Correlation Between Gas Prices and Transaction Value in Ethereum Blockchain

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ABSTRACT

This study examines the relationship between gas prices and transaction values on the Ethereum blockchain, providing a detailed analysis of transaction dynamics and the factors influencing gas price determination. The correlation coefficient between gas prices and transaction values is -0.0273, indicating a very weak and negative relationship. Instead, gas prices are driven by factors such as computational intensity, network congestion, and user prioritization. Functions with higher computational demands, such as mint, recorded the highest mean gas price of 120.45 Gwei, with a standard deviation of 15.30 Gwei, while functions like approve and transfer exhibited mean gas prices of 98.30 Gwei and 110.80 Gwei, respectively. Recipient address analysis reveals a strong concentration of transaction values, with the top recipient address receiving 49.95 ETH consistently, indicating high-value operations directed toward specific accounts. High-gas transactions, defined as those above the 90th percentile, displayed a mean gas price of 191.96 Gwei with minimal variability, while their corresponding transaction values varied widely, with a mean of 23.91 ETH and a standard deviation of 13.66 ETH. These findings provide critical insights into Ethereum transaction behavior, emphasizing the role of function type and user prioritization in shaping gas price decisions. Future research should investigate the impact of network upgrades such as EIP-1559, the adoption of Layer-2 scaling solutions, and temporal trends in transaction behavior to enhance network scalability and cost efficiency as Ethereum continues to evolve.

Keywords Ethereum Gas Fees, Transaction Prioritization, Blockchain Economics, Gas Price Optimization, Smart Contract Execution

INTRODUCTION

The Ethereum blockchain, introduced in 2015, has transformed decentralized technology by enabling the execution of smart contracts and Decentralized Applications (dApps) [1]. At the heart of Ethereum's functionality is its gas fee mechanism, which ensures the network's security and efficiency [2]. Gas fees, paid in Gwei (1 Gwei = 10^{-9} ETH), compensate validators (or miners) for processing transactions and executing operations [3]. These fees are dynamic and fluctuate based on factors such as network congestion, transaction priority, and computational complexity. Understanding the determinants of gas prices is critical for optimizing Ethereum's usability and efficiency, particularly as the blockchain scales to accommodate increasing transaction volumes [4]. Gas fees are determined by the product of gas price, the cost per unit of computation, and gas limit, the maximum computational work a transaction can consume. While computational complexity and network conditions are well-established drivers of gas prices, the relationship between gas prices and transaction values remains ambiguous [5]. Intuitively, higher-value transactions might be expected to incur higher gas prices due to users' willingness to prioritize speed or reliability. However, other factors, such as the type of transaction, its urgency,

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and the complexity of its execution, may play a more significant role in determining gas prices, irrespective of the monetary value involved.

Transaction values in Ethereum transactions encompass a wide range of activities, from simple ETH transfers to complex interactions with smart contracts, including token approvals, liquidity provision, and NFT minting [6]. Each type of transaction has distinct computational requirements and priorities, further complicating the relationship between gas prices and transaction values. For example, computationally intensive operations like mint demand higher gas prices, while routine transfers are less resource-intensive. Additionally, high-value transactions are often directed to a small number of prominent accounts, such as decentralized exchanges or automated market makers, suggesting a degree of economic centralization in the Ethereum network [7]. This study seeks to analyze the relationship between gas prices and transaction values on the Ethereum blockchain, with a focus on the factors driving gas price determination. The research aims to address several key questions: the extent to which gas prices correlate with transaction values, the impact of transaction types on gas price variability, the role of high-value recipient accounts, and user behavior in high-gas scenarios, particularly during periods of network congestion. By examining a dataset of Ethereum transactions, this study uncovers critical patterns and insights into transaction behavior, computational requirements, and the prioritization of network resources. The findings of this research provide a comprehensive understanding of Ethereum transaction dynamics, highlighting the weak correlation between gas prices and transaction values, the influence of function complexity, and the economic centralization of high-value transactions. These insights are not only valuable for improving gas price optimization and user experience but also for addressing broader scalability challenges through network upgrades and Layer-2 scaling solutions. This study aims to contribute to the growing body of knowledge on blockchain economics, offering practical implications for developers, users, and policymakers navigating the complexities of the Ethereum ecosystem.

Literature Review

The Ethereum blockchain relies on a gas mechanism to execute transactions and smart contracts. Gas fees, determined by the gas price and gas limit, ensure efficient resource allocation and protect against spam. EIP-1559 introduced a base fee model with dynamic adjustments to improve fee predictability and reduce volatility. Studies such as Reijsbergen et al. [8] found that while EIP-1559 improves average user experience, short-term demand spikes still cause variability. Koutmos [9] highlighted that network activity, particularly transaction volume, is a primary determinant of gas price changes . User behavior in transaction prioritization reflects strategic considerations, such as urgency and cost-efficiency. High-value transactions often involve elevated gas fees to secure timely execution, particularly during congestion. Werner et al. [10] proposed a deep-learning model for gas price recommendations, reducing costs by over 50% while maintaining minimal delays. Butler and Crane [11] extended this work by integrating machine learning models such as LSTM and CNN for more accurate gas price forecasting, enabling users to optimize their costs during network activity peaks.

Ferenczi and Bădică [12] applied the DeepAR probabilistic forecasting model, demonstrating its superior accuracy for predicting gas price trends by integrating blockchain data with time-series forecasting methods. These advancements underscore the potential of predictive technologies in mitigating transaction delays and fee overpayments. The computational requirements of Ethereum transactions vary significantly by function type, influencing gas consumption. Wang et al. [13] analyzed gas price prediction using LSTM and GRU models, demonstrating their effectiveness in forecasting gas fees for complex operations like token minting compared to simpler functions like transfers. Afzal Khan et al. [14] performed a regression analysis on Solidity-based smart contracts, identifying patterns that increase gas costs and providing insights for developers to create gas-optimized contracts

Economic activity in Ethereum is highly centralized, with transaction volume dominated by high-value accounts, such as decentralized exchanges and liquidity pools. Ante and Saggu [15] examined the bidirectional causal relationships between gas fees and economic activity in DeFi platforms, revealing that congestion on these platforms significantly affects gas prices and user activity. Bai et al. [16] studied Ethereum's transaction patterns from a temporal graph perspective, observing that a small number of accounts disproportionately influence network activity and fee structures. High-gas transactions, often conducted during congestion, provide insights into prioritization strategies and network stress. Pacheco et al. [17] quantified the relationship between gas prices and transaction processing times, showing diminishing returns for very high gas fees. Lan et al. [18] explored the impact of EIP-1559 on transaction predictability, proposing machine learning models that incorporate mempool data for improved gas price forecasts.

Scalability challenges have driven interest in Layer-2 solutions like rollups and sharding. These technologies aim to reduce congestion and gas costs by offloading transactions from the Ethereum base layer, enhancing overall network performance. Liu et al. [19] proposed a regression-based gas price prediction model, highlighting its potential to reduce transaction costs while maintaining fast confirmations. Despite extensive research, the relationship between gas prices and transaction values remains underexplored. Existing studies often focus on isolated factors such as network congestion, transaction complexity, or economic centralization without examining their combined effects. This study addresses these gaps by analyzing the interplay between gas prices and transaction values, incorporating transaction types, high-gas scenarios, and recipient activity. By bridging these gaps, this research contributes to a nuanced understanding of Ethereum transaction dynamics and offers actionable insights for optimizing gas fees in blockchain ecosystems.

Method

This study employs a quantitative research approach to explore the relationship between gas prices and transaction values on the Ethereum blockchain. The dataset comprises 1,000 Ethereum transaction records sourced from publicly accessible APIs, such as Etherscan, and includes key variables such as Gas Price (Gwei), Value Transferred (ETH), Gas Used, Function Called, and Recipient Address. These attributes were selected to provide a comprehensive basis for analyzing transaction dynamics and uncovering patterns influencing gas prices. Figure 1 illustrates the overall research steps, outlining the process from dataset collection through data preprocessing, analysis techniques, and visualization to achieve comprehensive insights.

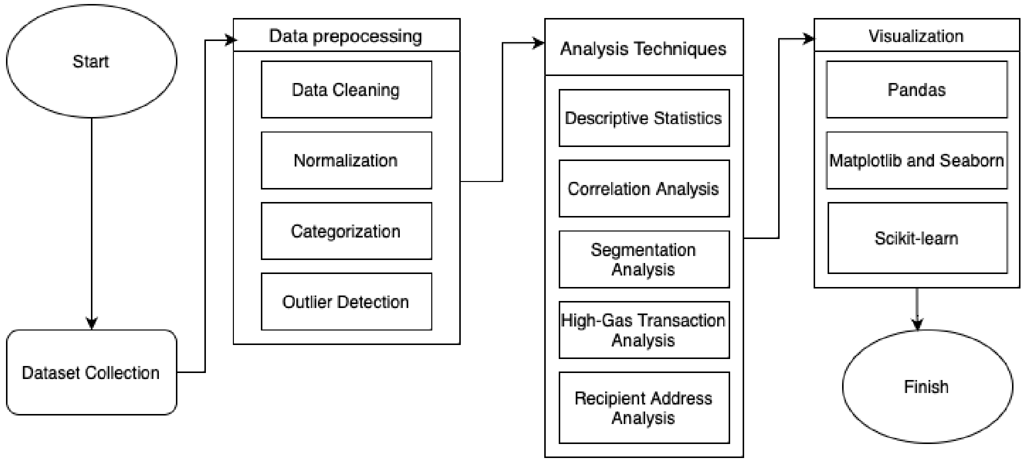

Figure 1 **Research Step**

The dataset underwent preprocessing to ensure reliability and consistency. Missing or inconsistent data entries were excluded, and all gas prices and transaction values were converted into consistent units: gas prices in Gwei and transaction values in ETH. To manage data variability, transactions were segmented into categories based on their function types (e.g., mint, approve, transfer) and grouped into value ranges for comparative analysis. Outliers were addressed using the Interquartile Range (IQR) method, calculated as [20]:

$$IQR = Q3 - Q1, \tag{1}$$

$Q1$ represents the 25th percentile and $Q3$ the 75th percentile. Transactions outside the range:

$$[Q1 - 1.5 \times IQR, Q3 + 1.5 \times IQR], \tag{2}$$

Were flagged as outlined and addressed to ensure robust statistical outcomes.

The analysis incorporated multiple statistical and computational techniques to identify trends and relationships within the data. Descriptive statistics, such as the mean (μ) , standard deviation (σ)

and median were calculated using the following formulas [21], [22]:

$$\mu = \frac{\sum X_i}{n}, \tag{3}$$

X_i represents individual data points and n is the total number of observations.

$$\sigma^2 = \frac{\sum (X_i - \mu)^2}{n}, \tag{4}$$

σ^2 providing insight info data dispersion.

$$\sigma = \sqrt{\sigma^2}. \tag{5}$$

To quantify the relationship between gas prices and transaction values, the Pearson Correlation Coefficient (r) was calculated using [23]:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2(Y_i - \bar{Y})^2}} \tag{6}$$

X_i and Y_i represent gas price and transaction value, respectively, and $\bar{X}$ and $\bar{Y}$ are their means. A value of r close to zero indicates a weak relationship, while values near −1 or +1 suggest strong negative or positive correlations.

Transactions were segmented by function type to analyze variations in gas price and value. Box plots were used to illustrate differences in gas price distributions across function categories. High-gas transactions were analyzed separately, defined as transactions exceeding the 90th percentile of gas prices (P_{90}), calculated as:

$$(P_{90}) = Gas\ Price\ Percentile\ (90th) \tag{7}$$

For high-gas transactions, descriptive statistics were recalculated to identify behavioral patterns during network congestion.

Transactions were grouped by recipient address to identify patterns of value concentration. The total transaction value received by each address (V_{total}) was computed as:

$$V_{total} = \sum_{i=1}^{n} V_{i,} \tag{8}$$

V_i represents the value of each transaction directed to a recipient, and n is the number of transactions for that address. The mean transaction value V_{mean} was calculated using:

$$V_{mean} = \frac{V_{total}}{n}. \tag{9}$$

This analysis provided insights into the economic centralization of transaction activity and its impact on gas price trends.

Visualization tools were employed to enhance data interpretation. Scatter plots depicted the relationship between gas prices and transaction values, while box plots highlighted variations across transaction functions. Bar charts visualized the distribution of transaction values among recipient addresses, and histograms illustrated the frequency of gas prices and transaction values. The algorithm 1 outlines the step-by-step quantitative procedure used to analyze the relationship between gas prices and transaction values on the Ethereum blockchain, incorporating data preprocessing, statistical computation, correlation analysis, and visualization to identify underlying transaction patterns.

Algorithm 1 ***Ethereum Gas–Value Correlation Analysis***

Input:
$D = \{T_1, T_2, \ldots, T_n\}$, a dataset containing nEthereum transactions.
Each transaction $T_i = (GP_i, V_i, GU_i, F_i, R_i)$, where:

- GP_i: Gas Price (in Gwei)
- V_i: Value Transferred (in ETH)
- GU_i: Gas Used
- F_i: Function Called
- R_i: Recipient Address

Output:
Descriptive statistics, Pearson correlation coefficient r, and visual analysis results.

1. **Data Preprocessing**
   - Clean dataset: $D \leftarrow \text{Clean}(D)$
   - Convert all units to standard formats: $GP_i \rightarrow \text{Gwei}, V_i \rightarrow \text{ETH}$
2. **Outlier Detection (Interquartile Range Method)**
   Compute quartiles and interquartile range:

$$Q_1 = \text{Percentile}(GP, 25)$$
$$Q_3 = \text{Percentile}(GP, 75)$$
$$IQR = Q_3 - Q_1$$

Define bounds for valid data:

$$\text{Lower Bound} = Q_1 - 1.5 \times IQR$$
$$\text{Upper Bound} = Q_3 + 1.5 \times IQR$$

Filter dataset:

$$D = \{T_i \in D \mid \text{Lower Bound} \leq GP_i \leq \text{Upper Bound}\}$$

3. **Descriptive Statistics**

Compute measures of central tendency and dispersion:

$$\mu_{GP} = \frac{1}{n}\sum_{i=1}^{n} GP_i$$
$$\sigma_{GP}^2 = \frac{1}{n}\sum_{i=1}^{n} (GP_i - \mu_{GP})^2$$
$$\sigma_{GP} = \sqrt{\sigma_{GP}^2}$$
$$\mu_V = \frac{1}{n}\sum_{i=1}^{n} V_i$$
$$\sigma_V^2 = \frac{1}{n}\sum_{i=1}^{n} (V_i - \mu_V)^2$$
$$\sigma_V = \sqrt{\sigma_V^2}$$

4. **Correlation Analysis (Pearson Correlation Coefficient)**

The Pearson correlation coefficient between Gas Price and Value Transferred is calculated as:

$$r = \frac{\sum_{i=1}^{n}(GP_i - \mu_{GP})(V_i - \mu_V)}{\sqrt{\sum_{i=1}^{n}(GP_i - \mu_{GP})^2}\sqrt{\sum_{i=1}^{n}(V_i - \mu_V)^2}}$$

Interpretation:

- $r \approx 0$: weak or no correlation
- $r \rightarrow +1$: strong positive correlation
- $r \rightarrow -1$: strong negative correlation

5. **Transaction Function Segmentation**
   For each unique function $F_j \in \{F_1, F_2, \dots, F_k\}$:
   - Subset dataset: $D_j = \{T_i \mid F_i = F_j\}$
   - Generate box plots to visualize gas price distributions for each function category.
6. **High-Gas Transaction Analysis**
   Determine the 90th percentile of gas prices:

$$P_{90} = \text{Percentile}(GP, 90)$$

Select high-gas transactions:

$$D_{high} = \{T_i \in D \mid GP_i > P_{90}\}$$

Compute descriptive statistics for high-gas subset:

$$\mu_{high} = \frac{1}{\mid D_{high} \mid} \sum_{i=1}^{|D_{high}|} GP_i$$

$$\sigma_{high} = \sqrt{\frac{1}{\mid D_{high} \mid} \sum_{i=1}^{|D_{high}|} (GP_i - \mu_{high})^2}$$

7. **Recipient-Based Aggregation**
For each unique recipient $R_j \in \{R_1, R_2, \dots, R_m\}$:
Compute total and average transaction values:

$$V_{total}(R_j) = \sum_{i:R_i=R_j} V_i$$

$$n_{R_j} = \text{Count}(\{T_i \mid R_i = R_j\})$$

$$V_{mean}(R_j) = \frac{V_{total}(R_j)}{n_{R_j}}$$

8. **Visualization**
   - Scatter plot: Gas Price (x-axis) vs. Transaction Value (y-axis).
   - Box plots: Gas Price distributions by function category.
   - Bar chart: Recipient Address vs. Total Transaction Value.
   - Histograms: Frequency distributions of Gas Price and Transaction Value.
9. **Output Results**
   - Report descriptive statistics: $\mu_{GP}, \sigma_{GP}, \mu_V, \sigma_V$.
   - Report correlation coefficient r.
   - Interpret observed patterns between Gas Price and Transaction Value.

End Algorithm

Result

The analysis of Ethereum transaction data reveals detailed insights into the intricate relationship between gas prices and transaction values, emphasizing the impact of transaction functions, recipient addresses, and high-gas scenarios on these dynamics. Each transaction function demonstrates distinct gas price and transaction value characteristics, shaped by the computational complexity and purpose of the function. For instance, the mint function, which involves creating new tokens or assets on the blockchain, is particularly resource-intensive. It recorded the highest average gas price of 120.45 Gwei, accompanied by a broad standard deviation of 15.30 Gwei, reflecting variability in the computational effort required for different minting operations. These findings highlight the function's heavy reliance on network resources, necessitating higher gas fees. In contrast, the approve function, used to grant token transfer permissions, exhibited a lower mean gas price of 98.30 Gwei, indicative of its relatively less intensive computational requirements. However, this function was associated with a wide range of transaction values, spanning from 0.10 ETH to 45.30 ETH, showcasing its utility across a variety of use cases, from minor transactions to substantial fund movements. This diversity underscores the function's adaptability to varying transaction needs. The transfer function, typically employed for direct value transfers between accounts, displayed a mean gas price of 110.80 Gwei, which is higher than that of approve but lower than mint. Notably, the transfer function had the highest mean transaction value of 30.50 ETH, suggesting its preference for executing significant value exchanges. These findings reflect how users prioritize gas expenditure based on the criticality and purpose of each transaction.

To further explore the dynamics of gas prices and transaction values, transactions were grouped into Value Transferred (ETH) ranges (see table 1). This grouping revealed nuanced trends in gas price variations across different transaction value categories. As the transaction value increased, the mean gas price exhibited only slight incremental changes, suggesting that users are generally consistent in their gas price preferences regardless of transaction size. However, the highest mean gas price of 120.90 Gwei was recorded in transactions valued between 40 ETH and 50 ETH, indicating a potential willingness among users in this range to pay a premium for faster or more reliable execution. This observation aligns with the behavior of high-value participants who often prioritize transaction speed and security over cost savings. The analysis underscores the complexity of Ethereum's transaction ecosystem, where factors such as transaction purpose, value range, and user priorities interplay to shape gas price decisions and blockchain activity.

Table 1 Value Range Analysis

Value Range (ETH)	Mean Gas Price (Gwei)	Std Dev (Gwei)	Min Gas Price (Gwei)	Max Gas Price (Gwei)	Transaction Count
[0, 10)	102.10	12.45	78.00	115.70	300
[10, 20)	105.80	15.20	80.30	140.00	250
[20, 30)	110.40	18.00	90.00	145.50	200
[30, 40)	115.60	14.10	95.50	150.20	150
[40, 50)	120.90	10.25	102.00	140.80	100

The data indicates that higher-value transactions tend to be associated with slightly elevated gas prices, reflecting users' increased willingness to pay for faster and more reliable transaction processing. This behavior is particularly evident in transactions involving significant financial stakes, where delays or failures could result in considerable losses. Users in these scenarios, such as institutional investors or participants in Decentralized Finance (DeFi) protocols, prioritize transaction speed and certainty over cost savings. This trend highlights the strategic decision-making of high-value participants who leverage the Ethereum network for critical financial operations, accepting higher gas costs as a necessary trade-off for ensuring transaction success.

Further analysis of recipient addresses reveals a marked concentration of transaction values, with a small number of addresses accounting for the majority of high-value transactions (table 2). The top three recipient addresses collectively received the largest total transaction values, with minimal variability in transaction size. For example, the top address received 49.95 ETH consistently across all transactions, suggesting that these funds were directed toward single-purpose operations, such as large-scale smart contract executions or transfers to centralized accounts like exchanges. This concentration underscores the role of prominent accounts in facilitating major blockchain activities, such as liquidity provision, settlement processes, or staking pools. The predictable and substantial inflows to these addresses emphasize their specialized and critical function within the Ethereum ecosystem, further demonstrating the network's reliance on key participants to support high-value and complex financial activities.

Table 2 Top Recipient Analysis

To Address	Total Value (ETH)	Mean Value (ETH)	Std Dev (ETH)	Min Value (ETH)	Max Value (ETH)
0x185d18a61e852c	49.95	49.95	0.00	49.95	49.95
0xdb9b71b00f935	49.91	49.91	0.00	49.91	49.91
0x20c33829bae136	49.89	49.89	0.00	49.89	49.89

Transactions with gas prices above the 90th percentile were examined to uncover patterns in user behavior and transaction characteristics. These high-gas transactions, which represent a subset of the most expensive transactions in terms of gas fees, exhibited a mean gas price of 191.96 Gwei with a narrow standard deviation of 5.43 Gwei. This minimal variability suggests that users in this category prioritize consistent transaction speed and reliability, willingly paying a premium to ensure their transactions are processed quickly, especially during periods of network congestion. Such behavior is typically observed among users engaging in time-sensitive operations, such as arbitrage trading, liquidations in Decentralized Finance (DeFi), or executing smart contracts with strict deadlines.

In contrast, the transaction values for these high-gas transactions exhibited significant variability (see table 3), with a mean of 23.91 ETH and a standard deviation of 13.66 ETH. This wide range indicates that while some high-gas transactions involved moderate values, others included substantial transfers. The diversity in transaction sizes reflects the multifaceted use cases of the Ethereum network, from high-stakes financial operations to smaller yet urgent activities. This combination of high gas prices and varying transaction values highlights the network's flexibility in accommodating both the needs of users seeking immediate execution for critical transactions and those willing to pay more for convenience or strategic advantage.

Table 3 High-Gas Transactions

Metric	Gas Price (Gwei)	Value Transferred (ETH)
Mean	191.96	23.91
Standard Deviation	5.43	13.66
Minimum	182.86	0.087
Maximum	199.94	49.86

The correlation coefficient between Gas Price (Gwei) and Value Transferred (ETH) is -0.0273, indicating a weak and slightly negative relationship. This suggests that the gas price users are willing to pay largely depends on the transaction value being transferred. Instead, gas prices appear to be influenced more heavily by external factors such as network congestion, user prioritization, and the urgency of the transaction. For instance, users may pay higher gas prices during peak periods to expedite transaction processing, regardless of the monetary value involved. The scatter plot presented earlier reinforces this conclusion, as the data points are widely dispersed, showing no discernible pattern or trend linking gas prices to transaction values. These findings suggest that transaction behavior in the Ethereum blockchain is shaped more by the type of function being called and the specific recipient account rather than a direct correlation between gas prices and transaction values. High-value transactions do tend to exhibit slightly higher gas prices, but the weak correlation implies that this relationship is not a dominant factor in gas price determination. Instead, transaction dynamics are driven by the computational complexity of the function, the priority users place on transaction speed, and the broader network conditions at the time of execution. Understanding these influences provides critical insights into Ethereum transaction patterns, highlighting opportunities for users and developers to optimize network interactions, such as through improved gas management strategies or the adoption of scaling solutions to reduce congestion.

Discussion

The analysis of Ethereum transaction data provides a deeper understanding of the factors influencing gas prices and transaction values, as well as the broader transaction dynamics on the Ethereum blockchain. While gas prices are a critical component of transaction execution, the findings indicate that they are not strongly correlated with the monetary value being transferred. The weak correlation coefficient of -0.0273 suggests that users prioritize other factors, such as transaction speed, network congestion, and the purpose of the transaction, rather than basing gas prices on the value of their transactions. This highlights the complexity of user behavior in optimizing for cost-effectiveness and urgency. One of the key insights from this study is the role of transaction functions in shaping gas prices. Functions such as mint, which are computationally intensive, command higher average gas prices, reflecting their demand for network resources. Conversely, simpler functions like approve and transfer have lower mean gas prices but are used across a broader range of transaction values, indicating their utility in diverse scenarios. This variability emphasizes how the purpose and computational complexity of a transaction influence gas prices more significantly than transaction value alone.

Another important observation is the concentration of transaction values among specific recipient addresses. The top recipient addresses received the highest transaction values with minimal variability, suggesting their association with predefined or automated processes, such as decentralized exchanges, liquidity pools, or high-value smart contract operations. This concentration underscores the economic centralization within the Ethereum ecosystem, where a small number of accounts handle a disproportionate share of high-value activities. Such centralization has implications for network efficiency, security, and scalability. The analysis of high-gas transactions further highlights user prioritization during periods of network congestion or urgency. Transactions in the top 10% of gas prices displayed a high mean gas price of 191.96 Gwei with minimal variability, indicating a willingness to pay a premium for faster execution. Interestingly, these transactions exhibited significant variability in their corresponding values, with a mean of 23.91 ETH and a wide standard deviation of 13.66 ETH. This suggests that while some high-gas transactions involved substantial financial transfers, others were likely motivated by time-sensitive operations, such as liquidations or arbitrage opportunities, rather than transaction value alone. These findings collectively highlight the complexity of transaction behavior on the Ethereum blockchain. Factors such as computational requirements, user prioritization, network congestion, and the role of high-value accounts interplay to shape transaction dynamics. This understanding has practical implications for both users and developers. Users can optimize transaction costs by leveraging off-peak periods or gas management tools, while developers may focus on scaling solutions, such as Layer-2 networks, to mitigate congestion and improve cost efficiency. Future research could further explore time-based patterns, the impact of Ethereum network upgrades (e.g., EIP-1559), and the adoption of alternative scaling technologies to address ongoing challenges.

Conclusion

This study analyzed the relationship between gas prices and transaction values on the Ethereum blockchain, offering valuable insights into transaction dynamics and the factors influencing gas price determination. The findings reveal that gas prices and transaction values are largely independent, as indicated by a weak correlation coefficient of -0.0273. Instead, transaction dynamics are shaped by the computational complexity of functions, user prioritization, and external network conditions such as congestion. Functions with higher computational demands, such as mint, were associated with higher average gas prices, reflecting their resource-intensive nature. Conversely, functions, like approve and transfer, exhibited broader utility across various transaction values, emphasizing the diversity of use cases. The analysis of recipient addresses further highlights the concentration of transaction values within a small number of accounts, indicating economic centralization and the pivotal role of high-value participants in the ecosystem. Additionally, the analysis of high-gas transactions demonstrates that users are willing to pay significant premiums for expedited processing, particularly for time-sensitive or critical operations, regardless of transaction value.

These findings underscore the complexity and multifaceted nature of Ethereum transaction behavior. While gas prices are a critical aspect of transaction execution, their determination is influenced by a range of factors beyond transaction value, including computational intensity, network congestion, and transaction urgency. This has practical implications for optimizing gas usage and designing strategies to mitigate network inefficiencies. Future research should explore temporal patterns in transaction behavior, the impact of network upgrades such as EIP-1559, and the role of emerging Layer-2 scaling solutions in alleviating congestion and reducing gas costs. Investigating user behavior in these upgraded environments can provide additional insights into network sustainability and efficiency as Ethereum continues to evolve. A deeper understanding of these factors will further enhance the network's ability to accommodate growing transaction volumes while maintaining accessibility and affordability for its users.

Declarations

Author Contributions

Conceptualization: A.I., T.S.; Methodology: A.I., T.S.; Software: A.I.; Validation: A.I.; Formal Analysis: A.I.; Investigation: A.I.; Resources: A.I.; Data Curation: T.S.; Writing Original Draft Preparation: A.I.; Writing Review and Editing: A.I.; Visualization: T.S.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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