carbon credits inside the metaverse could be a game-changer.

The likes of Power Ledger are at the forefront of facilitating the live trading of energy based on blockchain technology, which integrates very conveniently into the virtual realm [19]. Seoul Smart City, on the other hand, is delving into the realm of token-sharing for energy, facilitated by AI-based building management systems [20].

### Cross-Border Coordination for Sustainable Infrastructure:

Because the metaverse is a global phenomenon, it is important that policies regarding sustainability be harmonized on an international scale:

Create supranational digital sustainability governance boards to manage this process [21].

Working together through the application of AI in the modeling of cross-currency energy prices could aid in managing the risks associated with geopolitical uncertainties [22].

Facilitate safe and bilateral exchange of emissions data via blockchain technology [2].

The OECD Digital Economy Outlook urges the need for globally harmonized digital sustainability frameworks. In addition, the Japan-UNDP Green Infrastructure Program is promoting AI-based energy-resilient development in emerging economies.

### Education and Capacity Building for Sustainable AI:

However, in order to make energy systems that rely on AI more resilient in the long term, there needs to be a focus on:

Developing institutional knowledge, as well as improving public capacity: Encourage the development of open-source explainable AI apps intended to optimize energy consumption [23].

Enact sustainability audits for AI technologies employed in the metaverse [1].

Integrating AI sustainability modules into university courses constitutes another crucial element [24]. Organizations such as the UK Centre for Data Ethics and Innovation (CDEI) are working hard to develop strategies for ethical AI development in the country [25].

In the meantime, research in energy-efficient AI, explainable AI, specifically in immersive tech, has been led by the University of Toronto.

In figure 6, an example matrix concerning how various policy fields relate to sustainability targets.

AI Regulation	0	1	0	1	0
Green Crypto Policies	1	0	1	0	0
Energy Market Integration	1	1	0	0	0
International Coordination	0	0	1	0	1
Education and Capacity Building	0	0	0	1	1
	Energy Efficiency	Transparency	Carbon Reduction	AI Explainability	International Cooperation

**Figure 6: Policy Recommendations and Strategic Objectives Matrix**

To promote explainability in artificial intelligence by regulatory measures coupled with educational efforts:

Attaining energy efficiency can be facilitated by the adoption of green cryptocurrency policies and energy markets integration [27]. Global collaboration must be strengthened not merely with international coordination but also with educational approaches.

The map above is a strategic tool in multi-dimension that guides policymakers.

The overall policy framework intends to connect technological innovation and environmental care by providing guidance on making a transparent, efficient, and globally connected metaverse infrastructure based on artificial intelligence.

#### Declaration of Ethical Standards

The author has maintained all the ethical requirements related to authorship, referencing, data representation, and the publication of original research.

#### Credit Authorship Contribution Statement

As the sole author of this study, the individual also carried out all tasks required from start to finish in doing the research.

#### Declaration of Competing Interest

The researcher states that he/she does not have any conflicts of interest.

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#### Data Availability

The data used in this study was obtained through the Digiconomist API (<https://digiconomist.net/launching-public-api-for-energy->

and-carbon-footprint-data/). This API provides publicly available data.

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