ATTENTION IS ALL YOU NEED: AN ANALYSIS OF THE VALUATION OF ARTIFICIAL INTELLIGENCE TOKENS

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OPEN ACCESS

How to cite this paper: Akpan, M. (2024). Attention is all you need: An analysis of the valuation of artificial intelligence tokens [Special issue]. *Corporate Ownership & Control, 21*(3), 109–115.
https://doi.org/10.22495/cocv21i3siart9

ISSN Online: 1810-3057
ISSN Print: 1727-9232

Received: 08.07.2024
Accepted: 14.10.2024

JEL Classification: M41, O33, C63
DOI: 10.22495/cocv21i3siart9

Abstract

This study discusses the parameters that define the value of artificial intelligence (AI) tokens based on user interaction, their pricing mechanism, and their correlation with the predicted value thus evaluating AI token valuation based on user engagement, pricing, and website visits. This study tests hypotheses that examine the factors that influence the value of AI tokens. Using data from ten AI tokens, the study employs correlation and regression analyses to examine these relationships. The results show that monthly active users (MAU) and website visits significantly predict valuation, while pricing shows a marginal effect. This research provides insights for stakeholders in understanding economic factors affecting AI token values, emphasizing user engagement and pricing strategies.

Keywords: AI Tokens, Valuation, Monthly Active Users (MAU), Pricing, User Engagement, Website Visits, Regression Analysis

Authors' individual contribution: The Author is responsible for all the contributions to the paper according to CRediT (Contributor Roles Taxonomy) standards.

Declaration of conflicting interests: The Author declares that there is no conflict of interest.

1. INTRODUCTION

The constantly growing development of artificial intelligence (AI) has created new tokens as assets in the digital economy. These tokens, present during computing hours or specific functionalities of AI, are now essential for running and advancing AI-based systems (Lawton, 2023). Given the ever-growing AI market, it is important to identify the factors that influence the value of such tokens for developers, investors, and businesses. The price evaluation of AI tokens, which corresponds to the computational capabilities and rights of AI usage, is essential for participants in the digital economy (Jareño & Yousaf, 2023). A survey of the prior literature on AI shows that many early studies focused on the development and characteristics of AI systems. However, there is a gap, as highlighted by Qin et al. (2023) in understanding the economic features of AI that have started to appear, especially concerning the valuation of AI tokens, which is yet to be studied. This study seeks to contribute to this research gap by exploring the correlation between user engagement, pricing strategies, and the valuation of AI tokens.

The monthly active users (MAU) is an important metric of user engagement that exemplifies the number of consumers interacting with AI models on a monthly basis (Liu & Wagner, 2023). This high user interaction means that more users are adopting the AI model, which can increase the asset value (Xie-Carson et al., 2023). On the other hand, the cost of the functionalities that enable the use of AI, such as the price per million tokens, can determine the perceived value of those tokens and, thus, their usage rate. Recent work by Bitrián et al. (2021) proposed an alternative to the market fundamental ratios, which is the price-to-utility (P/U) ratio for the long-term expected returns of AI tokens considering the characteristics of blockchain accounting. This approach represents a clear proposal that it is possible to estimate the principles and factors that will determine the valuation of an AI token (Egli, 2023).

Based on this, this study puts forward a set of hypotheses to examine the factors that influence the valuation of AI tokens (see Section 2).

In this study, the following research questions are formulated within the framework of the stated objectives:

RQ1: What are the primary factors influencing the valuation of AI tokens in the digital economy?

RQ2: How does user engagement, as measured by MAU and website visits, impact the estimated valuation of AI tokens?

RQ3: What is the relationship between token pricing strategies and the perceived valuation of AI tokens?

Through these hypotheses, this study seeks to systematically examine the economic factors that impact the value of AI tokens. As such, the findings are believed to provide relevant information to key stakeholders, thus enhancing their wisdom and informing them on investment in and usage of AI tokens. The approach used in this study is descriptive, as it involves the use of statistical analysis of the collected data, engagement rates, and objective estimations of the prices and valuations of the selected few popular AI tokens. Descriptive statistics, correlation analysis, and multiple regression analysis were used in this study. This allowed to establish the relationships between these factors and their impact on token values in the AI market.

This study explores various aspects of AI tokens to substantially enrich the understanding of the still-evolving field of AI token economics and be useful to various firms and investors operating in this environment.

The rest of the study is structured as follows. Section 2 covers the relevant literature. Section 3 describes the models, methodology, and data. Section 4 presents the analysis and hypothesis testing. Section 5 presents a discussion of the implications of the results, and finally Section 6 presents the conclusions, limitations, and suggestions for future research.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Valuation of AI models is a multifaceted process that integrates technical performance, economic factors, and market dynamics. Despite significant advances in the development of sophisticated AI models, the economic valuation of AI tokens that represent computing power or access to AI functionality still needs to be explored in the academic literature (Ali et al., 2024). This section reviews existing research on AI model valuation, user engagement metrics, and pricing strategies, and identifies the gaps that this study aims to address.

2.1. AI model valuation

Vaswani et al. (2017) proposed the transformer model, which has become an essential component of natural language processing (NLP) because it does not use recurrent or convolutional neural networks. This model has proven to be very effective for machine translation tasks, providing the best results while training time was significantly shorter (Ali et al., 2024). Owing to its capacity to address long-range dependencies and its computation capacity to be parallelized, the transformer architecture has become the foundation for many AI applications, such as language modelling and text generation.

Network effects are critical in the valuation of AI tokens. Network effects occur when the value of a good or service increases with the number of people using it. This concept is well understood in economics and technology adoption literature. Katz and Shapiro (1985) note that technology products with network externalities exhibit rapid market penetration and dominance because users rely on popular products to ensure interconnectivity with other users. Network effects may provide additional value to AI tokens, making them more useful and valuable as more people use an AI system.

Several studies have focused on combining blockchain and AI, mainly on the tokenization of AI models and data. For instance, Marin et al. (2023) suggested that blockchain can foster the development of a decentralized AI marketplace where AI models and data can be tokenized and traded. This can be achieved by encouraging data sharing and collaboration using network effects and by increasing the value of AI tokens. In addition, implementing AI and blockchain helps solve problems concerning data protection and confidentiality, thus enhancing consumer trust and engagement (Choudhry, 2024).

Valuation frameworks for AI technologies must consider their technical capabilities and economic value. Brynjolfsson and McAfee (2017) emphasized that AI's primary value lies in its predictive accuracy, which enhances decision-making across various sectors. Quantifying AI's value is challenging due to its intangible nature. Agrawal et al. (2019) also highlight the difficulty of capturing AI's full economic contribution. These studies emphasize the need for a comprehensive approach incorporating user engagement and pricing strategies alongside traditional valuation methods.

2.2. User engagement metrics and pricing strategies

User engagement, quantified using metrics such as MAU, is essential for assessing the adoption and impact of AI models (Akpan, 2022). The MAU measures the number of unique users interacting with an AI service within a month, indicating the model's popularity and utility. Li and Hitt (2008) suggested that higher user engagement correlates with increased revenue and higher valuation for digital platforms. In the context of AI, user engagement reflects the model's utility and drives continuous improvement through user feedback and data generation. Jarrahi (2018) supported this view, noting that active user participation is crucial for refining AI algorithms and enhancing their performance. In the context of the above, the following hypothesis can be formulated:

H1: Higher MAU positively influences the predicted valuation of AI tokens.

The pricing of AI services, particularly token usage, significantly influences accessibility and adoption (Choudhry, 2024). Various pricing models, including pay-as-you-go and subscription-based models, have been explored. Cost efficiency is a critical factor when selecting AI services (Doo et al., 2023). A lower pricing per million tokens can attract a broader user base, potentially increasing the overall valuation of the AI model (Ahmed et al., 2024). However, the empirical study by Vaswani et al. (2017) linking pricing strategies directly to AI token valuation is limited, indicating a need for further research in this area. Thus, in the context of the above, the following hypotheses can be formulated:

H2: AI tokens with lower pricing per million tokens have higher predicted valuations owing to their cost efficiency.

H3: AI tokens with many website visits converted to MAU have a higher predicted value.

2.3. Research gap

Research gaps can be identified concerning the application of network effects to the valuation of AI tokens. Finally, more research is needed that focuses on determining the correlation between network effects and the value of AI tokens. Theories, applications, and specific statistics are scarce, particularly in the context of these studies. The relationship between the performance of an AI model and token valuation is not yet fully understood. Explaining the impact of the enhancements in the AI models on the token value can help understand the correlation between them and, therefore, the performance of AI models and token economics. A review of this issue is needed to identify the legal and ethical issues that arise when tokenizing AI models and data. These issues can be addressed, opening the door to the development of more robust and sustainable AI token ecosystems.

2.4. Contribution of this study

This study contributes to the existing literature by examining the relationship between MAU, price per million tokens, and predicted values of AI tokens. By testing the hypotheses that higher user engagement and cost efficiency positively influence AI token valuation, this study provides empirical evidence to support these claims. The AI Token Valuation Scale[1] offers a standardized tool for interpreting and comparing the value of AI tokens across different models. The findings of this study are expected to offer valuable insights for stakeholders, including developers, investors, and businesses, aiding in strategic decision-making and fostering a more informed approach to AI token investment and utilization.

3. METHODOLOGY

This study used a quantitative method to analyze the variables affecting the value of AI tokens in relation to users' activities and rates. This methodology was developed to test the above hypotheses proposed in this research framework.

3.1. Data collection

The samples include ten popular AI tokens selected across the market by 2023 (see Appendix). The dataset includes the following information:

- MAU (in millions of users);
- pricing per million tokens (in USD);
- website visits (in millions);
- estimated valuation (in billions of USD).

The information on MAU construction was collected from official channel reports, statistics, and analytics platforms. In cases where actual MAU values were not available for the AI models under consideration, website visits were estimated into MAUs using a conversion rate of one MAU per ten visits, which is typical for the industry (Jeyaraman et al., 2023). The price data came mainly from official AI providers' websites (see Appendix, Table A.1). Anticipated values are obtained from past and current financial statements, fundraising, and market research.

3.2. Data analysis

The analysis was conducted using the IBM SPSS Statistics software. The analytical process consisted of three main stages:

1. *Descriptive statistics*: Central tendency (mean) and variance (standard deviation, minimum, and maximum) were calculated for all variables to provide an overview of the characteristics of the dataset.

2. *Correlation analysis*: Bivariate Pearson correlations were calculated to examine the relationships between variables and test the three hypotheses. This analysis assessed the strength and direction of the associations between MAU, pricing, website visits, and estimated valuation.

3. *Multiple regression analysis*: To evaluate the interaction effects of the independent variables, (*MAU*, *Pricing*, and *Website visits*), with the *Estimated valuation* as the dependent variable, a multiple regression analysis was conducted. This analysis allowed us to understand the level of relevance of each factor in relation to the evaluation of AI tokens.

The regression model took the form:

$$Estimated\ valuation = \beta_0 + \beta_1(MAU) + \beta_2(MAUPricing) + \beta_3(Website\ visits) + \varepsilon \quad (1)$$

where, β_0 is the intercept $\beta_1, \beta_2, \beta_3$ are the regression coefficients ε is the error term.

Multicollinearity was further examined using the variance inflation factor (VIF). From the results obtained, a deeper assessment of the fitness of the model was performed using the coefficient of determination (R^2) and the adjusted coefficient of determination (Adjusted R^2).

3.3. Limitations

There are several limitations of the methodology that should be acknowledged:

1. The study sample consists of ten participants, severely restricting the statistical significance of the results and the extent to which the data could be generalized.

[1] An upcoming study by the Author introduces the AI Token Valuation Scale, which will offer a standardized framework for assessing and comparing the value of AI tokens across different models. The findings are expected to provide valuable insights for developers, investors, and businesses, aiding in strategic decision-making and fostering a more informed approach to AI token investment and use.

2. Utilizing website visits to estimate MAU may involve some measurement bias.

3. It is also important to note that the study used cross-sectional data; therefore, no causal correlation or temporal sequence in the valuation of AI tokens could be established.

4. By using estimated value, the study may include market value, which can change frequently due to fluctuations and speculation.

Nevertheless, the current study follows a systematic method to determine the relationship between user activity, price, and AI token value. Thus, given the hypotheses of the study, descriptive statistics, correlation analysis, and multiple regression help to examine all the hypotheses and significantly contribute to the development of AI token economics.

4. RESULTS

This section provides the findings of the investigation conducted on the valuation of token AI, concentrating on the correlations between MAU, pricing methodologies, and estimated token valuations. Descriptive statistics, correlation analysis, and multiple regression analysis were used to assess the validity of the hypotheses in the theoretical framework of the study. The findings are as follows. The implications for AI tokens' valuation are also stated with reference to extant theory.

4.1. Descriptive statistics

Table 1 presents the descriptive statistics for the key variables in this study.

Table 1. Descriptive statistics

Variables	*N*	*Minimum*	*Maximum*	*Mean*	*Std. deviation*
MAU (millions of users)	10	3	150	39.80	47.777
Pricing (millions of USD)	10	0.0	30.0	7.450	10.1282
Website visits (millions)	10	30	1500	398.00	477.768
Estimated valuation (billions of USD)	10	2	80	23.80	26.431
Valid N (listwise)	10				

Source: Author's elaboration.

Descriptive statistics revealed considerable variations across the dataset. *MAU* ranged from 3 million to 150 million users, with a mean of 39.80 million (SD = 47.777). *Pricing* strategies varied widely, from free tokens to $30 per million tokens, with a mean of $7.45 (SD = 10.1282). *Website visits* showed a similar pattern of variability, ranging from 30 million to 1.5 billion, with a mean of 398 million (SD = 477.768). *Estimated valuations* ranged from $2 billion to $80 billion, with a mean of $23.80 billion (SD = 26.431).

4.2. Correlation analysis

Bivariate Pearson correlations were calculated to examine the relationships between the variables and test the three hypotheses. The results are presented in Table 2.

Table 2. Correlation matrix

Variables	*Estimated valuation*	*MAU*	*Pricing*	*Website visits*
Estimated valuation	1			
MAU	0.871**	1		
Pricing	0.554	0.291	1	
Website visits	0.871**	1.000**	0.291	1

*Note: ** Correlation is significant at the 0.01 level (2-tailed).*

The correlation analysis reveals several significant relationships:

1. *MAU* and *Estimated valuation*: There strong positive correlation between MAU and estimated valuation (r = 0.871, p-value < 0.01), supporting *H1*.

2. *Pricing* and *Estimated valuation*: A moderate positive correlation exists between pricing and estimated valuation (r = 0.554, p-value = 0.097). This relationship warrants further investigation but is not statistically significant at the 0.05 level.

3. *Website visits* and *Estimated valuation*: Website visits showed a robust and positive correlation with estimated valuation (r = 0.871, p-value < 0.01), supporting *H3*.

4. *MAU* and *Website visits*: A perfect positive correlation (r = 1.000, p-value < 0.01) suggests that these variables may measure the same construct or are derived from each other.

4.3. Multiple regression analysis

A multiple regression analysis was conducted to further examine the relationships between variables and assess their combined effects on the estimated valuation. Table 3 presents the results.

Table 3. Multiple regression coefficients

Variables	*Unstandardized coefficients*		*Standardized coefficients*	*t*	*Sig.*	*VIF*
	Beta	*Std. error*	*Beta*			
(Constant)	0.354	5.155		0.069	0.947	
Pricing	0.855	0.390	0.328	2.192	0.064	1.093
Website visits	0.043	0.008	0.775	5.187	0.001	1.093
R-square = 0.857 Adjusted R-square = 0.816 F(2, 7) = 20.945 p-value = 0.001						

Note: Dependent variable — Estimated valuation.

The multiple regression model explained 85.7% of the variance in the estimated valuation ($R^2 = 0.857$, Adjusted $R^2 = 0.816$). The model is statistically significant ($F(2, 7) = 20.945$, p-value = 0.001), indicates that the regression model is highly statistically significant, suggesting a strong relationship between the independent variables (*MAU, Pricing, Website visits*) and the dependent variable (*Estimated valuation*). The p-value of 0.001 reflects that the probability for such findings to occur based on chance is very remote; this affirms the model's reliability to predict valuation. This significance, therefore, suggests that the independent variables together present a solid model in explaining the variation in valuations of AI tokens, hence underpinning both the hypotheses of validity and the importance of these key economic factors influencing token value.

Website visits emerged as a significant predictor of estimated valuation ($\beta = 0.775$, p-value = 0.001), while pricing approached significance ($\beta = 0.328$, p-value = 0.064). This means that the pricing variable showed a borderline effect on AI token valuation, indicating it was close to the conventional threshold for statistical significance (p-value < 0.05). This suggests that while pricing does not have a statistically significant impact at the 95% confidence level, it might still influence valuation trends. The VIF values were below 5, suggesting no problematic multicollinearity.

MAU was excluded from the regression model because of its perfect correlation with website visits, which caused multicollinearity issues.

5. DISCUSSION

The findings of this study provide valuable insights into the factors that influence AI token valuations. The results broadly support the proposed hypotheses and offer several implications for understanding the economic dynamics of AI tokens.

Results of testing H1. This hypothesis is supported by the strong positive correlation between MAU and estimated valuation ($t = 5.165$; $r = 0.871$ at p-value < 0.01). This finding supports the recent findings of Liu and Wagner (2023) and Xie-Carson et al. (2023), who emphasize that user activity determines the valuation of the model. From the results, we can deduce that popular AI tokens are regarded as having higher values because the network effects involving utilizing the tokens can lead to data-induced enhancement of AI.

Results of testing H2 showed that pricing was moderately positively correlated with estimated valuation ($r = 0.554$, p-value = 0.097). However, this correlation was not statistically significant at the conventional 0.05 level. Contrary to the hypothesis, higher-priced AI tokens tended to have higher valuations. This finding suggests that cost efficiency is not directly related to the valuation process as initially expected. Instead, it may indicate that higher prices reflect perceptions of luxury or advanced technology, which could drive higher valuations. This interpretation aligns with the value-based pricing model observed in specific technological markets (Doo et al., 2023).

Results of testing H3. The hypothesis suggesting that there is a positive relationship between visits to the website and the estimated valuation of the enterprise was found to be valid based on Pearson's correlation test yielding ($r = 0.871$, p-value < 0.01). The regression result found that website visits have the highest significance value, contributing to the estimated valuation ($\beta = 0.775$, p-value = 0.001). This leads to a definite conclusion that draws attention to usage activity and traffic as pillars for AI token valuation. This means that investors and stakeholders consider high levels of web activity as signals of market interest, growth, and successful general performance of the platform.

The zero interpolation between MAU and visits to the website ($r = 1.000$) should be interpreted with caution. This may be attributed to the data collection methodology, in which the number of website visits is sometimes utilized as a substitute for MAU. Future studies should strive to distinguish between these adjusters more clearly to provide a better and more precise picture of their effects on valuation.

The resulting regression model has a high accuracy score ($R^2 = 0.857$), thus revealing that user visits and pricing policies are determinants of the AI token value. The drastic effect of website visits shows the backdrop of network effects theory, first outlined by Katz and Shapiro (1985).

At that point, the near-significant positive influence of pricing on valuation is equal ($\beta = 0.328$, p-value = 0.064), which questions the fundamental hypothesis of cost efficiency. This study indicates a somewhat different pattern of integration of the concepts of pricing and perceived value in the context of the AI token market. Consumers may have to pay a premium price for the brand, quality, and sophistication, which are only available to a few. Alternatively, they may incorporate sophisticated technology to explain the high valuations. This interpretation aligns with the premium above the price that consumers are willing to pay in other related technology markets (Ahmed et al., 2024).

6. CONCLUSION

This study adds to the growing literature on AI token economics by providing an empirical analysis of the relationships between user activity, token price, and token value. The study revealed that more significant user interaction significantly correlates with AI token prices based on the website traffic index and MAU. The interconnection of pricing and valuation contradicts the simplistic models of cost and efficiency and implies the need for more subtle approaches to set the price in the AI token market. The information provided in this study may be helpful for AI developers, investors, and policymakers. It also emphasizes creating and sustaining engaged communities and having more complex yet smarter pricing models, which engage people while simultaneously making them feel that they are paying for something worth the best price. As the market for AI tokens develops, research is required to deepen the knowledge of economic processes and strategic decisions in this emerging field.

As this study has merits, it also has the following limitations that must be noted. The primary study limitations include the small sample size ($N = 10$), which restricts substantial generality and the study's statistical capability.

This study should be continued and expanded to a larger and more diverse sample of AI tokens to improve the generalizability of the results. This perfect correspondence between MAU and website visits calls for more elaborate measures of usage intensity. For further research, the author should endeavour to obtain data for these variables separately to distil their effects on the valuation. Considering these findings, a few limitations of the current study should be noted. First, a cross-sectional study only provides a snapshot of the participant's behaviour and cannot establish causality. Further investigation of the factors that underlie the constant changes in the values of AI tokens in relation to the token usage by users and changes in the token price may be obtained from longitudinal research studies on the subject.

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APPENDIX

Table A.1. Artificial intelligence models, 2023

AI token	***Website***	***MAU*** *(in millions of users)*	***Pricing*** *(in USD)*	***Website visits*** *(in millions)*	***Estimated valuation*** *(in billions of USD)*
1. GPT-4	https://openai.com	100	30.0	1000	80
2. GPT-3.5	https://openai.com	150	0.5	1500	60
3. Claude	https://claude.ai/	20	8.0	200	30
4. PaLM	https://palmai.tech/	30	1.0	300	25
5. DALL-E 2	https://openai.com	40	20.0	400	15
6. Midjourney	https://midjourney.com/	15	10.0	150	10
7. Stable Diffusion	https://stability.ai/	25	0.0	250	8
8. Llama 2	https://www.llama.com/llama2/	10	0.0	100	5
9. Cohere	https://cohere.com/	5	2.0	50	3
10. AI21 Labs	https://www.ai21.com/	3	3.0	30	2

Note: Data showing different AI models with their corresponding MAU, pricing, website visits, and estimated valuation as at 2023. At the time of writing, this manuscript utilizes the most up-to-date AI models and the available data for those models. Given the rapid advancements in AI platforms, the models and data referenced have changed since then.
Source: Author's research.