



Research Article

Article Submission Date: 29.04.2026

Article Acceptance Date: 28.06.2026

ANALYSIS OF PRICE DYNAMICS OF BLOCKCHAIN-BASED CARBON CREDIT TOKENS IN THE CRYPTOCURRENCY MARKET USING DEEP LEARNING METHODS

Aynur İncekırık^{1*}

^{1*}Aynur İncekırık, Manisa Celal Bayar University, aynur.incekirik@cbu.edu.tr; **ORCID:** 0000-0002-5029-6036

Abstract: The aim of this study is to analyze the price dynamics of blockchain-based carbon credit tokens, namely Base Carbon Tonne (BCT), Moss Carbon Credit (MCO2), and KlimaDAO (KLIMA) as well as mainstream crypto assets such as Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), and Solana (SOL) and the speculative asset Carboncoin (CARBON). In addition, the Fear & Greed Index, which represents investor sentiment, has been incorporated into the model in line with the role of sentiment-driven effects in price formation processes in cryptocurrency markets, as highlighted in the literature. The study utilized daily closing prices from the period October 21, 2021, to November 1, 2025; correlation analyses were performed on raw daily price series using the Pearson correlation method, which was chosen to examine the direction and strength of the linear relationship between variables. Prior to modeling, the dataset was cleaned, Min-Max normalization was applied, and it was split into a 70% training set and a 30% test set while preserving chronological integrity. While the assumption of stationarity in time series is important from the perspective of classical econometric approaches, this study focuses on deep learning-based methods within the scope of nonlinear modeling frameworks. The data used in the study were obtained from Yahoo Finance and the AI Key API. The findings indicate that there are strong internal linkages among carbon credit tokens. In particular, while a strong positive relationship was observed between BCT and MCO2, it was determined that these tokens exhibit a weak negative correlation with Bitcoin. This suggests that carbon credit tokens are only marginally linked to the broader crypto market but form a more cohesive structure within their own ecosystem. Additionally, it was observed that the CARBON asset exhibits relationships ranging from weak to moderate with major crypto assets. The Fear & Greed Index, meanwhile, showed moderate relationships with BTC, ETH, and SOL, and weaker relationships with carbon credit tokens. During the modeling process, LSTM, GRU, Transfer-LSTM, and Transfer-GRU architectures were used; the data was split into 70% training, 30% validation, and 30% test sets while maintaining chronological integrity; the models were evaluated using MSE, RMSE, MAE, MAPE, and R² metrics. The results show that the GRU architecture generally offers the highest prediction accuracy, while transfer learning models perform relatively better in predictions for the KLIMA and Fear & Greed (F&G) Index. Overall, the study demonstrates that deep learning and transfer learning approaches are effective in modeling price behavior in tokenized carbon credit markets. Here, it is assessed that transfer learning does not automatically provide an advantage in every scenario, but offers strategic contributions for specific asset groups. In conclusion, the study demonstrates that AI-based models can be used as a decision-support mechanism in the pricing of sustainable financial instruments in the digital economy.

Keywords: Digital Economy, Carbon Credits, Deep Learning, Cryptocurrency, Blockchain

JEL Code: C45, C55, G12, Q54, O33

KRİPTO PARA PİYASASINDA BLOCKCHAIN TABANLI KARBON KREDİ TOKENLERİNİN FİYAT DİNAMİKLERİNİN DERİN ÖĞRENME YÖNTEMLERİYLE ANALİZİ

Özet: Bu çalışmanın amacı, blockchain tabanlı karbon kredi tokenleri olan Base Carbon Tonne (BCT), Moss Carbon Credit (MCO2) ve KlimaDAO (KLIMA) ile ana akım kripto varlıklar olan Bitcoin (BTC), Ethereum (ETH), Cardano (ADA) ve Solana (SOL) ile spekülasyon nitelikli Carboncoin (CARBON)'in günlük kapanış fiyat dinamiklerini derin öğrenme modelleriyle analiz etmektir. Ayrıca yatırımcı duyarlılığını temsil eden Fear & Greed Endeksi, kripto para piyasalarında fiyat oluşum süreçlerinde duyarlılık kaynaklı etkilerin literatürde vurgulanan rolü doğrultusunda modele dahil edilmiştir. Çalışmada 21.10.2021–01.11.2025 dönemine ait günlük kapanış fiyatları kullanılmış; korelasyon analizleri ham günlük fiyat serileri üzerinden Pearson korelasyon yöntemi ile

gerçekleştirilmiş olup, bu yöntem değişkenler arasında doğrusal ilişkinin yönü ve gücünün incelemek amacıyla tercih edilmiştir. Veri seti modelleme öncesinde temizlenmiş, Min-Max normalizasyonu uygulanmış ve kronolojik bütünlük korunarak %70 eğitim ve %30 test seti olarak ayrılmıştır. Seriler üzerinde durağanlık varsayımı, klasik ekonometrik yaklaşımlar açısından önemli olmakla birlikte, çalışma doğrusal olmayan modelleme yapıları kapsamında derin öğrenme tabanlı yöntemlere odaklanmaktadır. Çalışmada kullanılan veriler Yahoo Finance ve AI Key API üzerinden temin edilmiştir. Elde edilen bulgular, karbon kredi tokenleri arasında güçlü içsel bağlantılar bulunduğunu göstermektedir. Özellikle BCT ve MCO2 arasında güçlü pozitif ilişki gözlenirken, bu tokenlerin Bitcoin ile zayıf negatif korelasyon sergilediği belirlenmiştir. Bu durum, karbon kredi tokenlerinin ana kripto piyasası ile sınırlı düzeyde bağlantılı olduğunu, buna karşın kendi içinde daha tutarlı bir yapı oluşturduğunu göstermektedir. Ayrıca CARBON varlığının ana kripto varlıklarla zayıf ile orta düzey arasında değişen ilişkiler sergilediği görülmüştür. Fear & Greed Endeksi ise BTC, ETH ve SOL ile orta düzeyde, karbon kredi tokenleri ile ise daha zayıf ilişkiler göstermiştir. Modelleme sürecinde LSTM, GRU, Transfer-LSTM ve Transfer-GRU mimarileri kullanılmış; modeller MSE, RMSE, MAE, MAPE ve R² ölçütleriyle değerlendirilmiştir. Hiperparametre optimizasyonu “grid search” yöntemiyle yapılmış; katman sayısı, öğrenme oranı, epoch ve batch boyutu kombinasyonları değerlendirilmiştir. Elde edilen sonuçlar, GRU mimarisinin genel olarak en yüksek tahmin doğruluğu sunduğunu KLIMA ve Fear & Greed (F&G) Endeksi tahminlerinde ise transfer öğrenme modellerinin görece daha iyi performans sergilediğini göstermektedir. Genel olarak çalışma, derin öğrenme ve transfer öğrenme yaklaşımlarının tokenleştirilmiş karbon kredi piyasalarının fiyat davranışlarını modellemede etkili olduğunu ortaya koymaktadır. Bununla birlikte, transfer öğrenmenin her senaryoda otomatik üstünlük sağlamadığı, ancak belirli varlık gruplarında stratejik katkı sunduğu değerlendirilmektedir. Sonuç olarak, çalışma dijital ekonomide sürdürülebilir finans araçlarının fiyatlanmasında yapay zekâ temelli modellerin karar destek mekanizması olarak kullanılabileceğini göstermektedir.

Anahtar Kelimeler: Dijital Ekonomi, Karbon Kredi, Derin Öğrenme, Kripto Para, Blockchain

JEL Kodu: C45, C55, G12, Q54, O33

Licence:  This work is licensed under Creative Commons Attribution-NonCommercial 4.0 International License

Introduction

In the 21st century, as digitalization has gained momentum on a global scale, economic structures have entered a process of fundamental transformation not only in terms of production and trade forms but also regarding environmental policies and sustainability approaches. The increasing share of the digital economy within global gross domestic product (GDP) indicates that knowledge-based value creation has become a strategic competitive factor (Kılıçarslan & Dumrul, 2023, pp. 1–6). In particular, digital technologies such as artificial intelligence, big data, blockchain, and the Internet of Things have not only transformed traditional sectors but have also enabled innovative business models that support the feasibility of sustainable development goals (Büyükkantarıcı Tolgay, 2023, p. 73). These developments point to the emergence of a new economic paradigm where digital infrastructure intersects with environmental sustainability policies.

The deepening global climate crisis has made the restructuring of carbon-intensive economic activities imperative. With the Paris Agreement, countries have undertaken binding commitments to reduce greenhouse gas emissions; carbon markets have emerged as key policy tools supporting the economic feasibility of these goals (İlhan & Şahin, 2025, p. 264). However, carbon markets face significant institutional constraints regarding cost-effectiveness, transparency, and verifiability (Thalhammer et al., 2022, pp. 23–25). In particular, structural issues in voluntary carbon markets such as the risk of double counting, the slowness of verification processes, and high intermediary costs limit the integrability of carbon credits with financial markets (Diaz-Valdivia & Poblet-Balcell, 2025, p. 12). It is precisely at this point that the distributed ledger architecture, immutable data structure, and security mechanisms offered by blockchain technology emerge as a strategic solution for the digitalization of carbon markets (Abiodun et al., 2025, p. 5451). The tokenization of carbon credits not only ensures that

transactions are conducted securely and traceably but also enhances the liquidity of credits and reinforces market participants' trust in the system. In this context, ecosystems such as BCT (Base Carbon Tonne) and MCO2 (Moss Carbon Credit) tokens, along with Carboncoin (CARBON) and KlimaDAO (KLIMA), are building a new sustainable finance architecture by digitizing carbon credits and carbon-themed assets. The rapid growth of tokenized carbon credits and assets in the markets is increasing the importance of this class both in terms of crypto investments and environmental financing mechanisms (Ballesteros-Rodriguez et al., 2024, pp. 3–5).

However, the price formation dynamics of carbon tokens have not yet matured theoretically or empirically (Sorensen, 2023, p. 77). The high-volatility characteristics of cryptocurrency markets, the rapid responsiveness of investor behavior, and the sudden impacts of global macroeconomic developments complicate the valuation processes of carbon credit tokens. Current academic literature has primarily examined the pricing of carbon markets using econometric methods; however, the performance, variable sensitivity, and predictive power of deep learning models in this asset class have been studied only to a limited extent (Tlili, 2025, p. 3). In particular, the potential contributions that modern artificial intelligence methodologies, such as transfer learning, could offer in data-constrained fields like the carbon market stand out as a significant gap in the literature.

This study aims to address this theoretical and methodological gap. The research aims to evaluate the price dynamics of blockchain-based carbon credit tokens not only based on their own market movements but also through their co-integrated relationships with leading assets in the crypto ecosystem. In this regard, assets with high trading volume and strong network effects, such as Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), and Solana (SOL), have been included in the model. Additionally, within the scope of carbon-themed assets, Carboncoin (CARBON), carbon credit tokens BCT and MCO2, and the carbon token KlimaDAO (KLIMA) have been included in the model. Furthermore, the Fear & Greed (F&G) Index, which represents investor sentiment, has also been integrated into the analysis (Alternative.me, 2024). Numerous studies have demonstrated that investor sentiment exerts significant effects on cryptocurrency asset prices and market volatility (Naeem et al., 2021, p. 498). Therefore, the inclusion of the Fear & Greed Index in the model enables the evaluation of carbon credit token price dynamics from a behavioral finance perspective as well.

In the context of applying artificial intelligence methods to carbon markets, this study compares three distinct model families within a comprehensive framework: classical LSTM and GRU models, transfer learning-based models, and hybrid architectures (Transfer-LSTM, Transfer-GRU). This approach makes it possible to test the performance advantages that transfer learning can offer in new asset classes with limited data. In the modeling process, daily raw price series for carbon credit tokens and related market indicators were used. Following data cleaning, all variables were scaled using Min-Max normalization, and the dataset was split into a 70% training set and a 30% test set. A detailed evaluation of model performance using MSE, MAE, RMSE, MAPE, and R^2 metrics enhances the statistical reliability of the results. The study also conducted descriptive statistics and Pearson correlation analysis to support the pre-analytical phase of the modeling process. Through descriptive statistics, the distribution structures, volatility levels, and outlier behaviors of the variables were analyzed, revealing the structural characteristics of the dataset. Pearson correlation analysis was applied to determine the direction and strength of the linear relationship between market variables which constitute the model inputs and carbon credit tokens; this allowed for a systematic evaluation of the relationships among variables prior to proceeding to the multivariate modeling phase. This analysis does not aim to test causality or long-term structural relationships; rather, it seeks to identify the concurrent linear patterns among the variables that will be used as inputs for deep

learning models at a preliminary analysis level. This pre-analytical approach aims to establish a pre-validation framework for the modeling process.

The study provides three key contributions: (i) It presents a comprehensive model framework that evaluates the price dynamics of tokenized carbon credits in conjunction with the structural characteristics of crypto markets and investor sentiment, (ii) It generates empirical findings demonstrating the feasibility of using transfer learning as a performance-enhancing strategy in this field, (iii) Demonstrating that deep learning models can be utilized as transparent and accountable decision-support mechanisms in financial markets. In these respects, the study provides a unique analytical contribution of strategic value to both academics and policymakers, situated at the intersection of the digital economy, sustainable finance, and artificial intelligence literatures.

Literature Review

In recent years, the digitization of carbon markets, blockchain integration, and tokenization have seen a marked rise in the academic literature. Carbon markets have long been addressed in the academic literature as a market-based policy tool in the fight against climate change. These developments are paving the way for new research paradigms at the intersection of environmental sustainability and financial innovation.

In their study, Hao et al. (2023) developed a transfer learning framework based on a hybrid GARCH-GRU model. Given that China's carbon market is still in its early stages, they aimed to address the issue of insufficient data for deep learning models. The proposed method achieved comparable prediction accuracy while requiring significantly less training data compared to standard deep learning. Additionally, a transferability metric was proposed to guide the selection of time series data from source domains, and its effectiveness was validated.

In their study, Saracık and İncekırık (2023) applied LSTM and GRU techniques in Google Colab to forecast stock prices for five companies in the XELKT index on the Borsa İstanbul. The dataset covers the period from January 2, 2013, to December 30, 2022. In analyses conducted over four different time frames, the most successful forecasts were identified. Since the model performance metrics yielded results below 1 for MSE and below 5% for MAPE, it was concluded that both techniques successfully predicted stock prices. A comparison between the two techniques revealed that the LSTM technique was slightly more successful than the GRU technique.

Zhang et al. (2023) proposed a new price prediction model based on transfer learning in their study. The model was pre-trained using the GRU algorithm on mature market data and then fine-tuned with target market samples. An integrated framework was presented that includes complexity decomposition for data preprocessing, sample entropy for feature selection, and support vector regression for post-processing. In an empirical analysis of China's new market, the model's RMSE, MAE, MAPE, and R^2 values were found to be 0.529, 0.476, 0.717%, and 0.501, respectively.

In their work, Ballesteros-Rodríguez et al. (2024) aim to clarify the current state of tokenized carbon credits and the blockchain-based ecosystem in detail, highlighting the interoperability and high liquidity of tokens as well as the existing barriers to trade. The study focuses on the interpretability of tokens and trading efficiency, analyzing technical and operational challenges in the sector. The findings provide important insights into the market dynamics of tokenized carbon credits, participant behavior, and the impact of technological infrastructure on sustainable carbon markets.

Eylasov & Çiçek (2024) compared the forecasting performance obtained by using ARIMA-GARCH and LSTM deep learning approaches to predict the returns of Bitcoin (BTC),

Ethereum (ETH), and Binance (BNB) cryptocurrencies. Daily data across different time intervals were used, and the data were split into 90% training and 10% testing sets. The methods were compared using RMSE and MSE evaluation criteria. Overall, in the BTC series, the ARIMA-GARCH method showed better results on the training data, while the LSTM method was more effective for the test data. In the BNB series, the LSTM method demonstrated superior performance for both training and test data. In the ETH series, however, the ARIMA-GARCH method yielded better results for both datasets.

Wang et al. (2024) proposed a new hybrid machine learning approach for predicting carbon price volatility in their study. Specifically, they proposed a research framework that combines Dilated Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) neural network algorithms. The advantage of the combined framework is that it makes feature extraction more efficient. Subsequently, based on the DILATED CNN-LSTM framework, the L1 and L2 parameter norm penalty regularization method was adopted for forecasting. Considering the high correlation between energy indicator prices and blockchain data observed in previous literature, blockchain-related indicators were prioritized and incorporated through the regularization process. Experimental results demonstrate that the DILATED CNN-LSTM framework outperforms the traditional CNN-LSTM architecture. Blockchain data enables effective price forecasting. In price forecasting, Ridge Regression (RR) with L2 regularization outperforms SCAD with L1 regularization. Therefore, the proposed RR-DILATED CNN-LSTM approach can effectively and accurately predict the volatility trend of carbon prices.

Wang et al. (2024), in their study, examined the relationship between the Crypto Fear and Greed Index (FGI) and the price synchronization of cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Monero) using data from February 2018 to June 2023. The findings revealed that the relationship between investors' collective sentiment (FGI) and price synchronization (measured by realized correlation) exhibits a non-linear U-shaped relationship. This marks the first study to document a U-shaped relationship between FGI-based online investor sentiment and the price synchronization of cryptocurrencies.

Yousufi & İncekırık (2024) focused in their study on the fundamental components of the digital economy and the prediction of Ethereum's price movements in the cryptocurrency market using deep learning techniques. Within the scope of the study, RNN, LSTM, and GRU models were used for Ethereum price predictions, and the performance of these models on time-series data was evaluated. The data underwent various preprocessing steps, including scaling, sequence creation, and model training, while performance evaluation was conducted using metrics such as MSE, MAE, and MAPE. The results demonstrated the potential and reliability of deep learning algorithms in financial market forecasting.

In his work, Gautam (2025) proposed a hybrid deep learning and machine learning model that combines LSTM trees and XGBoost for cryptocurrency price forecasting. While the LSTM component captures temporal dependencies in historical price data, XGBoost improves the forecast by modeling nonlinear relationships using auxiliary features such as sentiment scores and macroeconomic indicators. The model was evaluated on historical datasets for Bitcoin, Ethereum, Dogecoin, and Litecoin, incorporating both local and global exchange data. A comparative analysis using MAPE and Min-Max Normalized Root Mean Square Error (MinMax RMSE) demonstrated that the LSTM+XGBoost hybrid consistently outperformed standalone models and traditional forecasting methods.

Kaur et al. (2025) focused on exchange rate forecasts for the three leading cryptocurrencies by market capitalization: Ethereum (ETH), Bitcoin (BTC), and Litecoin (LTC). Two categories of recurrent neural networks, specifically Long Short-Term Memory

(LSTM) and Gated Recurrent Unit (GRU), were employed. Prediction accuracy was evaluated using four performance metrics: MSE, MAE, MAPE, and RMSE. The results indicated that the GRU model outperformed the LSTM. The GRU model was implemented as a two-layer deep learning network and optimized using Adam optimization with a dropout rate of 0.2% to prevent overfitting. The model was trained using normalized historical price data obtained from CryptoDataDownload with an 80/20 training-test split. The study demonstrated that the GRU is the best algorithm for developing a cryptocurrency price prediction model. The MAPE values for BTC, LTC, and ETH are 0.03540, 0.08703, and 0.04415, respectively, indicating that the GRU provides the most accurate predictions compared to the LSTM.

Li et al. (2025) proposed a new hybrid deep learning framework in their study that integrates dual-mode decomposition and the TKMixer-BiGRU-SA model for carbon price forecasting. In the model, the carbon price series was decomposed using Variable Mode Decomposition (VMD) and Empirical Wavelet Transform (EWT). The core forecasting model comprises three integrated branches: the first processes the raw carbon price and highly correlated external time series, the second processes the multiscale components obtained from VMD, and the third processes the components obtained from EWT. The model incorporates the TKMixer module, which was created by integrating Kolmogorov-Arnold Networks (KANs) into the Time Series Mixer (TSMixer) module. Each branch applies TKMixer alternately along the temporal and feature channels to capture dependencies between temporal steps and variables. Experimental evaluations were conducted using European Union Allowance (EUA) and Hubei Emission Allowance (HBEA) data. For example, the eMAPE values for EUA forecasts over 1–4 steps were found to be 0.2081%, 0.5660%, 0.8293%, and 1.1063%, respectively.

Yang et al. (2025) presented a blockchain and machine learning-focused approach in their study to address the current challenges of carbon emissions trading systems. The study designed a data storage mechanism on the blockchain, developed methods for storing and trading carbon emissions transactions on the blockchain, and established a process for issuing carbon credits. Additionally, a carbon trading price prediction model was developed using neural architecture search. By employing data augmentation and triple loss, accurate price predictions were achieved, thereby enhancing the reliability and security of carbon trading investments.

Kotsompolis et al. (2026) predicted carbon price movements using a nonlinear ARIMA model, XGBoost, and LSTM in their study. The dataset covers the period from December 1, 2010, to January 10, 2025. While the results show that both XGBoost and LSTM outperform the baseline ARIMA model, the hybrid model demonstrated statistically significant improvements in prediction accuracy.

This body of literature provides a comprehensive conceptual framework covering carbon credit tokenization, blockchain infrastructures, price forecasting models, investor sentiment, and sustainability-focused market dynamics. However, there is a limited body of research that examines the integration of price formation mechanisms for tokenized carbon credit assets (BCT, KLIMA, etc.) with crypto markets and the impact of behavioral indicators such as the Fear & Greed Index, in conjunction with transfer learning-based hybrid deep learning models (Transfer-LSTM, Transfer-GRU). By comprehensively modeling multivariate long-term datasets using modern deep learning techniques, this study aims to contribute to the literature both methodologically and practically through its extensive dataset, multidimensional variable structure, and hybrid prediction models.

Deep Learning Techniques

With the rapid development of the digital economy, traditional analytical methods have proven inadequate for managing complex and volatile market conditions; this situation has heightened the strategic importance of AI-based decision support systems. Machine learning comprehensively defines algorithms that automatically learn from data and improve their performance through experience (Mitchell, 1997, p. 2). The foundations of machine learning were laid in the 1950s with Alan Turing's paper "Computing Machinery and Intelligence," and today it is used in a wide range of fields such as finance, healthcare, energy, and sustainability. Machine learning is fundamentally divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning (Goodfellow et al., 2016, pp. 98–102). In this study, a supervised learning approach was chosen to predict future prices based on past prices and related variables (Saracık & İncekırık, 2023, p. 143).

Deep learning is an advanced subfield of machine learning that can automatically learn complex and nonlinear relationships in data through multi-layered artificial neural networks (LeCun et al., 2015, p. 436). Thanks to its capabilities such as feature extraction, long-term dependency analysis, and complex behavior modeling, deep learning demonstrates superior performance in image, language, and financial time series data, enabling a more accurate analysis of carbon credit token price dynamics. The deep learning techniques used in this study are described below;

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is an advanced architecture first developed by Hochreiter and Schmidhuber (1997) and designed to address the issues of vanishing gradients and exploding gradients commonly encountered in Recurrent Neural Networks (RNNs). Due to its ability to preserve long-term temporal dependencies, LSTM demonstrates high performance in applications such as time series forecasting, natural language processing, and sequential data modeling. The model performs the following calculations for each time step t :

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \quad (1)$$

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \quad (2)$$

$$g_t = \tanh(W_{ig}x_t + b_{gi} + W_{hg}h_{t-1} + b_{hg}) \quad (3)$$

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \quad (4)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (5)$$

$$h_t = o_t \odot \tanh(c_t) \quad (6)$$

In these expressions, h_t , c_t and x_t represent the hidden state, cell state, and input at time step t , respectively. h_{t-1} is the hidden state from the previous time step or the initial hidden state defined at the start. In Equations (1)– (4), the input gate (i_t), the forget gate (f_t), the candidate cell state (g_t), and the output gate (o_t) are calculated, respectively. In Equation (5), the cell state (c_t) is updated by scaling the previous cell state through the forget gate and adding the current input to memory via the input gate. Finally, in Equation (6), the hidden state (h_t) is obtained by filtering the updated cell state through the output gate. Here, $\sigma(\cdot)$ denotes the sigmoid activation function, $\tanh(\cdot)$ denotes the hyperbolic tangent function, and $\odot$ denotes the Hadamard product. The memory cell (c_t), which forms the core of the LSTM architecture,

is the central structure that manages the flow of information over time. The Forget Gate decides whether to retain or update past information, while the Input Gate determines which information from the current input is transferred to memory. The Output Gate, on the other hand, controls the amount of information the model transmits to the outer layers by managing the extent to which the memory state is reflected in the hidden state (Shen et al., 2020, p. 304).

Thanks to this architecture, LSTM achieves the capacity to efficiently represent long-term dependencies and offers a more stable learning process compared to traditional RNNs. Figure 1 shows the structural diagram of the LSTM model.

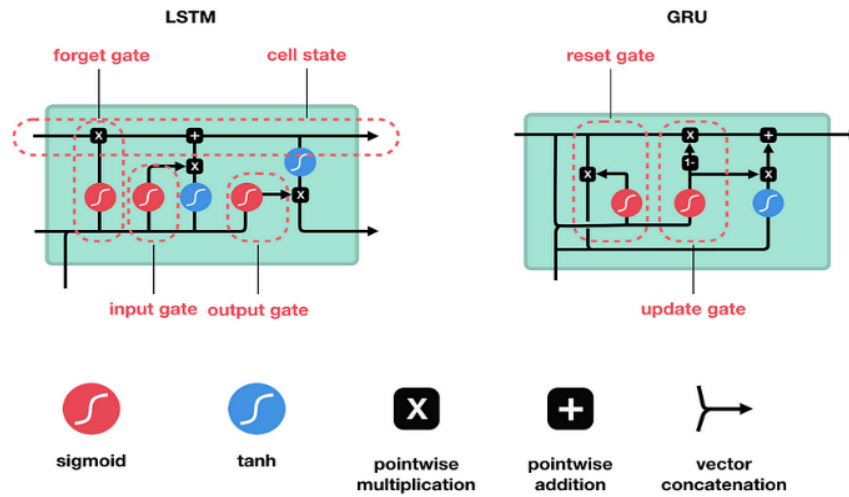


Figure 1. Structural Diagram of LSTM and GRU Models
Source: (Yousufi & İncekırık, 2024, p. 61)

Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU), proposed by Cho et al. (2014), is another RNN architecture developed to reduce the computational load and simplify the structure of LSTM. Unlike LSTM, which uses separate cell states, GRU manages the flow of information through a single hidden state. As a result, it contains fewer parameters and provides computational efficiency during the training process. For each time step t , the GRU computes the following functions:

$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \quad (7)$$

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \quad (8)$$

$$\tilde{h}_t = \tanh(W_{xh}x_t + r_t \odot W_{hh}h_{t-1} + b_h) \quad (9)$$

$$h_t = (1 - c_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (10)$$

Here, ' z_t ' represents the update gate, ' r_t ' represents the reset gate, ' $\tilde{h}_t$ ' represents the candidate hidden state, and ' h_t ' represents the new hidden state. The update gate and reset gate are calculated in Equations (7) and (8), respectively; these two gates determine the extent to which information is carried over from the past and how new input is integrated into the model. The candidate hidden state $\tilde{h}_t$ is obtained in Equation (9) by combining the current input with the previous hidden state under the influence of the reset gate. Finally, in Equation (10), the previous hidden state and the candidate hidden state are combined via the gate mechanisms to form the new hidden state h_t . The simple structure of the GRU offers a significant advantage

in terms of fast convergence and high performance, particularly when the dataset is relatively small (Chung et al., 2014, p. 4). Figure 1 above shows the structural diagram of the GRU model.

Transfer Learning

Transfer learning (TL) was first systematically defined by Caruana (1997) as a learning approach that enables machine learning systems to reuse previously acquired knowledge in solving different or similar problems. Transfer learning is also present in the foundation of human learning behavior; that is, individuals produce solutions for new and different situations by consciously or unconsciously drawing on their past experiences (Thompson, 2022, pp. 1–3). This approach offers an effective learning strategy, particularly in situations where the training dataset is limited or where rapid decisions are required.

The fundamental mechanism of transfer learning involves transferring the learned parameters of the source model to the target model. This parameter transfer is expressed as follows:

$$\theta_T^{(0)} \leftarrow \theta_S \quad (11)$$

As shown in Equation (11), this is achieved by using the parameter set of the source model, θ_S , as the initial parameters of the target model, $\theta_T^{(0)}$. The goal of this approach is for the representational power acquired in the source task to provide an initial advantage in the target task. Transfer learning can be applied in two main ways:

- Feature-based transfer: Specific layers of the model are kept fixed (frozen), and only the final layers specific to the target task are retrained.
- Fine-tuning: The entire model or specific layers are retrained using a low learning rate.

In this study, a pre-trained encoder $E(\cdot; \theta_S)$ is used to map time-series inputs into a feature space, that is:

$$z_t = E(x_t; \theta_S) \quad (12)$$

This process is carried out by obtaining feature representations z_t from the x_t inputs, as expressed in Equation (12). These obtained representations are used as input to the target model with the aim of accelerating the model's learning process and enhancing its generalization capacity (Cao et al., 2023, pp. 5–6).

Hybrid Models

Hybrid models are structures that combine multiple learning paradigms. In deep learning, this hybridization aims to achieve higher performance by integrating the advantages of different architectures into a single system (Çoban, 2025, p. 109). Within the scope of this study, hybrid models are structures that combine transfer learning with networks that model time-series dependencies (LSTM, GRU).

The primary motivations for using a hybrid model are as follows: a) Efficiency: the rapid adaptation of information transferred from the source model to the target model. b) Generalization ability: learning stronger and more generalizable representations through knowledge transfer among sequences with similar structural relationships. c) Benefits in cases of data scarcity: accelerating the training process and preventing the model from overfitting when data is limited (Bhattacharyya et al., 2022, pp. 3027–3029).

Hybrid models consist of the LSTM-Transfer Model and the GRU-Transfer Model. The two models mentioned are explained below in order.

LSTM-Transfer Model

The LSTM-Transfer model is based on transferring the learned parameters of a pre-trained LSTM network to a new financial time series. This structure combines LSTM's strong capacity for capturing long-term dependencies with the reuse mechanism of Transfer Learning, thereby enabling a faster and optimized learning process (He et al., 2019, pp. 4–6).

The input to the LSTM-Transfer model is defined in Equation (12) using the output of a pre-trained encoder $E(.; \theta_S)'$. This representation is transferred to the LSTM cell as the current input; the LSTM cell can be configured as follows during the transfer process:

- Parameters from the encoder are either frozen or fine-tuned.
- While some LSTM layers are fixed, the final layers are retrained.

In this configuration, the model output is updated only in the layers specific to the target task, and the prediction value is calculated as shown in Equation (13):

$$\hat{y}_t = W_y h_t + b_y \quad (13)$$

Here, ' h_t ' represents the transferred LSTM hidden state, while ' W_y ' and ' b_y ' denote the task-specific learnable parameters (Nguyen & Yoon, 2019, pp. 5–6).

GRU-Transfer Model

The GRU-Transfer model aims to achieve faster convergence, lower computational cost, and stable performance by combining the GRU's lightweight architecture with the transfer learning strategy. While it operates on a logic similar to LSTM-Transfer, the training time is relatively shorter due to the GRU's simpler gate mechanism. The feature vector from the pre-trained encoder forms the input sequence of the GRU cell and generates the model's updated hidden states throughout the time series. In the hybrid transfer model, the output of the target task is calculated using the hidden states obtained by the GRU, as shown in Equation (13) above. The fact that the GRU has a lower number of parameters compared to the LSTM provides significant advantages, particularly during the retraining phase of hybrid models, such as faster training and shorter computation times (Lin et al., 2023, p. 3).

Five fundamental metrics, which are standard in financial time series forecasting, were used to measure the performance of deep learning models: MSE, MAE, RMSE, MAPE, and R^2 . This combined set of metrics provides a standard basis for comprehensively evaluating the accuracy of the models. MSE and RMSE measure error magnitude on an absolute scale, MAE and MAPE measure relative error, while R^2 measures the model's proportion of explained data variance (Ene Yalçın, 2025, p. 7). Especially for financial instruments exhibiting high volatility, these metrics play a critical role in evaluating the model's generalization ability (Akarsu, 2025, p. 94).

Data Set and Application

In this study, the aim was to predict the price movements of the carbon token KlimaDAO (KLIMA) and the tokenized carbon credit representations Base Carbon Tonne (BCT) and Moss Carbon Credit (MCO2) using deep learning models, with Bitcoin (BTC), Ethereum (ETH), Solana (SOL), Cardano (ADA), Carboncoin (CARBON), and the Fear & Greed Index (F&G) were examined as key variables. The study encompasses the stages of data collection, preprocessing, model development, and performance evaluation. The dataset consists of approximately 1,471 daily observations covering the period from October 21, 2021, to November 1, 2025, and examines the changes in the closing prices of BCT, MCO2, and KLIMA

over time. The data used was collected via the “yfinance” library from Yahoo Finance and using the “AI Key” API from the CoinGecko platform; daily closing prices were defined as the target variables. The methodological approach adopted in this study addresses the stages of data collection, preprocessing, normalization, model training, and performance evaluation as part of a systematic process. The key components of this process are summarized in Table 1.

Table 1. Dataset and Model Characteristics

Data Time Type	Daily				
Transaction Date Range	October 21, 2021 to November 30, 2025				
Data Source	Yahoo Finance		CoinGecko (AI Key)		
Data Characteristics	Daily Price Data		Close		
Programming and Development Environment	Python				
	Google Colab				
Preliminary Analysis	Descriptive Statistics		Pearson Correlation Analysis		
Normalization Method	Min-Max Scale (0, 1)				
Data Split	Training data		Test data		
	%70		%30		
Independent Variables (input)	1	Lagged values up to 4 days			
	2	Trading days: BTC, ETH, SOL, ADA, CARBON			
	3	Trading days: BCT, MCO2, KLIMA, F&G			
Dependent Variable (output)	Daily Closing Price				
Methods Used	LSTM, GRU, Transfer-LSTM, and Transfer-GRU				
Hyperparameters and Range	Number of Windows		7, 14, 21 and 30		
	Batch Size		16, 32, 64 and 128		
	Number of Epochs		50, 100, 150 and 200		
	Optimization Algorithm		Adam		
	Loss Function		MSE		
Number of Combinations	2304				
Deep Learning Layer Structure	Input Layer	1st Hidden Layer	2nd Hidden Layer	Dropout	3rd Hidden Layer Dense
	(7, 9)	50	50	0.2	25
Evaluation Metrics	MAE, MSE, MAPE, RMSE and R ²				
Number of Rows and Columns in the Dataset	(1471, 9)				

Table 1 presents the characteristics of the dataset used in the study, the preliminary analysis steps, the model configurations, and the hyperparameter search space. The dataset consists of 1,471 daily observations covering the period from October 21, 2021, to November 30, 2025, and was obtained from the CoinGecko platform via the Yahoo Finance and AI Key APIs. Before proceeding to the modeling phase, descriptive statistics and Pearson correlation analysis were applied to examine the distribution characteristics of the variables and the linear relationships among them. Subsequently, all series were normalized to the [0,1] range using the

Min-Max method, with scaling parameters calculated solely based on the training set to prevent data leakage. The dataset was split into a 70% training set and a 30% test set while maintaining chronological integrity. Four deep learning architectures LSTM, GRU, Transfer-LSTM, and Transfer-GRU were trained using a three-layer network structure that included a dropout rate of 0.2 and the Adam optimization algorithm. To determine the optimal configuration for each target variable, a total of 2,304 hyperparameter combinations were evaluated using grid search across window size, batch size, and the number of epochs; model performance was compared using the MAE, MSE, RMSE, MAPE, and R^2 metrics.

Descriptive Statistics

The basic statistics of the variables used in the study are presented in Table 2. The dataset consists of 1,471 daily observations, with an equal number of observations for all variables. The distribution characteristics of the variables were evaluated using skewness, kurtosis, and Jarque-Bera test statistics. The results indicate that the time series in the dataset do not meet the assumption of normal distribution and exhibit heterogeneous distribution structures. These preliminary findings are significant for justifying the modeling approaches used in the study.

Table 2. Descriptive Statistics

	BTC	ETH	SOL	ADA	CARBON	BCT	MCO2	KLIMA	F&G
Number of observations	1471	1471	1471	1471	1471	1471	1471	1471	1471
Average	54,639.790	2,533,331	106,568	0.6178	0.0005	1.3135	2.5494	69,307	49.105
Standard Deviation	31,333.164	940,834	72,249	0.3546	0.0003	1.6032	3.4723	348,375	20.350
Minimum	15,787.284	993,639	9.6518	0.2419	0.0002	0.149	0.095	0.112	6
25%	27,349.229	1,757,637	30,743	0.366	0.0003	0.264	0.441	0.754	29
Median 50%	43,989.195	2,423.745	108,582	0.4997	0.0004	0.697	1.108	1,689	50
70%	71,365.121	3,250,228	167,9469	0.7761	0.0007	1.598	2.3390	3.2536	68
Maximum	124,752.531	4,831,349	261,870	2,274	0.0012	8.1704	17,509	3,683,571	94
Variance	98,176,719.8	885,168.27	5,219.86	0.1257	0.0000	2.5703	12,057	121,364.99	414,115
Distortion	0.6350	0.4772	0.1583	1.8205	0.6144	2.1354	1.7934	6.5928	-0.151
Flatness	-0.8825	-0.8062	-1.3291	4.0863	-0.9036	4.0699	2.0050	47.8546	-1.162
Jarque-Bera	146.490	95.690	114,327	1,825,322	142,514	2,122.02	1,030,65	150,020.55	88,305
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2 presents descriptive statistics for the variables included in the study. The analysis of daily price data clearly demonstrates that not all series meet the assumption of a normal distribution and exhibit a heterogeneous structure. Bitcoin (BTC) and Ethereum (ETH) exhibit relatively more mature distribution profiles but are characterized by high volatility; for BTC, the mean is 54,639.79 and the median is 43,989.20, while for ETH, the mean is 2,533.33 and the median is 2,423.75. Solana (SOL) and Cardano (ADA) in the altcoin group, however, exhibit a more irregular and speculative character; for SOL, the mean is 106.57 and the median is 108.58, while for ADA, the mean is 0.62 and the median is 0.50. Among carbon-themed assets, Carboncoin (CARBON) exhibits an asymmetric distribution at low price levels (mean 0.0005, median 0.0004), while Base Carbon Tonne (BCT) and Moss Carbon Credit (MCO2) show distinctly right-skewed distributions and high volatility; For BCT, the mean is 1.31 and the median is 0.70, while for MCO2, the mean is 2.55 and the median is 1.11. In the case of the KLIMA token, the extreme difference between the mean of 69.31 and the median of 1.69 indicates that the distribution is heavily right-skewed. The Fear & Greed (F&G) Index, with a

mean of 49.11 and a median of 50, exhibits a more balanced distribution compared to the other series.

Pearson Correlation Matrix

The results of the Pearson correlation analysis, which examines the linear relationships between variables, are presented in Table 3. The Pearson correlation matrix reveals different relationship dynamics between traditional crypto assets and carbon credit tokens.

Table 3. Pearson Correlation Matrix

	BTC	ETH	SOL	ADA	CARBON	BCT	MCO2	KLIMA	F&G
BTC	1	0.6940	0.8668	0.3951	0.9886	-0.2934	-0.3265	0.0221	0.4507
ETH	0.6940	1	0.8693	0.6884	0.6878	0.2325	0.1785	0.3521	0.4029
SOL	0.8668	0.8693	1	0.6367	0.8655	0.0559	-0.0207	0.2690	0.4147
ADA	0.3951	0.6884	0.6367	1	0.3954	0.6661	0.6232	0.6756	0.0882
CARBON	0.9886	0.6878	0.8655	0.3954	1	-0.2935	-0.3272	0.0223	0.4100
BCT	-0.2934	0.2325	0.0559	0.6661	-0.2935	1	0.9257	0.5948	-0.3691
MCO2	-0.3265	0.1785	-0.0207	0.6232	-0.3272	0.9257	1	0.5035	-0.4112
KLIMA	0.0221	0.3521	0.2690	0.6756	0.0223	0.5948	0.5035	1	0.0884
F&G	0.4507	0.4029	0.4147	0.0882	0.4100	-0.3691	-0.4112	0.0884	1

There are strong positive correlations ranging from 0.69 to 0.87 between BTC, ETH, and SOL, indicating that these assets are subject to similar market dynamics. Interestingly, the near-perfect positive correlation of 0.9886 between CARBON and BTC suggests that CARBON has a speculative nature closely tracking Bitcoin's market movements rather than being an independent carbon asset. Carbon credit tokens BCT and MCO2, on the other hand, exhibit a very high positive correlation of 0.9257 with each other, and also show a moderate-to-high positive relationship (0.62–0.67) with ADA. However, the fact that BCT and MCO2 exhibit weak negative correlations with BTC (-0.29 and -0.33) suggests that these carbon assets can move largely independently of the main crypto market. The KLIMA token, meanwhile, shows its strongest correlation with ADA (0.68) and BCT (0.60), while exhibiting almost no correlation with BTC (0.02). The Fear & Greed Index exhibits a moderate positive correlation (0.41–0.45) with BTC, ETH, and SOL, while showing a weak negative correlation (-0.37 and -0.41) with carbon credit tokens (BCT and MCO2). This finding can be interpreted to mean that carbon credit markets move relatively independently of general sentiment fluctuations in the crypto market.

Preparing the Dataset for Modeling and Tools Used in the Training Process

During the modeling phase, the data was split into a 70% training set (October 21, 2021–August 15, 2024) and a 30% test set (August 16, 2024–November 1, 2025), while maintaining chronological integrity. The training set includes the periods used in the models' learning process, while the test set covers the period during which the model's prediction performance is evaluated. The obtained data was scaled to the [0,1] range using the MinMaxScaler method and prepared for analysis and modeling. The scaling process was fitted only on the training dataset to prevent data leakage, and the obtained parameters were applied to the validation and test sets. LSTM, GRU, Transfer-LSTM, and Transfer-GRU models were trained using the normalized dataset, and their performances were evaluated. Considering the time series structure, data splitting was performed in chronological order using a sliding window approach.

The model architectures yielding the best results were selected to perform price predictions for BCT, MCO2, and KLIMA assets; the results were evaluated in a multivariate context alongside BTC, ETH, SOL, ADA, CARBON, and the Fear & Greed (F&G) Index. The forecast results were converted back to the original scale and compared with actual data; performance metrics such as MSE, MAE, RMSE, MAPE, and R^2 were calculated.

In the price forecasting process for the cryptocurrency market and carbon credit tokens, the large volume of data and the use of deep learning models increase hardware requirements. Python has gained popularity in scientific computing and artificial intelligence, and has become an industry standard, particularly in deep learning, with libraries such as PyTorch, Keras, and TensorFlow. In this study, the “Pandas,” “NumPy,” and “Matplotlib” libraries were used for data preparation and visualization. The training process was accelerated using Google Colab, Google’s cloud service that provides GPU-based infrastructure.

Model Training and Testing

Before predicting the BCT, MCO2, and KLIMA prices in our dataset, a training dataset was prepared, and experiments were conducted on the hyperparameters (lookback window, number of layers, learning rate, epoch, batch size) until the lowest error values were achieved. In the models, specifically in transfer learning-based models, BTC returns were used as the source task, and the weights were frozen and adapted to the target task. Using grid search, the number of days: (7, 14, 21, 30), epochs: (50, 100, 150, 200), and batch size: (16, 32, 64, 128) were selected from the best values in the literature and tested. To reduce the risk of overfitting, dropout (0.2) was applied, and the models were trained using the “Adam optimizer.” In the models’ prediction processes, BTC, ETH, SOL, ADA, Carboncoin, and the Fear & Greed (F&G) index were used as explanatory variables; price predictions for BCT, MCO2, and KLIMA were performed in a multivariate context.

Obtaining Model Prediction Results

Bitcoin (BTC) and Ethereum (ETH), which are the cornerstones of the cryptocurrency market, along with altcoins Solana (SOL) and Cardano (ADA), and carbon-themed assets such as Carboncoin (CARBON), carbon credit tokens represented by Base Carbon Tonne (BCT) and Moss Carbon Credit (MCO2), the carbon token KlimaDAO (KLIMA), and the Fear & Greed (F&G) Index, which indicates market sentiment, were considered as the variables for forecasting and performance evaluation in this study. Training and testing processes were conducted using LSTM, GRU, Transfer-LSTM, and Transfer-GRU models. Table 4 presents the performance metrics MSE, MAE, RMSE, MAPE, and R^2 for the models. The models yielding the lowest error rates were selected, and their performances were compared.

Table 4. Model Performance Comparison

Variable	Performance Metrics	Models							
		LSTM		GRU		Transfer-LSTM		Transfer-GRU	
		Day-Epoch-Batch		Day-Epoch-Batch		Day-Epoch-Batch		Day-Epoch-Batch	
BTC	MAE	30-100-32	1572.68	7-100-16	1548.82	7-50-16	4,176.898	7-50-16	2,781.814
	MSE		4,536,015.51		4,398,761.80		23,169,666.338		12,697,126.11
	RMSE		2129.7924		2097.3225		4,813.488		3563.303
	MAPE		1.71%		1.69%		4.24%		3.00%
	R^2		0.9868		0.9872		0.9325		0.9630
ETH	MAE	21-150-64	82.0843	7-100-32	80.1478	7-100-128	84.5044	7-50-128	136.3461
	MSE		13,534.9908		13262.6271		15,864.427		34,407.2235

	RMSE		116.3399		115.1635		119.1897		185.4918
	MAPE		2.77%		2.68%		2.81%		4.40%
	R ²		0.9807		0.981		0.9798		0.9510
SOL	MAE	7-100-16	5.7440	21-150-32	5.6292	14-150-64	6.3529	7-50-128	9.8546
	MSE		62.6463		60.4654		73.5359		168.4089
	RMSE		7.9149		7.7760		8.5753		12.9772
	MAPE		3.24%		3.20%		3.55%		5.47%
	R ²		0.9514		0.9531		0.9430		0.8694
ADA	MAE	21-150-32	0.02693	7-50-16	0.0263	14-100-32	0.0271	30-200-32	0.0297
	MSE		0.0019		0.0019		0.0019		0.0022
	RMSE		0.04361		0.0434		0.0440		0.0469
	MAPE		3.57%		3.51%		3.77%		4.01%
	R ²		0.9602		0.9606		0.9595		0.9540
CARBON	MAE	30-150-64	0.000007	21-150-64	0.000006	7-100-32	0.00003	7-50-128	0.00002
	MSE		0.0000000003		0.0000000002		0.000000001		0.000000001
	RMSE		0.000016		0.000015		0.00003		0.000029
	MAPE		0.87%		0.73%		3.14%		2.22%
	R ²		0.9916		0.9925		0.9581		0.9716
BCT	MAE	7-100-16	0.0149	21-150-32	0.0103	30-50-128	0.0501	14-200-128	0.0262
	MSE		0.0004		0.0003		0.0035		0.0011
	RMSE		0.0214		0.019		0.0593		0.0334
	MAPE		5.43%		3.01%		19.94%		9.76%
	R ²		0.9901		0.9925		0.9236		0.9757
MCO2	MAE	30-200-32	0.0174	7-100-16	0.0144	7-50-128	0.1564	7-100-16	0.0567
	MSE		0.0006		0.0005		0.0252		0.0045
	RMSE		0.0241		0.0222		0.1587		0.0675
	MAPE		7.74%		5.75%		80.26%		23.08%
	R ²		0.9679		0.9727		-0.3967		0.7475
KLIMA	MAE	7-100-32	0.4430	30-150-128	0.1021	7-200-128	0.3775	7-50-16	0.1715
	MSE		0.1963		0.0128		0.1915		0.0636
	RMSE		0.4430		0.1130		0.4377		0.2522
	MAPE		162.00%		29.31%		120.35%		22.95%
	R ²		0.3178		0.9556		0.3342		0.162
F&G	MAE	21-50-16	5.0073	7-150-32	4.9576	14-50-16	4.9646	7-50-16	5.8034
	MSE		48.2551		48.2508		48.5453		57.6361
	RMSE		6.9466		6.9463		6.9674		7.5918
	MAPE		11.41%		11.27%		11.22%		12.41%
	R ²		0.8519		0.8519		0.8509		0.8231

The performance results presented in Table 4 reveal that the predictive power of deep learning models varies significantly across different crypto and carbon assets. The findings indicate that the structural heterogeneity of financial time series directly influences model performance and that the “one-size-fits-all” approach is invalid. In the mature markets of BTC and ETH large-scale crypto assets characterized by both high trading volume and price stability the GRU model demonstrated the highest performance. For BTC, the GRU (7-day, 100 epochs,

16 batches) achieved the lowest MAPE of 1.69% and the highest R^2 of 0.9872, while the LSTM produced a nearly equivalent result of $R^2 = 0.9868$. This confirms that the GRU's simplified gate mechanism more effectively models long-term dependencies in high-frequency and non-stationary data. In contrast, transfer learning-based models experienced a significant decline in these assets; the fact that transfer-LSTM's MAPE dropped to 4.24% and its R^2 from 0.9531 to 0.9325 in BCT clearly demonstrates that the direct transfer of pre-trained representations to target domains with high volatility carries a risk of negative transfer. A similar " " pattern holds true for the altcoin group consisting of SOL and ADA: While GRU leads with an MAE of 5.6292 and R^2 in SOL, there was almost no discernible difference between LSTM and GRU in ADA, yet the transfer models again resulted in higher error rates. This demonstrates that even with the moderate volatility of altcoins, transfer learning does not provide a direct advantage for financial time series.

In the context of carbon-themed tokens, performance results vary significantly depending on the market structure of these assets. For relatively liquid tokens with regular price movements, such as CARBON and BCT, the GRU model demonstrated exceptional accuracy, achieving $R^2 = 0.9925$ and MAPE = 3.01% for BCT. This finding not only demonstrates that the price dynamics of carbon credit tokens can be modeled with high sensitivity using the GRU architecture but also provides academic support for the integration of such assets into prediction-focused decision support systems within the sustainable finance ecosystem. On the other hand, tokens such as MCO2 and especially KLIMA, characterized by low liquidity, right-skewed distributions, and outliers, posed a significant challenge for all models. The fact that the MAPE values for LSTM and Transfer-LSTM in KLIMA reached 162.00% and 120.35%, respectively, suggests that sudden shocks, manipulative movements, or external market interventions dominate the price behavior of this asset. Even under these conditions, the fact that GRU achieved the relatively best result in KLIMA with $R^2 = 0.9556$ and MAPE = 29.31% demonstrates that its architecture offers partial resilience in high-noise environments. Conversely, the drop in Transfer-LSTM's R^2 value to -0.3967 in MCO2 concretely demonstrates that the model's predictions are worse than those made in a stable environment and highlights that transfer learning can potentially be detrimental in such complex time series.

In the prediction of the Fear & Greed Index, all models exhibited similar, moderate performance with an R^2 of 0.85. This implies that the cyclical and contextual nature of behavioral indicators reflecting market sentiment must be modeled not only using past values but also in conjunction with external sentiment and news flows. In conclusion, the findings emphasize that model selection for crypto- and carbon-focused financial time series requires a financial instrument-based optimization process. GRU emerged as a superior architecture for liquid and stable tokens; LSTM, on the other hand, demonstrated relatively greater learning flexibility in series containing structural breaks, such as KLIMA and MCO2. The transfer learning approach, however, generally failed due to the high volatility, non-stationarity, and distributional imbalance of financial series; this represents a concrete empirical manifestation of the "domain shift" problem frequently noted in the literature. Technical decisions such as hyperparameter optimization (7–30-day window, 50–200 epochs, 16–128 batch size), a 0.2 dropout rate, and the Adam optimization algorithm have also enhanced the model's generalization ability and minimized the risk of overfitting. This study, therefore, academically confirms that at the intersection of sustainable finance, the digital economy, and deep learning, it is necessary not only to improve prediction accuracy but also to redefine the model-selection paradigm according to market microstructure. Figure 2 shows the comparative performance of the models used in BCT price forecasting.

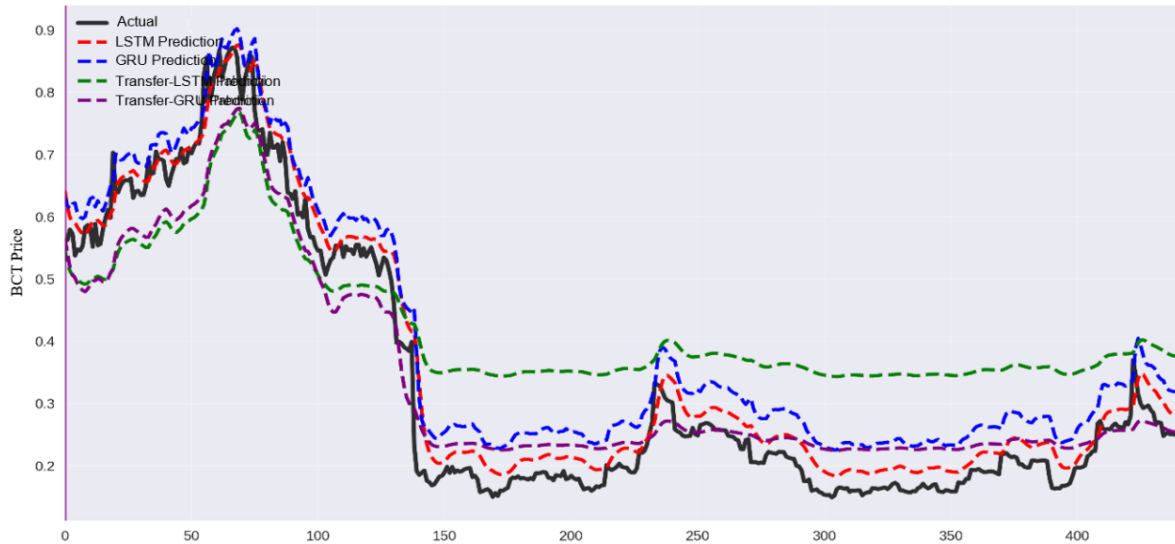


Figure 2. Comparative Performance of Models Used in BCT Price Forecasting

In Figure 2, the actual BCT prices are shown as a black line, while the outputs of the forecasting models are represented by the following: the red dashed line for LSTM, the blue dashed line for GRU, the green dashed line for Transfer-LSTM, and the purple dashed line for Transfer-GRU. Overall, the graph shows that LSTM and GRU forecasts track the actual price series more closely, particularly capturing the timing of upward and downward trends with high accuracy. In contrast, it is notable that Transfer-LSTM forecasts consistently exceed the actual values and exhibit a flatter structure, failing to adequately reflect short-term fluctuations. The Transfer-GRU model, while responding more sensitively to price movements during periods of increased volatility, has shown significant deviations from the actual series in certain segments. These observations indicate that the basic LSTM and GRU models can track BCT price dynamics with lower prediction errors during certain periods, while transfer learning-based models, despite having an advantage in capturing the general trend, exhibit a systematic upward deviation around the actual price series. Figure 3 presents the learning behavior of the GRU model throughout the training process and its prediction performance during the test period in a time-series view.

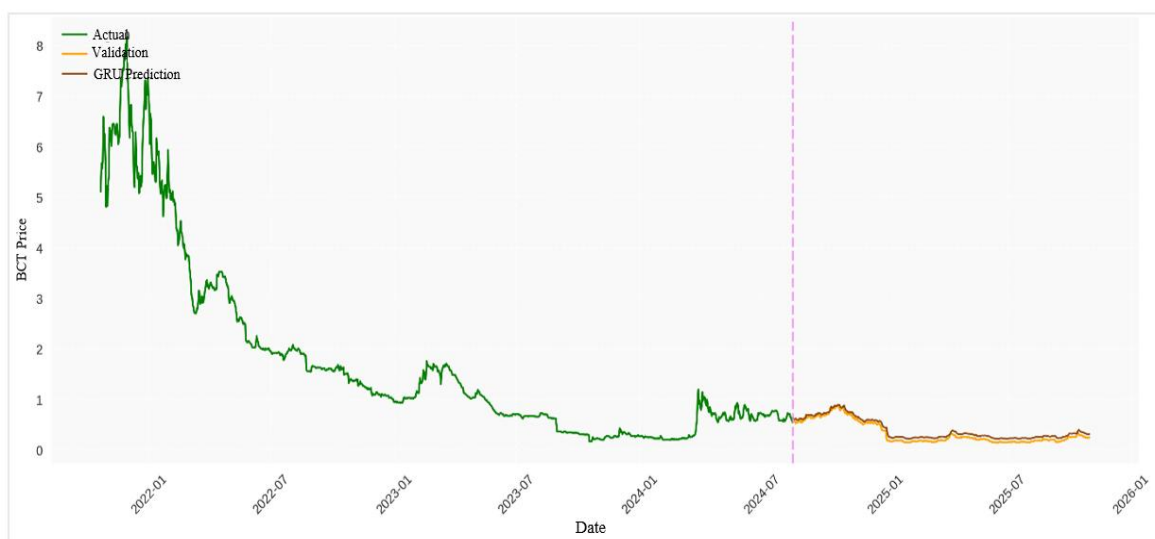


Figure 3. Actual, Validation, and Predicted Plots of the BCT Price Variable

In Figure 3, the GRU Model demonstrates strong convergence during the training phase and successfully tracks the trend during the validation period, thereby proving its generalization capability. The prediction line during the test period successfully captures major fluctuations despite volatile price movements; deviations are observed to be concentrated particularly at points where market volatility increases. This performance indicates that the model achieved a controlled and stable learning process by avoiding overfitting. In particular, the high-accuracy tracking of sharp price reversals during the 2024–2025 period demonstrates that the GRU architecture offers an effective solution that adapts to the dynamic structure of carbon credit tokens.

Based on the results obtained, it can be stated that the models used in this study demonstrate the successful applicability of deep learning-based forecasting systems a machine learning technique for carbon credit token markets. The findings indicate that financial factors such as market liquidity, volatility, and data continuity may negatively impact the model; it is anticipated that higher accuracy levels can be achieved in the future through the integration of different feature engineering and market microstructure variables.

Conclusion and Discussion

With the rise of the digital economy, blockchain technology and tokenized assets are forming the new backbone of sustainable finance. In particular, the tokenization of carbon credits offers a fundamental solution to transparency, liquidity, and accessibility issues in voluntary carbon markets, while also leading to strong interaction with the crypto ecosystem. Positioned precisely at this intersection, this study examines the price dynamics of tokenized carbon credits such as KLIMA, BCT, and MCO2 within a comprehensive analytical framework that considers not only their internal dynamics but also the structural leaders of the crypto market (BTC, ETH, SOL, ADA), other carbon-themed tokens (CARBON), and the Fear & Greed Index, which reflects investor sentiment. Descriptive statistics reveal that the dataset rejects the assumption of a normal distribution for all time series and indicates a dominant role of outliers, particularly in assets like KLIMA, characterized by right-skewness (skewness = 6.59, kurtosis = 47.85). This finding suggests that classical econometric approaches may be insufficient and that deep learning architectures resilient to distributional heterogeneity are required. In the correlation analysis, it is observed that BCT and MCO2 have weak negative correlations with BTC (−0.29 and −0.33), whereas they exhibit a high positive correlation of 0.9257 with each other. This result indicates a strong co-movement among tokenized carbon credits, suggesting that these assets may be sensitive to similar market conditions. However, correlation coefficients reflect only simultaneous linear relationships, and these findings do not support a claim of structural independence; such patterns require further validation through cointegration or causality analyses.

When the analysis results are evaluated within the framework of the three main contributions identified in the introduction of this study, it is evident that the empirical and methodological objectives have been consistently met. The first contribution the presentation of a comprehensive model framework that evaluates the price dynamics of tokenized carbon credits in conjunction with the structural characteristics of crypto markets and investor sentiment, was successfully implemented using a multivariate data structure, systematic variable selection, and chronological data partitioning. The second contribution testing the feasibility of using transfer learning as a performance-enhancing strategy in this field was empirically rejected; specifically, the drop in the R^2 value of Transfer-LSTM to −0.3967 in MCO2 and the rise in the MAPE values of transfer models above 120% in KLIMA concretely demonstrate that source-target mismatch in financial time series can act as a limiting factor for this approach. This result applies only to the asset classes and data period examined in this

study; further empirical validation is required before it can be generalized to other cryptocurrency or carbon markets. The proposed third contribution, the usability of deep learning models as transparent and accountable decision-support mechanisms in financial markets, is supported by results evaluated using standard metrics such as MAE, RMSE, MAPE, and R^2 . The GRU model's ability to generate predictions with high accuracy $R^2 > 0.99$ and $MAPE < 4\%$ for tokens such as BCT and CARBON demonstrates that such systems possess the capacity to be integrated into operational decision-making processes not only for academic purposes but also for regulatory bodies and market participants.

When evaluated in terms of its contribution to the literature, this study occupies a unique position by presenting a multivariate, deep learning-based forecasting framework for tokenized carbon credits; quantitatively revealing the level of integration between carbon markets and the crypto ecosystem through correlation structures and distributional characteristics; and empirically testing the limits of transfer learning in financial time series. The study's unique value lies in revealing the structural differences in the financialization processes of tokens, thereby creating critical awareness regarding token classification for policymakers and investors. The high correlation of 0.9886 between CARBON and BTC indicates a strong price co-movement between the two assets. While this finding suggests that CARBON's price behavior resembles that of speculative crypto assets, this correlation alone is insufficient to classify CARBON as a speculative crypto asset; additional analysis of trading motivations and the profile of market participants is required for such a classification; the fact that BCT and MCO2 move both in tandem with each other and in isolation from the main market suggests that genuine carbon credit representations follow a more balanced market dynamic. This situation provides an important analytical insight into the classification of carbon tokens for policymakers and investors.

Looking ahead, this study offers the following recommendations: (i) data augmentation techniques or hybrid models (CNN-LSTM, Transformer-based architectures) could be tested for low-liquidity tokens (KLIMA, MCO2); (ii) structural variables such as external sustainability news, KLIMA policies, or carbon market regulations could be integrated into model inputs; (iii) online learning or federated learning approaches could be tested for real-time predictions; (iv) findings could be generalized to other carbon protocols such as Toucan Protocol, C3, and Veridium to establish a comparative framework.

In conclusion, the digital financialization of carbon tokens is not merely a technological innovation but also brings about a profound transformation of market structures. This study demonstrates that by empirically mapping the dynamics of this transformation, it provides both the academic literature and sustainable finance practices with a data-driven, model-based decision-support tool. As carbon markets mature, it is anticipated that AI-driven analyses such as those in this study will play a strategic role in shaping the financial infrastructure.

Author Contributions

All processes of this study (design, data collection, analysis, writing, and editing) were carried out by Author.

Ethical Approval

This study does not require ethical committee approval.

Conflict of Interest Statement

This study contains no conflicts of interest with any individual or organization.

References

- Abiodun, T. P., Nwulu, N. I., & Olukanmi, P. O. (2024). Application of blockchain technology in carbon trading market: A systematic review. *IEEE Access*, 13, 5446-5470. <https://doi.org/10.1109/ACCESS.2024.3523672>
- Akarsu, O. N. (2025). Bitcoin Price Forecasting Using Machine Learning and Deep Learning Methods: Explaining the Most Effective Model via SHAP Analysis. In: Ok Ergün, H. & Ergün, T. (eds.), *Current Research in the Field of Digital Finance*. Özgür Publications. DOI: <https://doi.org/10.58830/ozgur.pub785.c3294>
- Alternative.me. (2025). Crypto Fear & Greed Index historical values [Data set]. <https://api.alternative.me/fng/?limit=0>, Accessed on (11/26/2025)
- Ballesteros-Rodríguez A, De-Lucio J, and Sicilia M-Á (2024). Tokenized carbon credits in voluntary carbon markets: the case of KlimaDAO. *Front. Blockchain* 7:1474540. <https://doi.org/10.3389/fbloc.2024.1474540>
- Bhattacharyya, A., Chakraborty, T., & Rai, S. N. (2022). Stochastic forecasting of COVID-19 daily new cases across countries with a novel hybrid time-series model. *Nonlinear Dynamics*, 107(3), 3025–3040. <https://doi.org/10.1007/s11071-021-07099-3>
- Büyükkantarcı Tolgay, S. (2023). *The impact of digital transformation on sustainable competitive advantage*. In C. Dumrul, Z. Kılıçarslan, & Y. Dumrul (Eds.), *Current research on digitalization and digital transformation* (pp. 73–89). Ekin Publishing House.
- Cao, H., Gu, H., & Guo, X. (2023). Feasibility of transfer learning: A mathematical framework. *arXiv preprint arXiv:2305.12985*.
- Caruana, R. (1997). Multitask learning. *Machine Learning*, 28(1), 41–75. <https://doi.org/10.1023/A:1007379606734>
- Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder–decoder for statistical machine translation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 1724–1734). Association for Computational Linguistics. <https://doi.org/10.3115/v1/D14-1179>
- Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*. <https://doi.org/10.48550/arXiv.1412.3555>
- CoinGecko. (2025). CoinGecko API. <https://www.coingecko.com/en/api>, Accessed on (11/26/2025)
- Çoban, E. (2025). Time Series-Based Temperature Forecasting for Isparta Province Using LSTM and Hybrid CNN–LSTM Deep Learning Approaches. *Uluborlu Journal of Vocational Sciences*, 8(3), 104-117. <https://doi.org/10.71445/umbd.1761095>
- Diaz-Valdivia, A., & Poblet-Balcell, M. (2025). The Governance of the ReFi Ecosystem: Integrity in Voluntary Carbon Markets as a Common Resource. *International Journal of the Commons*, 19(1).
- Ene Yalçın, S. (2025). Estimation of CO₂ Emissions in Transportation Systems Using Artificial Neural Networks, Machine Learning, and Deep Learning: A Comprehensive Approach. *Systems*, 13(3), 194. <https://doi.org/10.3390/systems13030194>

- Eylasov, N., & Çiçek, M. (2024). Forecasting Cryptocurrency Prices: A Comparison of ARIMA-GARCH and LSTM Methods. *Journal of Finance, Economics, and Social Research*, 9(1), 48-62. <https://doi.org/10.29106/fesa.1380870>
- Gautam, M. (2025). Crypto price prediction using LSTM+XGBoost. *arXiv preprint arXiv:2506.22055*.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
- Hao, J., Bao, X., Guan, S., & Jiang, G. (2023). *Transfer Prediction for the Price Volatility of Carbon Trading with Hybrid Gated Recurrent Unit*. Available at SSRN 4648762.
- He, Q. Q., Pang, P. C. I., & Si, Y. W. (2019). Transfer learning for financial time series forecasting. In *Pacific rim international conference on artificial intelligence* (pp. 24-36). Cham: Springer International Publishing.
- Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9(8), 1735–1780.
- İlhan, C., & Şahin, A. E. (2025). Evaluation of the EU Aviation Sector's Progress Towards Net-Zero CO2 Emission by 2050. *Süleyman Demirel University Visioner Journal*, 16(45), 261–277. <https://doi.org/10.21076/vizyoner.1500869>
- Kaur, R., Uppal, M., Gupta, D., Juneja, S., Arafat, S. Y., Rashid, J., ... & Alroobaea, R. (2025). Development of a cryptocurrency price prediction model: leveraging GRU and LSTM for Bitcoin, Litecoin, and Ethereum. *Peer J Computer Science*, 11, e2675.
- Kılıçarslan, Z., & Dumrul, Y. (2023). *On digitalization and its effects on the economy*. In C. Dumrul, Z. Kılıçarslan, & Y. Dumrul (Eds.), *Current research on digitalization and digital transformation* (pp. 1–27). Ekin Publishing House.
- Kotsompolis, G., Cheilas, P., Konstantakis, K. N., Sfakianakis, E., Goutte, S., & Michaelides, P. G. (2026). Smart forecasting of carbon prices using machine learning and neural networks: when ARIMA meets XGBoost and LSTM. *Journal of Forecasting*, 45(1), 47-60.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.
- Li, Y., Yang, N., Bi, G., Chen, S., Luo, Z., & Shen, X. (2025). Carbon Price Forecasting Using a Hybrid Deep Learning Model: TKMixer-BiGRU-SA. *Symmetry*, 17(6), 962. <https://doi.org/10.3390/sym17060962>
- Lin, R., Zhang, D., Ling, L., Huang, J., & Cai, G. (2023). *Transfer learning based on long short-term memory network for financial time series forecasting*. In M. Tanveer, S. Agarwal, S. Ozawa, A. Ekbal, & A. Jatowt (Eds.), *Neural information processing* (pp. 1–12). Springer. https://doi.org/10.1007/978-981-99-1645-0_1
- Mitchell, T. M. (1997). *Machine Learning*. New York: McGraw-Hill.
- Naeem, M. A., Mbarki, I., & Shahzad, S. J. H. (2021). Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. *International Review of Economics & Finance*, 73, 496-514.
- Nguyen, T.-T., & Yoon, S. (2019). A Novel Approach to Short-Term Stock Price Movement Prediction using Transfer Learning. *Applied Sciences*, 9(22), 4745. <https://doi.org/10.3390/app9224745>
- Saracık, Ö., & İncekırık, A. (2023). Stock Price Forecasting with Deep Learning Techniques. *Alphanumeric Journal*, 11(2), 137-156. <https://doi.org/10.17093/alphanumeric.1357466>

- Shen, Z., Zhang, Y., Lu, J., Xu, J., & Xiao, G. (2020). A novel time series forecasting model with deep learning: A case study on international tourism demand. *Neurocomputing*, 396, 302–313. <https://doi.org/10.1016/j.neucom.2018.12.084>
- Sorensen, D. (2023). Tokenized carbon credits: Opportunities and challenges in voluntary markets. *Ledger*, 8, 283–304. <https://doi.org/10.5195/ledger.2023.294>
- Thalhammer, F., Schöttle, P., Janetschek, M., & Ploder, C. (2022). Blockchain use cases against KLIMA destruction. *Cloud Computing and Data Science*, 3(2), 60–76. <https://doi.org/10.37256/ccds.3220221277>
- Thompson, A. (2022). Transfer learning with time series prediction: Review. SSRN. <https://doi.org/10.2139/ssrn.4214809>
- Tlili, H. (2025). Blockchain and tokenized carbon markets: Empirical evidence on market efficiency and transaction dynamics. *Sustainable Futures*, 10, 101109.
- Turing, A. M. (1987). Computing machinery and intelligence (1950). *Mind*, 59(236), 33-60.
- Wang, H., Pang, Y., & Shang, D. (2024). Carbon price fluctuation prediction using blockchain information: A new hybrid machine learning approach. *arXiv preprint arXiv:2411.02709*.
- Wang, J. N., Liu, H. C., & Hsu, Y. T. (2024). A U-shaped relationship between the crypto fear-greed index and the price synchronicity of cryptocurrencies. *Finance Research Letters*, 59, 104763.
- Yahoo Finance. (2025). Historical daily closing prices for BTC-USD, ETH-USD, KLIMA-USD, and other carbon tokens [Data set]. <https://finance.yahoo.com/> Accessed on (11/26/2025)
- Yang, F., Abedin, M. Z., Hajek, P., & Qiao, Y. (2025). Blockchain and machine learning in the green economy: Pioneering carbon neutrality through innovative trading technologies. *IEEE Transactions on Engineering Management*.
- Yousufi, M. L., & İncekırık, A. (2024). An analysis of Ethereum price forecasting in the digital economy using deep learning techniques. In GENÇLERLE 360° 10th International Student Congress / The Circular Economy in a Globalizing World – Recycling / Circular Economy in the Globalizing World (Vol. 1, (1), 58–66). Manisa Celal Bayar University. <https://genclerle360.mcbu.edu.tr/wp-content/uploads/sites/11/2025/01/01.08.-Onuncu-bildiri-kitabi.pdf>
- Zhang, X., Dou, Y., Mao, J., Liu, W., & Han, H. (2023). Carbon Price Forecasting Approach Based on Multi-Scale Decomposition and Transfer Learning. *Journal of Beijing Institute of Technology*, 32(2), 242–255.