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IMPACT OF THE LAUNCH OF CHATGPT ON AI TOKEN RETURNS AND INVESTOR PREFERENCES*

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Abstract

This study examines the impact of the launch of ChatGPT on November 30, 2022, on returns from cryptocurrency tokens based on artificial intelligence (AI) and investor behavior dynamics. The study employs Granger causality analysis to examine Bitcoin (BTC), Ethereum (ETH), and four significant AI tokens (FET, GRT, INJ, and NEAR). The empirical analysis encompasses three distinct periods: the full sample, the pre-ChatGPT launch, and the post-ChatGPT launch. Results from the pre-launch period reveal limited causal linkages, predominantly characterized by BTC's unidirectional influence on FET and internal AI token interactions. Post-launch results demonstrate intensified BTC dominance over AI tokens, including bidirectional causality between BTC and GRT and unidirectional causality from BTC to FET and NEAR. Additionally, stronger interconnectedness emerged among AI tokens, particularly bidirectional causality between FET and GRT. The study concludes that the launch of ChatGPT significantly changed the structure of the cryptocurrency market, enhancing BTC's impact on AI tokens and fostering a greater interdependence among them.

Keywords: *Artificial intelligence, ChatGPT, Bitcoin, Cryptocurrency, Granger causality, Time series analysis.*

JEL Codes: C22, G10, G23, O16

CHATGPT'NİN YAPAY ZEKÂ TOKEN GETİRİLERİ VE YATIRIMCI TERCİHLERİ ÜZERİNDEKİ ETKİSİ

Öz

Bu çalışma, 30 Kasım 2022'de ChatGPT'nin piyasaya sürülmesinin, yapay zekâ (YZ) tabanlı kripto para tokenlerinin getirileri ve yatırımcı davranış dinamikleri üzerindeki etkisini incelemektedir. Çalışma, Bitcoin (BTC), Ethereum (ETH) ve dört önemli YZ tokenini (FET, GRT, INJ ve NEAR) incelemek için Granger nedensellik analizini kullanmaktadır. Analiz, üç farklı dönemi kapsamaktadır: tüm örneklem, ChatGPT lansmanı öncesi ve ChatGPT lansmanı sonrası. Lansman öncesi dönemden elde edilen sonuçlar, sınırlı nedensel bağlantılar ortaya koymaktadır. Bu bağlantılar, ağırlıklı olarak BTC'nin FET'i ve YZ tokenleri arasındaki etkileşimleri üzerindeki tek yönlü etkisiyle karakterize edilmektedir. Lansman sonrası sonuçlar, BTC ve GRT arasındaki çift yönlü nedensellik ve BTC'den FET ve NEAR'a tek yönlü nedensellik dahil olmak üzere, YZ tokenleri üzerinde BTC'nin hakimiyetinin yoğunlaştığını göstermektedir. Ek olarak, YZ tokenleri arasında, özellikle FET ve GRT arasında çift yönlü nedensellik olmak üzere daha güçlü bir karşılıklı bağlantı ortaya çıkmıştır. Çalışma, ChatGPT'nin lansmanının kripto para piyasasının yapısını önemli ölçüde değiştirdiği, BTC'nin YZ tokenleri üzerindeki etkisini artırdığı ve aralarında daha büyük bir karşılıklı bağımlılık oluşturduğu sonucuna varmaktadır.

Anahtar kelimeler: *Yapay zekâ, ChatGPT, Bitcoin, Kripto para birimi, Granger nedenselliği, Zaman serisi analizi.*

JEL Kodları: C22, G10, G23, O16

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1. INTRODUCTION

The advent of Artificial Intelligence (AI) represents a paradigm shift in global economic productivity, fundamentally reshaping financial markets. Productivity is one of the key prerequisites for a growing economy. Productivity plays an active role in ensuring the welfare of human beings, who constitute the foundation of economic activities and underlie their formation. Productivity has existed with humanity and continues to exist alongside human beings. It undergoes its development, transformation, and even revolution together with humanity. When examining the developmental and transformational phases of humanity, it becomes evident that accomplishing more work or tasks with less energy or power has significantly influenced these phases. In other words, humanity and productivity exist in an interactive relationship that mutually supports and develops one another. Today, we are in a process where this relationship is evolving to a different point. The main actor in this process is the artificial intelligence factor. AI refers to technical or software-based agents capable of completing sophisticated activities that lie within humanity's competence set. AI, conceptually introduce by John McCarthy in 1956, is a comprehensive concept that refers to technological systems capable of executing functions requiring cognitive abilities specific to humans (Lee and Qiufan, 2021: 1). These systems incorporate complex algorithms and computational architectures designed to simulate mental processes exhibited by the human mind. These architectures systematically and methodologically derive inferences from data pools with the aim of performing cognitive functions such as modeling learning processes, reasoning through deductive and inductive methods, and developing solution strategies for complex problems (Phelan, 2025: 81). The development of the AI concept continues within a certain process following its emergence. Today, a milestone has been achieved in this process, and even those without technical knowledge can now directly communicate and interact with AI.

One of the most striking examples of this major event is ChatGPT, launched by OpenAI in late 2022. ChatGPT, as a breakthrough in natural language processing technology, has enabled human interaction with AI. Users can perform complex tasks, receive answers to their questions, and create various content through natural language without requiring technical infrastructure or programming knowledge. This interaction model is likely to bring about a revolutionary increase in productivity in accessing information, solving problems, and creative processes. Individuals use this technology in their daily lives for various purposes, such as summarizing texts, conducting research, receiving coding support, and accelerating learning processes. In terms of the democratization and accessibility of information, this development represents a leap in the historical evolution of productivity.

The finance sector is one of the areas that benefits most from this technological transformation. Financial analysts, investors, and finance professionals use large language models (LLMs) such as ChatGPT to extract meaningful insights from complex financial data, conduct risk analyses, and develop investment strategies (Arslanian and Fischer, 2019: 181; Azeema et al., 2023: 1). This new dimension of human-AI interaction provides increased efficiency in financial decision-making processes and enables faster analysis of market dynamics. Understanding algorithmic trading strategies, portfolio optimization, and developing financial risk assessment models have now become much more accessible (Azeema et al., 2023: 3; Dong et al., 2024: 4). This situation is changing the operational dynamics of financial markets and reshaping the competitive environment in the sector.

Cryptocurrency markets, being one of the areas where financial innovations are rapidly adopted and corresponding developments occur, have assumed a pioneering role in the integration of AI technologies. Cryptocurrency exchanges and trading platforms have rapidly adopted ChatGPT technology, pursuing the path of improving user experience. The inherently open structure of the decentralized finance (DeFi) ecosystem to technological innovations has prepared the ground for the rapid adoption of opportunities offered by LLMs such as ChatGPT. Cryptocurrency investors use these technologies to automate market analyses, predict price movements, and enhance their trading strategies to a better level (Azeema et al., 2023: 9; Pelster and Val, 2023: 4). Additionally, AI technologies are utilized in areas such as risk management, fraud detection, and combating money laundering (Azeema et al., 2023: 9). Particularly in cryptocurrency markets characterized by high volatility, AI-supported sentiment analysis, social media scanning, and technical indicator evaluation provide investors with competitive advantages. This rapid adaptation process reflects the innovative character of the cryptocurrency ecosystem and demonstrates that it is more open to technological transformation compared to traditional financial institutions.

Following the launch of ChatGPT, the cryptocurrency ecosystem has also made significant progress in capitalizing on this technological breakthrough. Indeed, AI-focused cryptocurrency projects have shown remarkable growth in the months following ChatGPT's launch (Saggu and Ante, 2023: 1). For instance, AI-focused projects such as The Graph (GRT), Ocean Protocol (OCEAN), Fetch.ai (FET), Injective (INJ), and Near Protocol (NEAR) have attracted investor attention and experienced significant increases in their market capitalizations. These projects aim to provide decentralized AI solutions by integrating AI technologies such as machine learning, natural language processing, and big data analytics with blockchain infrastructure.

The rapid developments in OpenAI's ChatGPT models, particularly the launch of ChatGPT-3.5 followed by the more advanced ChatGPT-4, have led to notable fluctuations in the market dynamics of AI-focused cryptocurrency projects (Almeida et al., 2024: 194). Each new model update has expanded the capacity and capabilities of AI algorithms, which has caused significant changes in the valuations of crypto assets associated with AI (Saggu and Ante, 2023: 1; Almeida et al., 2024: 192). For instance, following the launch of ChatGPT-4 in March 2023, the SingularityNET (AGIX) token gained over 200% in value within less than a month. Similarly, projects such as Fetch.ai (FET) and The Graph (GRT) also experienced significant price increases during this period. These fluctuations also reveal the paradigm shift in investor behaviors. Developments in ChatGPT and similar LLMs have strengthened investors' confidence in the potential of AI technologies and changed their risk perception toward projects in this field. The successes demonstrated by advanced AI models in real-world applications have increased speculative interest in cryptocurrency projects utilizing these technologies, triggered herd behavior regarding investment in these projects, and ultimately led to the emergence of a new investment trend called the "AI season" (Ante and Demir, 2024: 34; Ballis and Anastasiou, 2023: 169).

In this context, the fundamental motivation of our research is to systematically examine the impact of the launch and subsequent developments of ChatGPT on AI-focused cryptocurrencies. Our study aims to analyze the changes occurring in the price movements of AI crypto assets when a new ChatGPT version is made available to users by OpenAI. In parallel with this study objective, there are existing studies that directly examine the impact of ChatGPT's launch or developments in ChatGPT on AI-themed tokens from different perspectives. Among these studies, Saggu and Ante (2023) and Ante and Demir (2024) addressed the changes in AI token returns with ChatGPT's launch using synthetic difference-in-differences and event study methodologies, respectively. Similarly, Almeida and Gonçalves (2024) examined how the launch of ChatGPT-3 changed the market efficiency of AI-themed tokens. Furthermore, Ballis and Anastasiou (2023) analyzed investor attention in AI tokens with ChatGPT's launch within the framework of herd psychology. Finally, Nguyen et al. (2023) investigated volatility spillover among AI tokens with the launch of ChatGPT. In contrast to other studies, the present study examines how investors react to the mentioned ChatGPT developments, in which direction the tendency regarding investment in AI tokens evolves, and how these factors affect the performance of AI cryptocurrencies. In other words, our study analyzes the shift in investor preference toward AI tokens (AI token preferences) with ChatGPT's launch and developments in ChatGPT. Within the scope of the analysis, a causality analysis was conducted to examine how the identified AI tokens interact with each other and with coins such as Bitcoin (BTC) and Ethereum (ETH), which are the two cryptocurrencies with the highest market capitalization. In addition to this analysis, the return performances of AI tokens during and between the mentioned processes were also addressed. Our study holds a different position from other studies in terms of analytical methods and the results to be presented about the analysis of the relationship between ChatGPT and AI tokens. Therefore, it is believed that the study outputs will provide significant contributions to the mentioned literature.

2. LITERATURE REVIEW

Although there are many studies examining the relationship between AI development and financial markets, studies directly examining the relationship between ChatGPT's launch and AI tokens remain limited. In this regard, literature has focused on and examined studies that investigate the interaction between developments in AI and financial markets.

In their study, Saggu and Ante (2023) examined whether there was a return differential between AI-themed and other tokens with ChatGPT's launch. Additionally, if a return differential occurred, they investigated whether it stemmed from Google searches or media factors. Within the scope of the research, they used the synthetic difference-in-differences methodology. In the study examining data between October 1, 2022, and January 31, 2023, it was determined that AI tokens provided positive returns despite poor market conditions (bear market) with ChatGPT's launch. Accordingly, the study findings indicated that AI tokens achieved returns of 10.7% to 15.6% in a one-month period and 35.5% to 41.3% in a two-month period following ChatGPT's launch. ChatGPT's launch increased individual investor attention along with Google searches, and the increased interest was reflected in the valuations of AI tokens. However, it was concluded that the effect provided through online media (online newspapers, magazines, etc.) was not at a sufficient level and that institutional investors did not significantly contribute to the returns provided by AI tokens.

Similarly, Ante and Demir (2024) analyzed the presence of excess returns in the returns of AI-themed tokens with ChatGPT's launch. Within the scope of the analysis, data between July 1, 2022, and December 14, 2022, were utilized. In this context, price data of 10 AI-themed tokens were used, and Bitcoin price data were utilized as a fundamental indicator for comparison purposes. In this study using the event study methodology, it was stated that AI tokens achieved positive abnormal returns with ChatGPT's launch. The study findings indicated that AI tokens achieved abnormal returns of 2.71% on ChatGPT's launch day, 7.69% in a 5-day period including the launch day, 18.26% in a one-week period, and finally 41.68% in a two-week period. Additionally, it was stated that 90% of AI tokens had positive abnormal returns in the two-week period. As a result of the study, it was expressed that demand for major AI tokens increased with ChatGPT's launch, and this demand was sensitive to AI development news; in other words, AI tokens moved with their own unique sentiment and were partially affected by the market (Bitcoin prices).

In addition to these studies, Vidal-Tomás and Bartolucci (2023) investigated whether the impact of ChatGPT's launch on AI tokens (returns, increased investor attention, etc.) was temporary. Within the scope of the research, data between May 1, 2022, and May 1, 2023, were utilized. In this context, price data of tokens classified as AI by CoinGecko and AI & Big Data by CoinMarketCap, respectively, and included in these classifications were used to analyze the pre- and post-launch process of ChatGPT. In the study, the Backward Sup Augmented Dickey-Fuller test, developed by Phillips and Shi and known as the PSY method, was used to examine the bubble phenomenon. In addition to the mentioned method, the Wavelet Coherence Approach methodology was used to examine the causal relationship between AI token returns and Google trend searches. In addition to these methods, network analysis of AI tokens was also analyzed using Pearson Correlation and Minimum Spanning Tree (MST) methods. The study findings determined that ChatGPT's launch increased the returns of AI tokens in the short term, but this return increase did not show persistence in subsequent periods; therefore, ChatGPT's impact on AI token returns was temporary.

In parallel with the mentioned studies, Ballis and Anastasiou (2023) analyzed whether there was herd behavior among investors toward investment in AI tokens with ChatGPT's launch. Within the scope of the analysis, data between November 2022 and February 2023 were utilized. In this context, price data of 4 major AI cryptocurrencies (GRT, AGIX, FET, and OCEAN) were used. In this study using the Cross-Sectional Absolute Deviation (CSAD) methodology, market returns were utilized alongside the returns of the 4 AI cryptocurrencies mentioned. As a result of the study, it was emphasized that the dispersion in the returns of major AI tokens decreased with ChatGPT's launch, particularly during times when the market was in a downward direction; therefore, this situation constituted an example of herd behavior.

Almeida and Gonçalves (2024) addressed the increase in market efficiency of AI-themed tokens with ChatGPT's launch. In the study, data between November 22, 2022, which is ChatGPT's launch date, and March 31, 2024, were examined. Within the scope of the examination, data from coins classified as generative AI, AI big data, cybersecurity, and distributed computing and return data from major cryptocurrencies were utilized. Within the scope of the study analysis, the Adjusted Market Inefficiency methodology developed by Tran and Leirvik (2019) was used. The study findings determined that the market efficiency of AI-themed tokens increased with ChatGPT's launch. As a result of the study, it was stated that in a 60-day rolling window, tokens other than those in the cybersecurity classification showed efficient market characteristics, and it was expressed that those not showing market efficiency also became more efficient when the period was extended.

In their study, Wang et al. (2025) analyzed the effects of risks and errors arising from AI system-related incidents recorded by the OECD (AI Incidents Monitor - AIM) on AI-themed and other tokens. In the analysis, the launch date of ChatGPT 3.5 was used as a time-dividing period. The study analysis covers the period between January 1, 2021, and June 30, 2024, and this scope is divided into two parts: before and after ChatGPT 3.5. Regarding return analysis, price data from 30 AI-themed and 30 non-AI-themed tokens were utilized. In the study, 150,000 English news articles were scanned by the OECD for incidents involving issues such as transparency, robustness, and explainability. The GJR-GARCH model was used as the study methodology, and incident news about AI systems was used as an exogenous variable to analyze the conditional mean and variance of token returns. The study findings indicated that incidents related to AI topics that occurred and were published with the launch of ChatGPT 3.5 had an impact on AI tokens. According to the findings, it was revealed that AI incidents occurring in areas such as transparency, explainability, security, and robustness determined by the OECD created a statistically significant effect on AI token returns. Additionally, it was stated that developments in the AI field increased interest in AI tokens; this interest was significantly affected by these developments, and the effect also caused volatility in AI tokens. As a result of the study, it was noted that AI-themed token returns could be affected positively or negatively according to developing news and constitute a risk factor for investors.

In their study, Almeida et al. (2024) examined the existence of interconnectedness between sustainability-themed and AI-themed token returns. In this context, data from these themed tokens were used within the 2018-2024 data range to cover both before and after ChatGPT-3's launch. In line with the study analysis, the Time-Varying Parameter Vector Autoregression (TVP-VAR) model was utilized to examine volatility spillover between sustainability coins and AI tokens and coin return changes. A quantile-based approach was adopted in the study to analyze the interconnectedness between the mentioned tokens in a way that would encompass different market conditions. The study findings revealed the situation before and after ChatGPT-3. According to this, while sustainability tokens were in a position to influence AI tokens during bear market periods before ChatGPT-3's launch, the influence of sustainability tokens on other coins decreased after ChatGPT-3, and AI tokens came to a position where they were completely influenced by their own dynamics under all market conditions and reflected this influence on other tokens. As a result of the study, it was stated that investor attention in AI tokens increased along with AI developments, and interest in sustainability-themed coins decreased. Within the framework of this result, it was revealed that the impact of measures taken against climate change decreased specifically in the cryptocurrency market and fell to a secondary position.

Finally, Mafrur (2025) attempted to reveal whether AI-based crypto tokens truly offer a decentralized AI ecosystem. The study systematically analyzed the technical documentation and industry reports of leading AI-token projects such as RENDER, AGIX, and OCEAN, particularly examining market reactions during the 2022-2023 period when ChatGPT was launched. Within the framework of the study analysis, a qualitative comparative evaluation approach was adopted. The findings obtained in the study revealed that most AI-token platforms maintain centralized control in fundamental functions and that tokens are traded for speculative purposes rather than actual AI service usage. As a result of the study, it was stated that AI tokens are used more as speculative financial instruments, and their decentralization is questionable. Against this background, the present study aims to fill the gap by examining how the launch and subsequent developments of ChatGPT reshape investor preferences and interconnectedness among AI tokens, providing a complementary perspective beyond existing return- and volatility-focused analyses.

3. DATA AND METHODOLOGY

3.1. Data

In this study, BTC and ETH, the major cryptocurrencies, and FET, GRT, INJ, and NEAR, which have a high market capitalization and access to a wide range of price data, have been preferred. The study period is between June 1, 2021, and December 31, 2024. In this date range, two separate periods are considered, before and after the launch of ChatGPT on November 30, 2022. Figure 1 shows the time series of the price for the relevant data. The vertical red line marks the separation between the time series before and after the launch of ChatGPT.

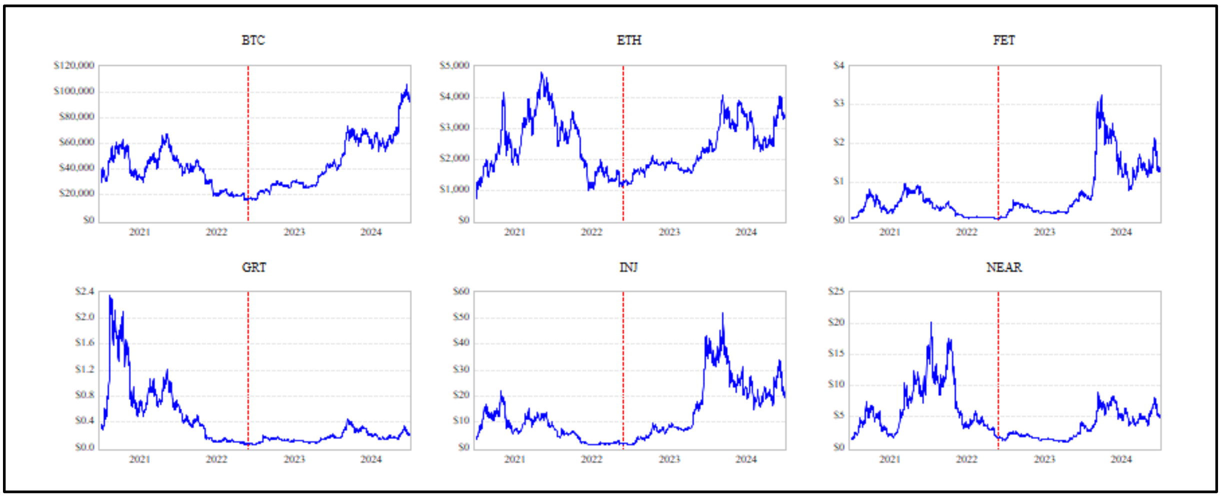

Figure 1: Time series of price data

Figure 1 shows a significant increase in BTC and ETH prices, especially at the end of 2024. BTC reached an all-time high of $108,268.45 on December 17, 2024, while ETH reached an all-time high of $4,891.70 on November 16, 2021. A similar trend of an increase in AI tokens is observed in 2024. However, for GRT, the trend diverges in the opposite direction. GRT fell by approximately 92% to $0.2347 from its highest price of $2.88 on February 12, 2021.

The dataset consists of daily prices, and logarithmic returns for each cryptocurrency are calculated as in *Equation 1*. Price data has been obtained from CoinMarketCap, a reliable source of cryptocurrency data.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where, R_t denotes the return on day *t*, P_t, denotes the price on day *t*, and P_{t-1}, denotes the price on day *t-1*. The summary of the data set in the study is presented in Table 1.

Table 1: Summary information about the cryptocurrencies and tokens used in the study

Cryptocurrencies and tokens	Symbol	Price ($)	Market cap ($)	24-hour trading volume ($)
Bitcoin	BTC	97,670.96	1,934,476,001,506	19,402,934,878
Ethereum	ETH	3,610.73	434,998,812,072	14,290,351,222
FET.ai	FET	1.46	3,573,512,019	195,834,609
The Graph	GRT	0.2347	2,241,234,735	64,131,570
Injective	INJ	22.95	2,271,259,827	107,403,876
NEAR Protocol	NEAR	5.68	6,634,205,585	231,319,411

Note: Price, market cap, and 24-hour trading volume data were obtained on January 5, 2025, at 14:00 UTC. Data sourced from CoinMarketCap (https://coinmarketcap.com/). FET.ai, in collaboration with SingularityNet and Ocean Protocol, aims to create a universal AI token, the Artificial Superintelligence Alliance (ASI).

Table 1 shows that major cryptocurrencies (BTC and ETH) and AI tokens (FET, GRT, INJ, and NEAR) have a daily trading volume of over $34 billion and a total market capitalization of over $2 trillion.

3.2. Methodology

In this study, we first conduct unit root tests (ADF and PP) for major cryptocurrencies and AI tokens. Afterwards, Vector Autoregression (VAR) model is constructed. Finally, Granger causality analysis is conducted between the variables. In this section, we provide detailed explanations about the methodologies used.

3.2.1. Unit root test

In time series analysis, it is crucial whether the series are stationary or not. Since non-stationary series may lead to misleading results, stationarity is checked by applying unit root tests in the analysis of such series (Gujarati, 2002: 792). There are many tests to determine the existence of a unit root. Among these tests, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are the most widely used (Dickey and Fuller, 1981; Phillips and Perron, 1988).

The ADF test was developed by adding lagged values of the dependent variable to the equation used in the DF test to eliminate the autocorrelation between error terms. In this study, the ADF test is applied. There are also three different versions of this test. These versions are without constant & trend, constant, and with constant term & trend. These are shown in *Equation 2*, *Equation 3*, and *Equation 4*, respectively.

Without constant & trend model:

$$\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

Constant model:

$$\Delta y_t = \mu + \theta Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

With constant & trend model:

$$\Delta y_t = \mu + \beta_t + \theta y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{4}$$

where Δy_t, is the first difference of the variable. μ is the constant term, β_t is the trend term, θ is the coefficient used to test the stationarity of the series and ε_t is the error term.

The PP test has emerged as an alternative to the ADF test. This test is more flexible against possible autocorrelation and heteroscedasticity problems of the error terms. The PP test allows the error terms to be freely distributed and uses a nonparametric method to estimate the parameters. These tests often give the same conclusions as the ADF tests and suffer from many of the same important limitations. As with the ADF test, the PP test can be performed by including constant, constant & trend or neither in the test regression (Gujarati, 2002: 818; Brooks, 2014: 364; Asteriou and Hall, 2021: 374).

3.2.2. Vector autoregression (VAR) model

If the series is stationary at all levels, the next step is estimated with VAR. The VAR model is a frequently preferred econometric method in multivariate time series analysis (Keating, 1990: 453-454). In this model, all variables are defined as endogenous, with no distinction between endogenous and exogenous variables.

VAR models present a structure in which each variable interacts not only with its own lagged values but also with the lagged values of other variables (Sims, 1980). VAR models are those in which each vector variable has a linear relationship with its lagged values and other variables. The presence of lagged values of the dependent variables in the model allows for more robust and consistent forecasts (Kumar et al., 1995: 365). The goal of VAR analysis is not to determine parameter estimates, but to determine the interrelationship among variables (Enders, 2015: 291).

The structure of VAR(*p*) models, which is a multidimensional representation of the AR(*p*) model, is similar to the AR(*p*) model structure (Brooks, 2014: 327). For the two-variable case, the values of the variable y_t over time are affected by the current and past values of the variable z_t. Similarly, the z_t variable is affected by the current and past values of y_t (Enders, 2015: 285).

The *p-th* order VAR(*p*) model with two variables is expressed as in *Equation 5* and *Equation 6*:

$$y_t = \delta_t + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=1}^{p} \beta_i z_{t-i} + \varepsilon_{yt} \tag{5}$$

$$z_t = \delta_t + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=1}^{p} \beta_i z_{t-i} + \varepsilon_{zt} \tag{6}$$

where y_t and z_t are stationary variables. ε_{yt} and ε_{zt} are white-noise error terms with standard deviations σ_y and σ_z, respectively. ε_{yt} and ε_{zt} are uncorrelated white-noise disturbances.

3.2.3. Granger causality

The Granger causality test is an econometric method commonly used to determine the causality relationship between two or more variables. This test is used to estimate the relationship between variables using a VAR model. The main purpose of the test is to analyze whether a dependent variable is affected not only by its own lagged values but also by the lagged values of other independent variables (Granger, 1969).

The Granger causality of one variable on another variable is expressed when its past values have the power to predict the current or future values of the other variable. For example, a variable y_t is said to Granger cause z_t if z_t can be predicted with greater accuracy by using past values of the y_t variable rather than not using such past values, all other terms remaining unchanged (Asteriou and Hall, 2021: 349).

The Granger causality test for the two stationary variables (y_t and z_t) involves estimating the VAR model in *Equation 5* and *Equation 6*.

The following hypotheses are tested in the Granger causality test:

H_0: Variable z_t is not the Granger cause of variable y_t.

H_1: Variable z_t is the Granger cause of variable y_t.

If the H_0 hypothesis is rejected, it is concluded that the past values of z_t make a significant contribution in explaining y_t and in this case z_t is accepted as the Granger cause of y_t.

4. EMPIRICAL FINDINGS

This section of the study analyzes the findings for both the full sample and the periods before and after the launch of ChatGPT. The findings are examined in terms of descriptive statistics, unit root test results, and Granger causality test results. In addition to these findings, the correlation matrices between the variables are presented in Appendix 1.

4.1. Findings for the full sample

This section presents the results of the analysis for the full sample. Table 1 presents the descriptive statistics and unit root test results for the variables. Panel A shows the mean, standard deviation, minimum and maximum, skewness, kurtosis, Jarque-Bera test statistic, and number of observations for major cryptocurrencies (BTC and ETH) and AI tokens (FET, GRT, INJ and NEAR). Panel B presents the ADF and PP unit root test results to test the stationarity of the series.

Table 2: Descriptive statistics and unit root test results for the full sample

	BTC	ETH	FET	GRT	INJ	NEAR
Panel A: Descriptive statistics						
Mean	0.0008	0.0010	0.0022	-0.0004	0.0011	0.0009
Std. Dev.	0.0324	0.0418	0.0716	0.0653	0.0669	0.0654
Minimum	-0.1741	-0.3175	-0.4380	-0.4870	-0.4196	-0.4436
Maximum	0.1718	0.2307	0.3614	0.4755	0.4007	0.3610
Skewness	-0.1406	-0.2945	0.2654	0.2092	-0.0123	0.0655
Kurtosis	6.4981	8.6509	6.7324	11.8592	6.7564	7.7902
Jarque-Bera	749.71***	1,965.04***	865.18***	4,788.41***	859.01***	1,397.91***
N	1,461	1,461	1,461	1,461	1,461	1,461
Panel B: Unit root test						
ADF	-39.3947***	-39.7290***	-40.5931***	-39.0714***	-40.6421***	-39.4151***
PP	-39.3768***	-39.6993***	-40.5465***	-39.0726***	-40.6430***	-39.3965***

Note: ADF stands for Augmented Dickey Fuller test, and PP stands for Phillips-Perron test. Constant models are used in ADF and PP tests. ***, indicate statistical significances at 1% level. All statistics consist of 1,461 observations.

Panel A provides important information about cryptocurrencies. The results show that the INJ token has the highest average return (0.11%), while the GRT token has the lowest average return (-0.04%). Moreover, only the GRT token has a negative average return. The standard deviation results show that major cryptocurrencies have a lower volatility than AI tokens; therefore, they indicate lower risk. The maximum and minimum changes show that the GRT token has both the highest (47.55%) and the lowest (-48.70%) range of variation. The results of the Jarque-Bera test reveal that the variables do not satisfy the assumption of normal distribution.

In Panel B, ADF and PP test results show that the series of each cryptocurrency are stationary. Once we have established the stationary nature of the series, the VAR(2) model is the most appropriate model for the period before the launch of ChatGPT. Table 3 presents Granger causality results for the full sample.

Table 3: Granger causality results for the full sample

Variables	χ^2	Prob.
ETH => BTC	5.9177*	0.0519
BTC => ETH	1.0189	0.6008
FET => BTC	0.5780	0.7490
BTC => FET	5.7842*	0.0555
GRT => BTC	2.2748	0.3206
BTC => GRT	3.5968	0.1656
INJ => BTC	0.0742	0.9636
BTC => INJ	1.0486	0.5920
NEAR => BTC	0.2442	0.8851
BTC => NEAR	1.2380	0.5385
FET => ETH	0.4458	0.8002
ETH => FET	0.7595	0.6840
GRT => ETH	0.8089	0.6673
ETH => GRT	1.1788	0.5547
INJ => ETH	1.5729	0.4555
ETH => INJ	0.6676	0.7162
NEAR => ETH	1.7086	0.4256
ETH => NEAR	1.1577	0.5605
GRT => FET	4.2084	0.1219
FET => GRT	17.5842***	0.0002
INJ => FET	1.1849	0.5530
FET => INJ	0.1656	0.9205
NEAR => FET	3.7231	0.1554
FET => NEAR	3.9721	0.1372
INJ => GRT	0.5397	0.7635
GRT => INJ	0.8459	0.6551
NEAR => GRT	5.5810*	0.0614
GRT => NEAR	4.1401	0.1262
NEAR => INJ	0.0909	0.9556
INJ => NEAR	0.6374	0.7271

*, **, and *** indicate statistical significances at 10%, 5%, and 1% levels, respectively.

The Granger causality test results for the full sample show that there are significant findings between major cryptocurrencies and AI tokens. Among the major cryptocurrencies, there is a significant unidirectional Granger causality from ETH to BTC. This result suggests that BTC's return can be predicted by looking at ETH's return. On the other hand, there is no causality from BTC to ETH. In other words, it can be said that ETH cannot be predicted by looking at BTC's return.

Among BTC and AI tokens, there is a significant unidirectional Granger causality from BTC to FET. Accordingly, it is seen that FET can be predicted by looking at the return of BTC. However, there is no significant causality relationship between BTC and other AI tokens. Similarly, there is no statistically significant Granger causality between ETH and AI tokens.

Among the AI tokens, there is a significant unidirectional Granger causality from FET to GRT and from NEAR to GRT. These results suggest that GRT can be predicted by looking at the returns of FET and NEAR. There is no statistically significant Granger causality among other AI tokens. The causality relationship is shown in Figure 2.

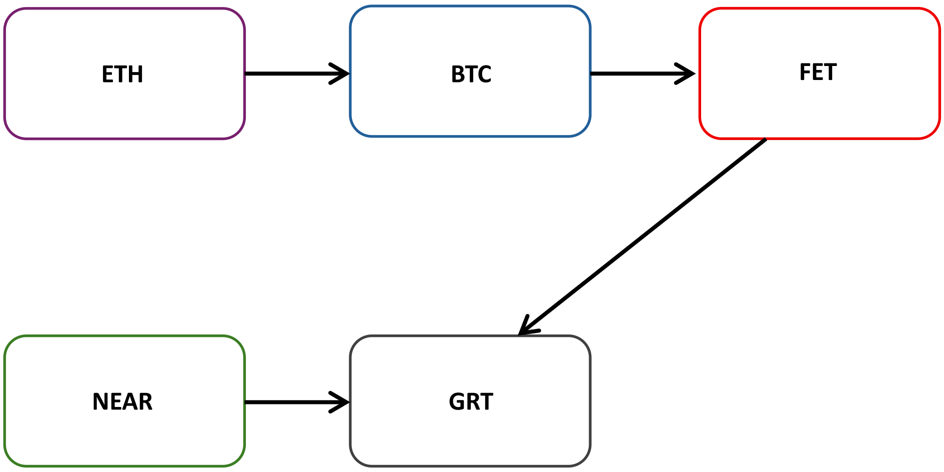

Figure 2: Granger causality analysis: Full sample

4.2. Findings for before the launch of ChatGPT

This section presents the results of the analysis of the before the launch of ChatGPT. Table 4 shows the descriptive statistics and unit root test results.

Table 4: Descriptive statistics and unit root test results before the launch of ChatGPT

	BTC	ETH	FET	GRT	INJ	NEAR
Panel A: Descriptive statistics						
Mean	-0.0008	0.0008	0.0003	-0.0024	-0.0012	0.0003
Std. Dev.	0.0388	0.0522	0.0782	0.0763	0.0764	0.0778
Minimum	-0.1741	-0.3175	-0.4380	-0.4870	-0.4196	-0.4436
Maximum	0.1718	0.2307	0.3614	0.4755	0.4007	0.3610
Skewness	-0.2390	-0.3912	-0.0030	-0.1385	-0.1836	-0.0698
Kurtosis	5.5009	6.7283	6.8417	10.1879	6.8616	6.7892
Jarque-Bera	188.81***	422.68***	429.84***	1,507.00***	438.25***	418.74***
N	699	699	699	699	699	699
Panel B: Unit root test						
ADF	-27.3002***	-27.3678***	-28.1373***	-26.7587***	-29.0629***	-26.8645***
PP	-27.2863***	-27.3556***	-28.0964***	-26.7620***	-29.1965***	-26.8645***

Note: ADF stands for Augmented Dickey Fuller test, and PP stands for Philipps Perron test. Constant models are used in ADF, and PP tests. ***, indicate statistical significances at 1% level. All statistics consist of 699 observations.

Panel A presents descriptive statistics for major cryptocurrencies and AI tokens in the period before the launch of ChatGPT (from June 1, 2021, to November 30, 2022). Analyzing the average returns, BTC (-0.08%), GRT (-0.24%), and INJ (-0.12%) have negative average returns, while the others exhibit positive average returns. The standard deviation shows that major cryptocurrencies have lower volatility compared to AI tokens, indicating that these are less risky. The minimum and maximum return show that GRT exhibits the highest variation. The results of the Jarque-Bera test reveal that the variables do not satisfy the assumption of normal distribution.

In Panel B, ADF and PP test results show that the series of each cryptocurrency are stationary. Once we have established the stationary nature of the series, the VAR(2) model is the most appropriate model for the period before the launch of ChatGPT. Table 5 presents the Granger causality results for the period before the launch of ChatGPT.

Table 5: Granger causality results for the sample period before the launch of ChatGPT

Variables	χ^2	Prob.
ETH => BTC	2.0270	0.1545
BTC => ETH	1.9097	0.1670
FET => BTC	1.0107	0.3147
BTC => FET	13.7962***	0.0002
GRT => BTC	0.1388	0.7095
BTC => GRT	0.0538	0.8166
INJ => BTC	0.1610	0.6882
BTC => INJ	1.5193	0.2177
NEAR => BTC	0.0988	0.7533
BTC => NEAR	0.6564	0.4178
FET => ETH	0.7901	0.3741
ETH => FET	2.5269	0.1119
GRT => ETH	0.0542	0.8159
ETH => GRT	0.9149	0.3388
INJ => ETH	2.3785	0.1230
ETH => INJ	0.1679	0.6820
NEAR => ETH	0.0000	0.9982
ETH => NEAR	0.8626	0.3530
GRT => FET	0.0245	0.8757
FET => GRT	0.6379	0.4245
INJ => FET	3.3760*	0.0662
FET => INJ	0.2827	0.5950
NEAR => FET	8.5463***	0.0035
FET => NEAR	2.1268	0.1447
INJ => GRT	0.7383	0.3902
GRT => INJ	0.0000	0.9950
NEAR => GRT	0.7696	0.3803
GRT => NEAR	1.5448	0.2139
NEAR => INJ	0.1843	0.6677
INJ => NEAR	1.5787	0.2089

*, **, and *** indicate statistical significances at 10%, 5%, and 1% levels, respectively.

The Granger causality test results for ChatGPT before its launch show that there is no causal relationship between the major cryptocurrencies. This means that BTC's return cannot be predicted by ETH by looking at BTC's return, and BTC's return cannot be predicted by looking at ETH.

Among BTC to AI tokens, there is a significant unidirectional Granger causality from BTC to FET. This suggests that FET can be predicted by looking at BTC's return. There is no significant causality between BTC and ETH and other AI tokens.

Among AI tokens, there is a significant unidirectional Granger causality from INJ to FET and from NEAR to FET. According to these results, the returns of FET can be predicted by looking at the returns of INJ and NEAR. There is no statistically significant Granger causality between the other AI tokens. The causality relationship is shown in Figure 3.

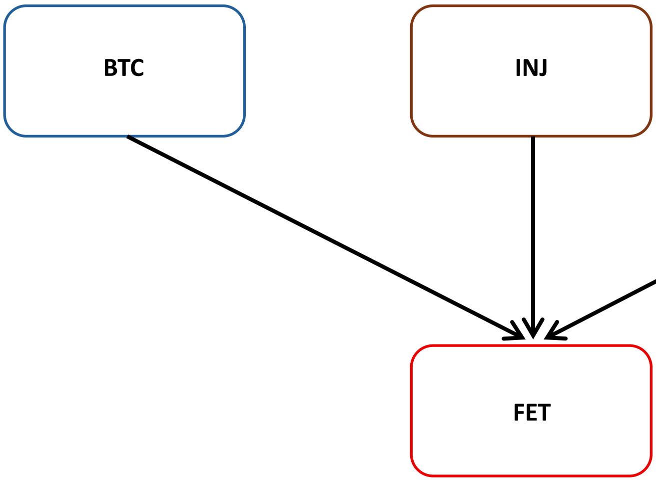

Figure 3: Granger causality analysis: Before the launch of ChatGPT

4.3. Findings for after the launch of ChatGPT

In this section of the study, we finally analyze the results after the launch of ChatGPT. Table 6 shows the descriptive statistics and unit root results after the launch of ChatGPT.

Table 6: Descriptive statistics and unit root test results after the launch of ChatGPT

	BTC	ETH	FET	GRT	INJ	NEAR
Panel A: Descriptive statistics						
Mean	0.0022	0.0012	0.0039	0.0015	0.0032	0.0014
Std. Dev.	0.0250	0.0292	0.0650	0.0532	0.0568	0.0514
Minimum	-0.0871	-0.1081	-0.2587	-0.1818	-0.1921	-0.1775
Maximum	0.1146	0.1762	0.3326	0.4675	0.2065	0.3218
Skewness	0.4748	0.4416	0.7222	1.2254	0.4616	0.5211
Kurtosis	5.3990	6.5914	5.8142	11.8646	4.2041	6.3394
Jarque-Bera	211.35***	434.28***	317.68***	2,685.65***	73.10***	388.56***
N	762	762	762	762	762	762
Panel B: Unit root test						
ADF	-28.3624***	-28.8026***	-29.2095***	-28.7307***	-27.7055***	-29.2495***
PP	-28.3519***	-28.8026***	-29.1882***	-28.7154***	-27.7286***	-29.2155***

Note: ADF stands for Augmented Dickey Fuller test, and PP stands for Philipps Perron test. Constant models are used in ADF, and PP tests. ***, indicate statistical significances at 1% level. All statistics consist of 762 observations.

Panel A presents descriptive statistics for major cryptocurrencies and AI tokens after the launch of ChatGPT (from December 1, 2022, to December 31, 2024). Accordingly, both major cryptocurrencies and AI tokens all exhibit positive average returns. Among AI tokens, FET (0.39%) and INJ (0.32%) have the highest returns, while among major cryptocurrencies, BTC (0.22%) has the highest average return. All cryptocurrencies and AI tokens exhibited positive returns during this period, indicating a positive performance for investors. Major cryptocurrencies have lower standard deviation values than AI tokens. This indicates that major cryptocurrencies are lower risk. At the same time, AI tokens are characterized by higher volatility and therefore higher risk. In terms of maximum and minimum daily returns, GRT (46.75%) registered the highest return, while FET (-25.87%) registered the lowest return. The results of the Jarque-Bera test reveal that all series do not follow a normal distribution.

In Panel B, ADF and PP test results show that the series of each cryptocurrency are stationary. Once we have established the stationary nature of the series, the VAR(2) model is the most appropriate model for the period before the launch of ChatGPT. Table 3 presents Granger causality results for the full sample. Table 7 presents the Granger causality results for the period after the launch of ChatGPT.

Table 7: Granger causality results for the sample period after the launch of ChatGPT

Variables	χ^2	Prob.
ETH => BTC	1.6207	0.4447
BTC => ETH	4.9343*	0.0848
FET => BTC	0.1711	0.9180
BTC => FET	6.8858**	0.0320
GRT => BTC	6.1586**	0.0460
BTC => GRT	9.4983***	0.0087
INJ => BTC	3.2609	0.1958
BTC => INJ	3.8806	0.1437
NEAR => BTC	0.1402	0.9323
BTC => NEAR	5.1064*	0.0778
FET => ETH	1.3024	0.5214
ETH => FET	4.2142	0.1216
GRT => ETH	4.9701*	0.0833
ETH => GRT	2.6263	0.2690
INJ => ETH	3.1269	0.2094
ETH => INJ	0.6971	0.7057
NEAR => ETH	0.3099	0.8565
ETH => NEAR	0.8953	0.6391
GRT => FET	11.8933***	0.0026
FET => GRT	15.0645***	0.0005
INJ => FET	9.5688***	0.0084
FET => INJ	0.1733	0.9170
NEAR => FET	1.8748	0.3917
FET => NEAR	1.3182	0.5173
INJ => GRT	1.7173	0.4237
GRT => INJ	2.0584	0.3573
NEAR => GRT	1.2909	0.5244
GRT => NEAR	3.3740	0.1851
NEAR => INJ	0.1239	0.9399
INJ => NEAR	2.9287	0.2312

*, **, and *** indicate statistical significances at 10%, 5%, and 1% levels, respectively.

The Granger causality test results for the period after the launch of ChatGPT provide important insights into the relationship between major cryptocurrencies and AI tokens. Among major cryptocurrencies, there is a one-way Granger causality from BTC to ETH.

Analyzing the relationship between major cryptocurrencies and AI tokens, there is no Granger causality from ETH to any AI tokens. However, there is a unidirectional Granger causality from GRT to ETH. BTC has a more pronounced impact on AI tokens. There is a unidirectional Granger causality from BTC to FET and NEAR and a bidirectional Granger causality between BTC and GRT. These results reveal the impact of BTC on AI tokens after the launch of ChatGPT.

Analyzing the relationships between AI tokens, there is a bidirectional Granger causality between GRT and FET. This shows that there is a mutual and strong interaction between these two AI tokens. Moreover, there is a one-way Granger causality from INJ to FET. However, there is no significant Granger causality relationship between the other AI tokens.

In conclusion, it is notable that there is a significant Granger causality of BTC on AI tokens in the period after the launch of ChatGPT, and in particular a Granger causality relationship between BTC and GRT and FET. Similarly, in the relationships between AI tokens, FET and GRT have been found to affect each other in a bidirectional. The causality relationship is shown in Figure 4.

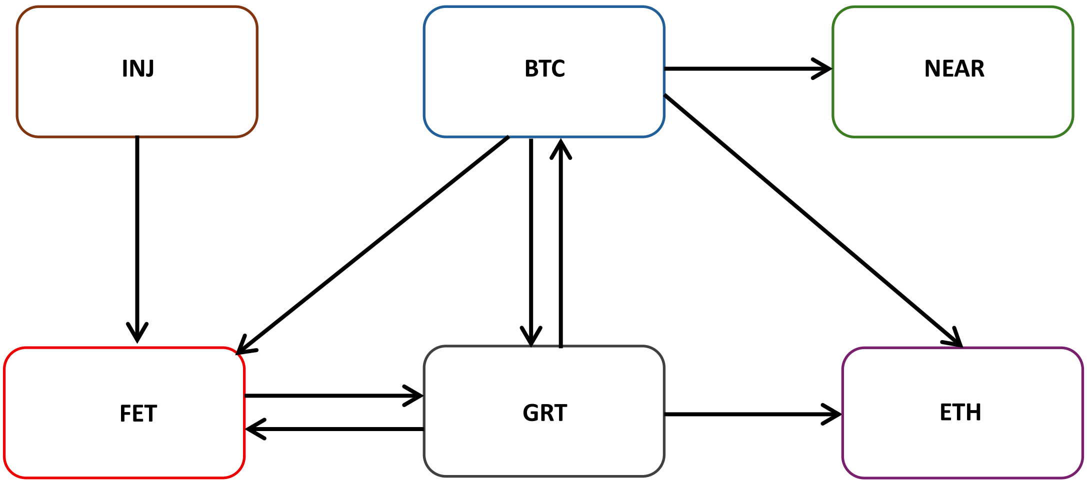

Figure 4: Granger causality analysis: After the launch of ChatGPT

5. CONCLUSION AND DISCUSSION

This study analyzes the relationship between the launch of ChatGPT and the returns of major cryptocurrencies (BTC and ETH) and AI tokens (FET, GRT, INJ, and NEAR). Additionally, causality analysis is performed to determine the direction of investor preferences between major cryptocurrencies and the specified AI tokens, as well as among the AI tokens themselves. In the study, the full sample and the periods before and after the launch of ChatGPT were examined separately. Using Granger causality methodology, we have analyzed how the launch of ChatGPT has affected the dynamics of AI tokens. Our findings provide important insights into the evolving structure of the cryptocurrency market and reveal the impact of AI-driven innovations on investor behavior and markets, aligning with the growing body of literature that examines technological disruptions in cryptocurrency markets.

The empirical results delineate distinct structural shifts in the relationships between major cryptocurrencies and AI tokens in the periods before and after the launch of ChatGPT, which is consistent with previous research demonstrating the transformative impact of AI developments on digital asset markets. In the period before the launch, the market exhibited relatively higher volatility and a weaker relationship between major cryptocurrencies and AI tokens. During this period, a unidirectional Granger causality relationship has been detected from BTC to FET, INJ to FET, and NEAR to FET. This finding suggests that before ChatGPT's launch, AI tokens were primarily driven by systematic market risk rather than idiosyncratic, AI-specific factors. This supports the idea that AI tokens were not yet a separate asset class with characteristics.

On the other hand, after the launch of ChatGPT, the impact of BTC on AI tokens has become significantly more pronounced, especially due to its market leadership. The analysis reveals that there is a unidirectional Granger causality relationship from BTC to ETH, BTC to FET, and BTC to NEAR, as well as a bidirectional Granger causality relationship between BTC and GRT. These findings suggest that BTC has had a significant impact on AI tokens following the launch of ChatGPT, which aligns with Ante and Demir's (2024) observation that AI tokens became partially affected by the market (Bitcoin prices) while developing their own unique sentiment following ChatGPT's launch. This increased Bitcoin dominance in the AI token space supports the literature's findings that major cryptocurrencies continue to serve as fundamental indicators for the broader cryptocurrency market, even as specialized sectors emerge (Ante and Demir, 2024).

Our results corroborate Saggu and Ante’s (2023) findings that ChatGPT’s launch significantly increased individual investor attention in AI tokens, leading to substantial positive returns despite poor market conditions. The strengthened causal relationships we observed between Bitcoin and AI tokens in the post-ChatGPT period support their conclusion that increased investor attention was reflected in the valuations of AI tokens. Similarly, our findings are consistent with Almeida et al.’s (2024) research, which demonstrated that after ChatGPT-3’s launch, AI tokens developed a position where they were completely influenced by their own dynamics under all market conditions while reflecting this influence on other tokens.

Furthermore, when the relationships between AI tokens are analyzed, it is seen that there is a idirectional Granger causality relationship between FET and GRT. This suggests that there is a mutual relationship between these two AI tokens, indicating the emergence of intrasectoral dynamics within the AI token ecosystem. Moreover, a unidirectional Granger causality relationship has been found from INJ to FET. This suggests that FET has an increasing market impact among AI tokens, which may reflect its growing recognition as a leading AI token platform. These inter-token relationships support Ballis and Anastasiou’s (2023) findings regarding the emergence of herd behavior among investors toward AI token investments following ChatGPT’s launch, particularly during market downturns when the dispersion in returns of major AI tokens narrowed.

The temporal analysis of our study also provides evidence that contradicts Vidal-Tomás and Bartolucci’s (2023) conclusion that ChatGPT’s impact on AI token returns was temporary. Our findings suggest that the structural changes in causality relationships between major cryptocurrencies and AI tokens have persisted beyond the immediate post-launch period, indicating a more fundamental shift in market dynamics rather than a temporary phenomenon.

Furthermore, our results support Wang et al.’s (2025) assertion that developments in the AI field significantly affect AI token returns and create volatility in the market. The strengthened causality relationships we observed following ChatGPT’s launch suggest that AI tokens have become increasingly sensitive to AI-related developments, confirming that these tokens are significantly influenced by technological advancements in the AI sector.

The evolution of market structure revealed in our study also aligns with Almeida and Gonçalves’ (2024) findings regarding the increased market efficiency of AI-themed tokens following ChatGPT’s launch. The more defined causality relationships we observed in the post-ChatGPT period suggest that the AI token market has developed more structured interconnections, potentially contributing to improved market efficiency.

In conclusion, this study demonstrates that ChatGPT's launch acted as a structural break, fundamentally altering the dynamics that fundamentally altered the dynamics of the cryptocurrency market, particularly in the relationship between major cryptocurrencies and AI tokens. The emergence of stronger and more complex causality relationships in the post-ChatGPT period suggests that AI tokens have evolved from being merely speculative instruments to becoming a distinct asset class with its own market dynamics, while still maintaining significant connections to broader cryptocurrency market movements. These findings contribute to the understanding of how technological innovations can reshape financial market structures and provide valuable insights for investors, policymakers, and researchers interested in the intersection of AI and cryptocurrency markets.

Disclosure Statements (Beyan ve Açıklamalar)

1. The authors of this article confirm that their work complies with the principles of research and publication ethics (Bu çalışmanın yazarları, araştırma ve yayın etiği ilkelerine uyduğunu kabul etmektedirler).

2. No potential conflict of interest was reported by the authors (Yazarlar tarafından herhangi bir çıkar çatışması beyan edilmemiştir).

3. This article was screened for potential plagiarism using a plagiarism screening program (Bu çalışma, intihal tarama programı kullanılarak intihal taramasından geçirilmiştir).

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APPENDIX

Appendix 1: Correlation matrices

	BTC	ETH	FET	GRT	INJ	NEAR
Panel A: Correlation matrix for full sample						
BTC	1.0000					
ETH	0.8181***	1.0000				
FET	0.5538***	0.5798***	1.0000			
GRT	0.6377***	0.6559***	0.6232***	1.0000		
INJ	0.5715***	0.6156***	0.5320***	0.5720***	1.0000	
NEAR	0.5937***	0.6191***	0.5664***	0.6179***	0.5447***	1.0000
Panel B: Correlation matrix before launch of ChatGPT						
BTC	1.0000					
ETH	0.8234***	1.0000				
FET	0.5873***	0.6213***	1.0000			
GRT	0.6506***	0.6641***	0.5877***	1.0000		
INJ	0.5677***	0.6380***	0.5249***	0.5620***	1.0000	
NEAR	0.5774***	0.6147***	0.5706***	0.5990***	0.5180***	1.0000
Panel C: Correlation matrix after launch of ChatGPT						
BTC	1.0000					
ETH	0.8126***	1.0000				
FET	0.5066***	0.5286***	1.0000			
GRT	0.6117***	0.6485***	0.6844***	1.0000		
INJ	0.5809***	0.5838***	0.5437***	0.5895***	1.0000	
NEAR	0.6299***	0.6360***	0.5689***	0.6563***	0.5974***	1.0000

*** indicate statistical significance at 1% levels.