Winter 12-10-2022

User Adoption and Sustainable Growth of Web3 Platforms

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Completed Research Paper

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Abstract

The recent rise of decentralized blockchain-based Web3 platforms has received mounting attention from the public. Using a unique dataset of 2,557 Web3 platforms, we examine the dynamics driving platform user adoption and sustainability during two growth phases (i.e., development and expansion). We cluster platform transaction time series in each phase to differentiate sustainable platforms from those in jeopardy. PVAR analysis is used to compare user adoption and network effects between clusters. We find that new user acquisition is critical during the first phase as the initial drive of the growth dynamics. With the user base being stabilized, in the second phase, returning users significantly account for the platform activeness while new users are still indispensable. Our work highlights the key role of new user acquisition in the growth of Web3 platforms as a result of their minimal switching costs and high forkability.

Keywords

Web3 platforms, sustainability, growth, user adoption, platform lifecycle.

Introduction

Unlike traditional Web2 platforms (e.g., Amazon, expedia.com) which hold centralized authority and are rent maximizers, Web3 platforms, underpinned by blockchain technology, co-create and share rents with platform participants using crypto tokens (Tönnissen et al., 2020), in return of user attention for participatory governance and development. Crypto tokens are used to manage market activities, incentivize platform services, fund development (e.g., creating content, validating transactions, building infrastructure components, and providing APIs), and enable acquirers a certain governance right. According to recent data (Momtaz, 2021), more than 6,500 blockchain-based platforms have sought funds through Initial Coin Offerings (ICOs) by 2021 and captured a total investment of 183 billion dollars. The Web3 industry has grown to a 3 trillion dollar crypto-token economy involved with more than 300 global exchanges.

For example, TripEcoSys [1] is a travel platform that combines social media, travel booking, and cryptocurrency exchanges on the same platform. This platform disintermediates multiple rent-seekers, such as travel agencies and currency exchanges, and prevents fake reviews while incentivizing contributors such as travel bloggers, and ticket agents to offer services on the platform in exchange for fungible crypto tokens. Such Web3 platforms thrive on user adoption, i.e., network effects, as well as the value increase of their crypto tokens. Importantly, they incentivize stickiness through rent-sharing mechanisms that platform owners can opt-in for.

Characterized by forkability, Web3 platforms have minimal switching costs (Choudary 2022; Fritsch et al., 2021), whereas traditional Web2 platforms capture value from network effects through higher switching costs (Subramanian et al., 2021). Our research studies the growth of Web3 platforms in terms of user

[1] https://www.tripecosys.com

adoption which is jointly measured by new, returning, and one-time users, and analyzes factors that promote the network effects of user adoption. Motivated by early studies on platform lifecycles (Fisher et al., 2016; Lin & Maruping, 2022; Moore, 1993), we take a data-driven approach to divide a Web3 platform's early-stage growth into two phases: Phase 1 (Development Phase), where development is undergoing with new users just onboarded, and Phase 2 (Expansion Phase), where the platform is scaling to the market need with full functionality (Kim & Yoo, 2019). We formulate the following research questions:

- ***RQ-1****: What are the typical patterns of transaction trajectory that a sustainable Web3 platform needs to follow during each phase of adoption?*
- ***RQ-2****: What user-adoption factors, in particular, new users, returning users and one-time users, may influence the growth of the platform during each phase?*

In order to address our research questions, we create a unique dataset of 2,557 Web3 platforms from multiple data sources such as icobench.com and etherscan.io. This dataset consists of both static information, such as funding schedules, and temporal micro-level blockchain transaction records. We apply time-series clustering on platform transaction trajectories in each phase to differentiate sustainable platforms from those in jeopardy. To understand what drives platform growth and sustainability, we conduct PVAR (panel vector autoregression) analysis to compare user adoption and network effects between clusters.

Our paper has three important findings. First, Web3 platforms surviving Phase 1 are more likely to thrive in Phase 2. Second, by comparing user adoption metrics in different clusters, we find that new user acquisition is important to the platform growth during both phases. It is particularly critical in Phase 1 as it leads to the formation of user bases together with a quick user-transition mechanism: converting new users and one-time users to returning users. In Phase 2, as the user base has been stabilized, returning users begin to play a role in the platform growth, but new user acquisition is still indispensable due to the lack of platform lock-in. Thirdly, transactions considerably contributed by one-time users could be a red flag to platform growth as it implies speculation behaviors ("Pump-and-Dump" scheme).

Our study has three primary contributions. Firstly, we investigate the growth of Web3 platforms using a unique dataset curated from user transaction data on the blockchain and business data from the aggregators. Instead of assuming a Web3 platform in a constant context, we fit our research into the lifecycle mechanism (Moore, 1993) and consider the changing growth context in each phase with distinctive operational focuses. Secondly, our analysis highlights different roles played by new, returning and one-time users, and delineates growth trajectories leading to platform sustainability. These insights can help entrepreneurs formulate effective business growth strategies. Finally, our work enriches the literature on platforms. We show that Web3 platforms differ from traditional ones in the constantly critical roles of new user acquisition due to their low switching cost. Moreover, departing from the mainstream studies on platform fundraising or token performance, we contribute to the literature an empirical study on the dynamics between user adoption factors and micro-level transactions.

Theory and Related Literature

This work extends two research streams: lifecycle theories and users' network effects.

Platform Lifecycles

Although Web3 platforms embrace new business models and disruptive innovation, their business nature allows us to treat them as normal technology enterprises that sell platform services and attract users. Prior literature has identified three main stages in the lifecycle of a technology firm, i.e., conception, growth and maturity (Fisher et al., 2016; Kim & Yoo, 2019; Lin & Maruping, 2022; Moore, 1993). In line with these studies, we introduce the lifecycle of Web3 platforms but only focus on the first two stages since most of them have not been mature yet.

During the conception stage, Web3 platform creators solidify their ideation, including "the generation, selection and prototyping of the ideas for the creation" of a new platform (Lin & Maruping, 2022). Then they issue crypto tokens to users for initial funding to support future development. Once funded, the Web3 platform enters the growth stage with a small initial user base. This stage consists of two separate phases:

a development phase and an expansion phase (Fisher et al., 2016; Lin & Maruping, 2022). In the development phase, most platforms fail because they are unable to sustain and expand user interest. If a platform manages to develop a mature service with a well-functional crypto token, it proceeds to the expansion phase with a focus on a larger user base to increase its market share and strengthen its competitive advantages.

Extant research has focused on Web3 platforms' fundraising and determinants critical to the success of fundraising efforts during the conception stage. Scholars have identified various indicators that signal a project's quality and drive ICO success, such as team characteristics, technical capability, and the quality of public disclosures (Fisch & Momtaz, 2020). Scholars have analyzed post-ICO token performance using financial metrics, such as token return, volatility and institutional investors' backing (Fisch & Momtaz, 2020; Lyandres et al., 2022). Our paper is unique since we focus on the growth stage of Web3 platforms and examine their user adoption and sustainability using a dynamic system of variables.

Platform Network Effects

A digital platform continuously increases its value by attracting more user attention and facilitating repeated user interactions so that it can monetize network effects (Parker et al., 2017; Song et al., 2018). Digital platforms support two types of network effects: direct (same-side) and indirect (cross-side) network effects (Clements, 2004; Thies et al., 2018). The direct network effect exists when a user's utility and therefore the platform value increase with more users joining in. Social media platforms such as Twitter and Facebook are built on the direct network effect. In multi-sided platforms, the indirect network effect comes into play when the increase of participants on one side attracts participants on another side. Apple store users increase with the growth of IOS App developers and therefore Apps.

Web3 platforms exhibit direct network effects (Cong et al., 2021) due to their support of "trustful" transactions on the blockchain. As users increase, it becomes easier for them to find transaction counterparties, thereby increasing the usefulness of a token. Second, Web3 platforms also show indirect network effects. For example, an increase of users on a platform can facilitate platform development on the developer side through feedback effects and participatory governance (Chen et al., 2020). By co-owning and co-governing the platform with its users, often Web3 platforms distribute a substantial number of operational responsibilities to users.

This paper will focus on the direct network effects of user adoption in terms of transactional effects and user stickiness in Web3 platforms. Prior research has suggested the importance of network effects to the growth and sustainability of digital platforms (McIntyre & Srinivasan, 2017). Digital platforms can lock in network effects by high switching costs (Zhu et al., 2006). However, the lower barriers to entering Web3 ecosystems, the transparency of blockchain, decentralized data control, and interoperability between blockchain protocols make network effects less defensible in a Web3 platform, as competitors can immediately access and benefit from the user base (Choudary 2022; Murray et al., 2022). Moreover, it is implicitly assumed that the network effects can arise and maintain constantly across different contexts. Few studies investigate the network effects from an evolution perspective and even fewer examine the Web3 platform's growth as a temporally dynamic process.

Data: Platform Information and Blockchain Transactions

We construct a unique dataset of blockchain transactions from Web3 platforms. We wrote a robot to crawl all data pertaining to Web3 platforms from ICObench.com until February 2021. We collected multiple features including token name, token ticker, ICO start date and ICO end date. We added missing information from icodrops.com and trackico.io for about 10% of the Web3 platforms. We drop observations with missing information. Next, we scrape the publicly available blockchain ledger to collect platform transactions. About 86% of the platforms in our sample operate on Ethereum with transactions listed on etherscan.io. We collected time-stamped transactions for each platform from its inception until February 2021 using the API provided by etherscan.io and a Selenium web-scraper[2]. From each transaction record,

[2] We searched for each crypto token's wallet addresses in Etherscan.io by its token name. We manually validated the mapping between each token and the found addresses. Then we retrieved all transactions associated with these addresses using Ethereum ETL (https://github.com/blockchain-etl/ethereum-etl).

we collected the sender and receiver wallet addresses. Considering that the growth stage starts after the fundraising concludes, we use only the transactions committed after ICO start dates. After removing samples that failed during ICO fundraising[3], our final dataset consists of 2,557 Web3 platforms.

Variable Descriptions and Summary Statistics

Leveraging lifecycle theories (Moore, 1993), we attempt to understand how platforms behave during the development and expansion phases. Previous studies define phases by critical milestones, e.g., ranking recognition for mobile applications. Alternatively, prior research has documented the high mortality of new technology firms in the first 2 years (Mayer & Goldstein, 1961; Reynolds, 1987). It has been empirically evident that the first 2 years are the most critical period in determining the sustainability of a new venture. During this period, the venture needs to build up the necessary capabilities (Li et al., 2010), establish its competitive position in the market (Mayer & Goldstein, 1961), and prepare itself for long-term sustainability. We postulate that 2 years (104 weeks) can be a critical milestone for a Web3 platform, a new venture by its nature. We plot the mean and median numbers of transactions per week in Figure 1. Token transactions stay stagnant roughly for the first 2 years and later surge indicating the expansion phase. Thus, we use 2 years as the cutoff point to separate the development phase from the expansion phase.

We create a time-series panel with user activities and service usage from token transactions to represent the growth of a Web3 platform. We choose the weekly count of transactions (denoted as TransCount) as the indicator of service usage[4]. We compute several metrics with the awareness that a sustainable user base plays a central role in network effects and therefore a platform's success (Stummer et al., 2018; Suarez & Kirtley, 2012). Prior literature has documented the importance of user acquisition in sustaining a (Web3) platform's growth (Cennamo & Santalo, 2013; Gu et al., 2022; Sangaralingam et al., 2012). Only platforms that are able to sustain user activities can achieve network effects and final success (Aral & Walker, 2011; von Briel & Davidsson, 2019). Thus, we break users into "New users", "Returning users" and "One-time Users" groups (Sayyed-Alikhani et al., 2021). Accordingly, for each week t, we compute the numbers of new wallets[5] (NewUserCnt), existing wallets which issue transactions again (ReturningUserCnt), and the wallets that traded only once by time t (OnetimeUserCnt) to measure these three groups, respectively. Considering crypto tokens as digital products, we analogize token transactions to the concept of product purchasing behavior, and solely focus on buyer wallets that receive tokens when calculating these user metrics (Gan et al., 2021). Our panel has 255,728 weekly transaction records across 2,557 Web3 platforms, among which 203,963 records across 2,557 projects in Phase 1 and 51,765 records across 1,304 projects in Phase 2.

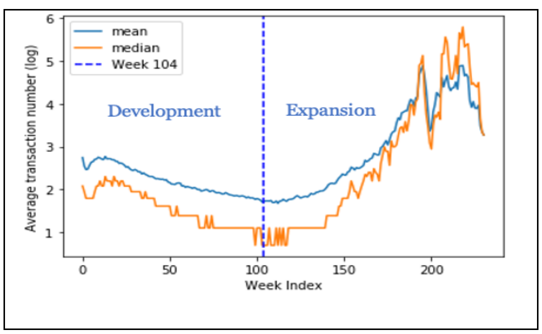

Figure 1 Identifying Platform Stages by Transaction Patterns

Table 1 describes key variables and Table 2 shows the summary statistics and correlations of selected variables. We apply the natural logarithmic transformation to variables "TransCnt", "NewUserCnt", "ReturningUserCnt", "OnetimeUserCnt and "BTC", to mitigate their skewness. In Table 2, only 51% (1,304 out of 2,557) of funded platforms survived the development phase and entered the expansion phase after 2 years. This high failure rate is consistent with the findings about platform risks in the industry report

[3] Since ICO typically lasts for less than one month, we consider platforms with a transaction history shorter than 4 weeks as failed.
[4] We prefer transaction counts to the token volume in transactions because the volume metric may be inflated by a small portion of transactions that transfer large quantities of tokens.
[5] It is possible that a user may have multiple wallets. Due to anonymity, it is difficult to associate a wallet with its actual owner. We use the number of unique wallet addresses found in transactions as a proxy to measure a platform's user base.

(Fromberger & Haffke, 2019). This finding prompts us to differentiate thriving platforms from those in jeopardy and characterize each type by clustering.

Variable	**Definition**	**Source**
$TransCnt_t$	The total number of transactions at week t	Calculation from transaction data
$NewUserCnt_t$	The total number of new users at week t	
$ReturningUserCnt_t$	The total number of users repurchasing tokens at week t	
$OnetimeUserCnt_t$	The accumulative number of users that purchase tokens only once prior to week t.	

Table 1. Variable Definitions

Variable	# of obs.	Mean	SD	Min	Max	Pearson's correlation			
						$TransCnt_t$	$NewUserCnt_t$	$ReturningUserCnt_t$	$OnetimeUserCnt_t$
Phase 1 (2557 projects)									
$TransCnt_t$	203,963	2.26	2.37	0	12.45	-			
$NewUserCnt_t$	203,963	1.54	1.87	0	12.32	0.94			
$ReturningUserCnt_t$	203,963	2.38	1.67	0	11.73	0.93	0.88		
$OnetimeUserCnt_t$	203,963	6.13	2.62	0	13.24	0.57	0.52	0.61	
BTC_t	203,963	8.87	0.39	6.40	10.52	-0.04	-0.04	-0.04	-0.001
Phase 2 (1304 projects)									
$TransCnt_t$	51,765	2.00	2.24	0	10.91	-			
$NewUserCnt_t$	51,765	1.31	1.69	0	10.74	0.94			
$ReturningUserCnt_t$	51,765	1.28	1.61	0	8.84	0.96	0.92		
$OnetimeUserCnt_t$	51,765	7.99	2.01	0	13.24	0.61	0.58	0.58	
BTC_t	51,765	9.37	0.45	8.12	10.52	0.02	0.03	0.0078	0.02

Note: The variables of TransCnt, NewUserCnt, ReturningUserCnt and OnetimeUserCnt above are in natural logarithm.

Table 2. Summary Statistics and Pairwise Correlations

Experiment 1: Clustering Platform Transaction Trajectories (RQ-1)

To answer our research question RQ-1, we apply K-Means to cluster the time series of transaction counts in Phase 1 and Phase 2 separately. In particular, we would like to capture the dynamic patterns of platform service usage during each phase to inform whether a platform can grow along a healthy trajectory. Since these time series vary in their lengths, we adopt Dynamic Time Swapping (DTW) as the distance measure. DTW can compare time series in different sizes and is robust to shifts or dilatations across the time dimension (Petitjean et al., 2010). For two time series $\boldsymbol{x} = \{x_1, x_2, \dots, x_p\}$ and $\boldsymbol{y} = \{y_1, y_2, \dots, y_q\}$, let $A = \{a_{i,j}\}^{p\times q}$, where $a_{i,j} = 0$ or 1, be a matrix of pairwise element mapping between $\boldsymbol{x}$ and $\boldsymbol{y}$. $a_{i,j} = 1$ indicates x_i is aligned with y_j with a distance $\delta(x_i, y_j) = \parallel x_i - y_j \parallel$ (i.e., Euclidean distance). Every element in $\boldsymbol{x}$ must be mapped to at least one element in $\boldsymbol{y}$ and vice versa, i.e., $\forall\, i, j, \sum_i a_{i,j} \geq 1, \sum_j a_{i,j} \geq 1$. Then we find the best alignment A^* such that the sum of the distances of the mapped element pairs is minimized, i.e.,

$$DTW(\boldsymbol{x}, \boldsymbol{y}) = \sum_{a_{i,j}=1,\ a_{i,j}\in A^*} \delta(x_i, y_j), \text{ where } A^* = \underset{A}{\operatorname{argmin}} \sum_{a_{i,j}=1,\ a_{i,j}\in A} \delta(x_i, y_j) \quad (1)$$

To illustrate, we plot the alignment between two randomly selected platforms (denoted as A and B) in Figure 2. A has transactions across 40 weeks while B has 23 weeks. DTW matches the troughs and peaks with the same pattern, and there is no observation left out for both curves. The DTW distance between A and B in Figure 1 is as high as 13.8, since they are not similar.

After calculating the pairwise DTW distances between samples, we perform K-Means clustering based on these distances. The centroid of a cluster is a time series that minimizes the sum of its DTW distances to all the time series within the cluster. Formally, given a set of time series $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_m\}$, the centroid of the set, denoted as $\boldsymbol{c}^*$, is a time series such that:

$$c^* = \underset{c}{\operatorname{argmin}} \sum_{i=1}^{m} DTW(x_i, c) \qquad (2)$$

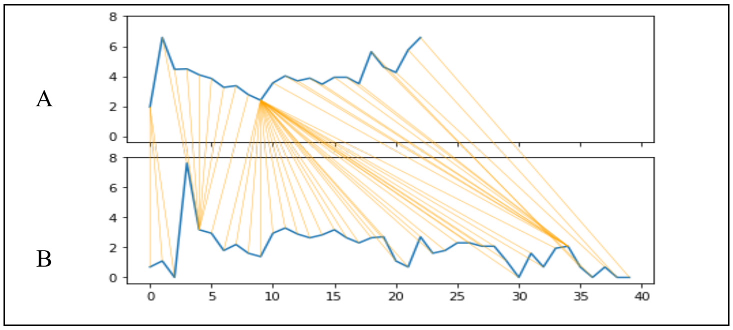

Figure 2. Matching in DTW distance

Equation (2) can be solved by an algorithm called DTW barycenter averaging (DBA) which iteratively refines an initial centroid following an Expectation-Maximization strategy (Petitjean et al., 2011)[6]. Based on the cluster inertia and the DTW distances between centroids, we found the optimal cluster number is 3 for both phases. Figure 3 shows the centroids of each cluster. We label these clusters in Phase 1 (the development phase) as: (a) Inactive where platforms have minimum transactions (mean = 2 transactions per week), (b) Growing where platforms consistently have a large number of transactions (mean = 284 transactions per week), and (c) Uncertain where transactions trend down. Unfortunately, a majority of platforms (56%) belong to the Inactive cluster. Similarly, platforms in Phase 2 consist of an Inactive cluster (averagely 2 transactions per week), a Mature cluster (averagely 544 transactions per week), and a Sluggish cluster with infrequent transactions. Only 8% (113 out of 1304) platforms belong to the Mature cluster.

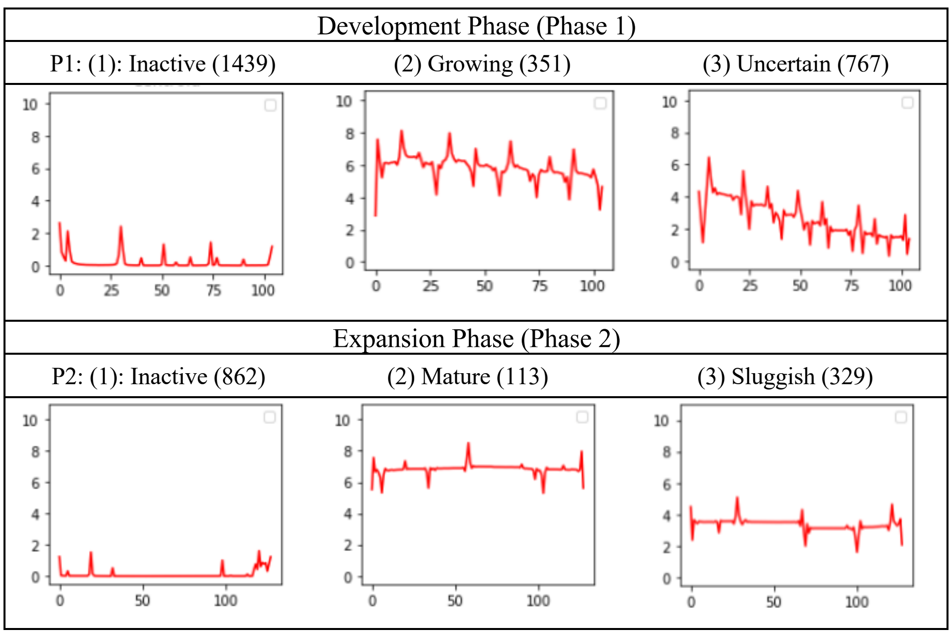

Figure 3. Clustering results for each phase

Each cluster can be interpreted as a state of Web3 platforms. We use Table 3(a) to illustrate how Web3 platforms transition from Phase 1 states to Phase 2 states. First, in Phase 1, Growing platforms have the highest probability (32%) to enter the Mature state in Phase 2, while the other two states have very slim chances to thrive. Second, 91% (1311 out of 1429) Inactive platforms in Phase 1 remain Inactive or become terminated in Phase 2 and 73% (513 out of 707) of Uncertain platforms in Phase 1 have become inactive or been terminated in Phase 2. Thirdly, Inactive platforms in Phase 1 have the highest failure rate as 64% (925 out of 1429) of them have been terminated in Phase 1. This result not only confirms the high-risk tendency

[6] This algorithm is implemented by Python package tslearn (https://tslearn.readthedocs.io/en/stable/index.html).

observed in Web3 platforms but also suggests that platform growth in the development phase is critical to the platform survival in the long term.

To analyze the differences amongst clusters within each phase, in Table 3(b), we compute the descriptive statistics of our variables by phase. In addition, we conduct a series of T-tests to examine the difference between clusters. As shown in Table 3(b), there exists a statistically significant positive difference between Inactive platforms and Growing platforms in Phase 1 in terms of all four variables. The Growing platforms have 10 times more new users and returning users than the Inactive ones (4.10 vs 0.38, 3.88 vs 0.27, respectively), the average transaction counts of these two groups differ by almost 7 times (5.65 vs 0.62), but the one-time user counts differ by merely 1 time (8.82 vs 4.3). This implies that a greater number of users of Inactive platforms are one-shot game players, who purchase and dump the platform tokens for speculations. Similar observations can be found in Phase 2 where these four variables for the Mature cluster are all significantly higher than those for Inactive cluster. After identifying prospering and struggling platforms, next, we attempt to explain their differences by the dynamics that drive the user-adoption network effects and therefore the growth of Web3 platforms.

(a) State Transition

S1 \ S2		Platforms Transitioned to Phase 2 (Expansion)				Terminated in Phase 1	Currently in Phase 1
		(1) Inactive	(2) Mature	(3) Sluggish	Total		
Phase 1 (Development)	(1) Inactive	386	1	10	397	925	117
	(2) Growing	21	101	181	303	1	47
	(3) Uncertain	455	11	138	604	58	105
Total		862	113	329	1304	984	269

(b) Variable Statistics by Cluster and Phases

		TransCnt		NewUserCnt		ReturningUserCnt		OnetimeUserCnt	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Phase 1 (Development)	(1) Inactive	0.62	1.10	0.38	0.84	0.27	0.58	4.30	2.04
	(2) Growing	5.65***	1.77	4.10***	1.77	3.88***	1.55	8.82***	1.81
	(3) Uncertain	2.71*	1.85	1.77	1.55	1.60**	1.25	7.12**	1.81
Phase 1 (Expansion)	(1) Inactive	0.48	0.78	0.27	0.51	0.24	0.47	6.96	1.86
	(2) Mature	6.30**	1.37	4.65***	1.41	4.56***	1.15	10.27***	1.15
	(3) Sluggish	3.04**	1.38	1.89***	1.16	1.86**	1.02	8.93*	1.22

Note: The significance of the difference between clusters is indicated by "***" ($p<0.01$), "**" ($p<0.05$), "*" ($p<0.1$). The cluster (1) Inactive in both phases is the reference cluster for T-tests.

Table 3. State Transition and Statistics of User-Related Variables

Experiment 2: Dynamic system analysis using PVAR by phase (RQ-2)

Given the central role of users in Web3 platforms, we draw our attention to user adoption and investigate its dynamic interaction with platform growth. We postulate that user adoption and network effects may help explain the differences in the platform clusters and shed light on the growth mechanism unique to each phase. We use PVAR to examine the dynamic mechanism of how the user base increase (i.e., new user count) and the use engagement (i.e., returning and one-time user counts) can interact with the service usage (i.e., transaction count). For each phase, we implement a PVAR model on these variables for each cluster. Since the first two clusters for both phases form a stronger contrast to tell the platform growth dynamics, in particular, we are interested in comparing *Growing* platforms with *Inactive* platforms in Phase 1 (i.e., development phase), and *Mature* platforms with *Inactive* platforms in Phase 2 (i.e., expansion phase).

PVAR imposes a statistical model on the movements of the variables and suggests a true simultaneity among them. PVAR does not distinguish between exogenous and endogenous variables but rather treats all variables as jointly endogenous (Abrigo & Love, 2016; Wang et al., 2021). More importantly, PVAR enables us to peek into the long-term dynamics between variables through impulse response functions. Our PVAR model is specified in Equation (4):

$$\begin{pmatrix} \text{NewUserCnt} \\ \text{ReturningUserCnt} \\ \text{OnetimeUserCnt} \\ \text{TransCnt} \end{pmatrix}_{i,t} = \sum_{s=1}^{p} \boldsymbol{\Phi}_s \cdot \begin{pmatrix} \text{NewUserCnt} \\ \text{ReturningUserCnt} \\ \text{OnetimeUserCnt} \\ \text{TransCnt} \end{pmatrix}_{i,t-s} + \boldsymbol{\beta} \cdot \text{BTC}_{i,t-1} + \boldsymbol{f}_i + \boldsymbol{\varepsilon}_{i,t} \qquad (4)$$

where the independent variable is a four-element column vector for each project i at week t; $\boldsymbol{\Phi}_s$ are the 4×4 coefficients matrix for endogenous variables; p is max lag order. To control for market sentiment, we include the average Bitcoin price at week *t-1* of project i as an exogenous variable and $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4)^T$ is the 4-element vector coefficients. The panel data structure by nature incorporates $\boldsymbol{f}_i = (f_{i,1}, f_{i,2}, f_{i,3}, f_{i,4})^{\boldsymbol{T}}$ as time-invariant unobserved project-specific effects; $\boldsymbol{\varepsilon}_{i,t}$ is the 4-element error vector $(\varepsilon_{i,t,1}, \varepsilon_{i,t,2}, \varepsilon_{i,t,3}, \varepsilon_{i,t,4})^T$ satisfying the normality and independence assumption of $E(\boldsymbol{\varepsilon}_{i,t}) = \mathbf{0}$ and $Cov(\boldsymbol{\varepsilon}_{i,m}, \boldsymbol{\varepsilon}_{i,n}) = \mathbf{0}$.

We follow the standard procedures for the PVAR method (Wang et al., 2021). We perform Fisher-Type root unit tests to verify the absence of unit roots and the satisfaction of stationary assumption. From the stationary test, all the variables in Equation (4) are stationary except OnetimeUserCnt. We then take the first difference order of OnetimeUserCnt and confirm the stationarity of this newly generated variable. With the lag order selection, we find the optimal lag order is 1 as it gives the largest overall coefficient of determination (CD). Besides, we make Helmert transformation to remove the skewness and improve the model fit (Arellano & Bover, 1995). After running each PVAR model, we compute the impulse response function (IRF) to examine the longer-term dynamics. IRF demonstrates the longer-term response of each of the PVAR endogenous variables to one unit shock of the other endogenous variable through Monte Carlo simulation with 100 repetitions. It helps us check whether the effects are transitory or not.

PVAR results of Development Phase (Phase 1)

Table 4 describes the short-term dynamics obtained by PVAR for the *Growing* and *Inactive* groups. We notice two key user transitions in Growing platforms. First, the new user increase of the preceding week (t-1) may positively and significantly affect the returning users in the current week (t). It indicates that there exists a quick transition from new users to returning users. Second, the returning users of the preceding week (t-1) can inversely affect the one-time users of the current week (t). It implies that a significant number of one-time users has been converted to returning users in week t-1, making one-time users in week t dropped. Although these two transitions can also be observed in *Inactive* platforms, their impact sizes are dramatically reduced by 67% (12% vs. 20%) and 77% (17% vs. 30%), respectively. In addition, the weekly transactions of Growing platforms are contributed considerably by new users rather than by returning users, and one-time users even have a negative effect on it. In contrast, these patterns are missing in *Inactive* platforms.

	Dependent Variables			
"*Inactive*" group				
Independent Variables	TransCnt $_{i,t}$	NewUserCnt $_{i,t}$	ReturningUserCnt $_{i,t}$	OnetimeUserCnt $_{i,t}$
TransCnt $_{i,t-1}$	0.41***	0.03***	0.08***	0.07***
NewUserCnt $_{i,t-1}$	**0.18*****	0.45***	**0.12*****	0.14***
ReturningUserCnt $_{i,t-1}$	**0.16*****	0.16***	0.31***	**-0.17*****
OnetimeUserCnt $_{t-1}$	**0.16*****	0.18***	0.01	0.02**
BTC $_{i,t-1}$	-0.56***	-0.37***	-0.22***	0.05***
"*Growing*" group				
Independent Variables	TransCnt $_{i,t}$	NewUserCnt $_{i,t}$	ReturningUserCnt $_{i,t}$	Onetime-UserCnt $_{i,t}$
TransCnt $_{i,t-1}$	0.54***	-0.09***	0.10***	0.13***
NewUserCnt $_{i,t-1}$	**0.23*****	0.85***	**0.20*****	0.14***
ReturningUserCnt $_{i,t-1}$	**0.04*****	0.06***	0.52***	**-0.30*****
OnetimeUserCnt $_{t-1}$	**-0.03****	0.00	-0.04***	0.02***
BTC $_{i,t-1}$	-0.81***	-1.13***	-0.26***	0.05***
Note: p<0.01: ***, p<0.05: **, p<0.1: *				

Table 4. Estimation Results for PVAR (Phase 1)

Furthermore, IRF plots in Figure 4(a) show that the aforementioned short-term differences between Growing and Inactive platforms are persistent and still evident in a longer term. Our findings suggest that a healthy platform in Phase 1 is able to attract new users and convert new and one-time users to returning users quickly. In this way, it can retain user activities and tend to form a stable user base. To validate the findings, in Figure 4(b), we plot the average proportions of transactions contributed by user users and returning users across platforms in each group. For growing platforms, new users initially bring a larger portion of transactions than returning users. As more users retain their activities and become returning users, the proportion by returning users surges drastically and outnumbers that by new users. In contrast, an Inactive platform is unable to hold its users to build a stable user base as it lacks those healthy user-transition mechanisms. Its platform usage shrinks as fewer new users return and fewer returning users retain.

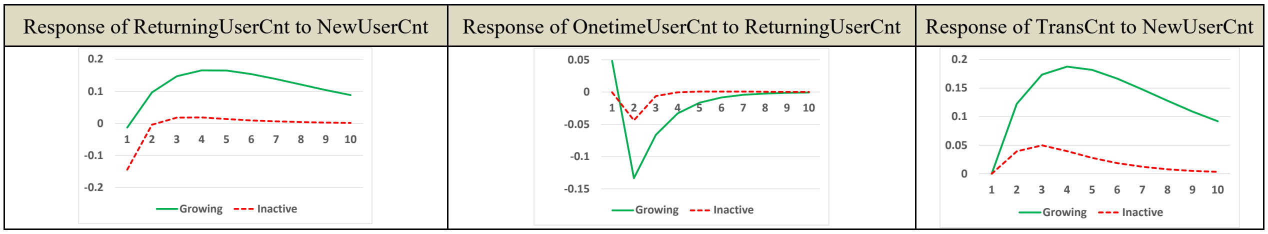

Figure 4(a). Impulse Response Plot for Growing and Inactive Groups (Phase 1)

Figure 4(b). The proportion of transactions by new users and returning users by group (Phase 1)

PVAR results of Expansion Phase (Phase 2)

The PVAR results for Phase 2 are shown in Table 5. Similar to Phase 1, Mature platforms in this phase also exhibit two types of user transitions among new, returning, and one-time users. Differently, returning users of the preceding week (t-1) have an increasingly greater impact on the transaction count of the current week (t). In addition, the self-driven forces of new users and returning users in Mature platforms are about three times larger than those in Inactive platforms (0.70 vs. 0.24 and 0.51 vs. 0.17). With more users joining at week t-1, the value of a Web3 platform increases, thereby attracting more new users at week t. Returning users of week t are highly positively associated with those in week t-1, indicating repeated use. As returning users play a decisive role in Phase 2, they become determinant in the weekly transactions count.

Figure 5(a) shows the subplots that show key longer-term patterns between the Inactive group and the Mature group. As shown in Figure 5(a)-(1-2), the impact of new users or returning users of week t-1 on the transaction count of week t is larger and lasts longer in Mature platforms. The plots in Figure 5(a)-(3-4) show that the self-driven forces of new users and returning users in Mature platforms are more persistent than in Inactive platforms. These observations together imply that both new-user acquisition and users' repeated usage are important to the platform growth in this phase. Importantly, as shown in Figure 5(b), the user base in this phase has been stabilized as the contributions of new users and returning users have been flattened out. It is imperative to form a virtuous cycle that can dynamically maintain and further expand such a user base. For instance, the increase in new users attracts more other new users by signaling the platform value; existing users constantly engage with the platform to form a sustainable user base. On the contrary, inactive platforms shrink, because it appears that new user increase is not sufficient enough to attract more users, and existing users cannot continuously remain active.

	Dependent Variables			
"Inactive" group				
Independent Variables	TransCnt $_{i,t}$	NewUserCnt $_{i,t}$	ReturningUserCnt $_{i,t}$	OnetimeUserCnt $_{i,t}$
TransCnt $_{i,t-1}$	**0.17*****	0.01	0.05^{**}	0.01^{*}
NewUserCnt $_{i,t-1}$	**0.18*****	**0.24*****	0.12^{***}	0.01^{***}
ReturningUserCnt $_{i,t-1}$	**0.19****	0.16^{***}	**0.18*****	-0.01^{*}
OnetimeUserCnt $_{i,t-1}$	-0.05	0.08	0.03	0.08
BTC $_{i,t-1}$	0.12^{***}	0.09^{***}	0.03^{***}	0.001^{***}
"Mature" group				
Independent Variables	TransCnt $_{i,t}$	NewUserCnt $_{i,t}$	ReturningUserCnt $_{i,t}$	OnetimeUserCnt $_{i,t}$
TransCnt $_{i,t-1}$	**0.51*****	-0.09^{***}	-0.04	0.001^{***}
NewUserCnt $_{i,t-1}$	**0.11*****	**0.70*****	0.18^{***}	0.01^{***}
ReturningUserCnt $_{i,t-1}$	**0.14****	0.12^{***}	**0.51*****	-0.01^{***}
OnetimeUserCnt $_{i,t-1}$	-0.05	0.12	-1.42^{**}	0.24^{***}
BTC $_{I,t-1}$	-0.05^{**}	0.08^{**}	-0.11^{***}	-0.01^{***}
Note: p<0.01: ***, p<0.05: **, p<0.1: *				

Table 5. Estimation Results for PVAR (Phase 1)

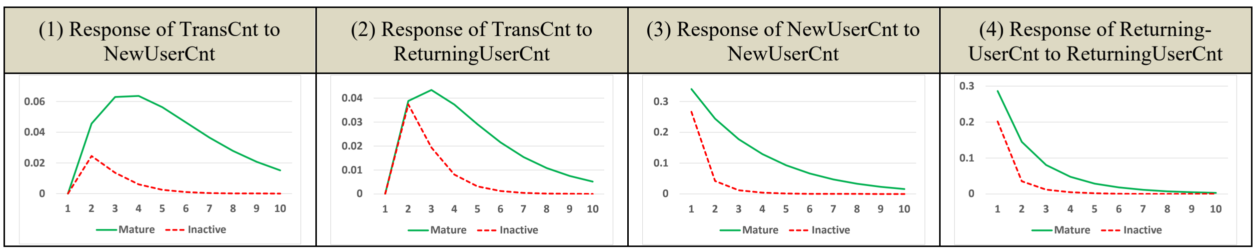

Figure 5(a). Impulse Response Plot for Mature and Inactive Groups (Phase 2)

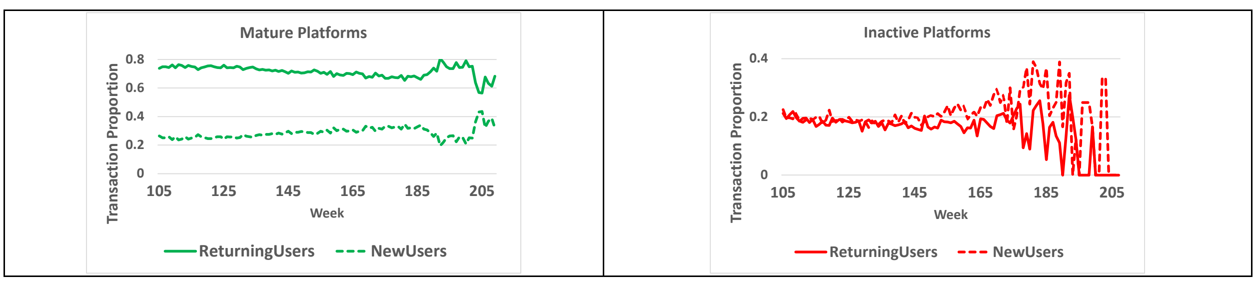

Figure 5(b). The proportion of transactions by new users and returning users by group (Phase 2)

To sum up, in Phase 1, a Web3 platform starts with very few users and is in urgent need of a scalable user base. Hence it is important to acquire new users and quickly transform them into returning users to form an initial user base. Upon Phase 2, the initial user base has been stabilized by acquiring and retaining users. Thus, both new users and returning users significantly account for the platform activeness. It is notable that new users always play an important role throughout the growth stage of Web3 platforms, which is different from Web2 platforms. In the presence of high switching costs, the growth of Web2 platforms is dominantly driven by repeated usage of returning users whereas new users have a less central position in the platform expansion (Subramanian et al., 2021). In contrast, Web3 platforms are inborn with minimal switching costs and high forkability due to their decentralization nature (Choudary 2022), so it is equally important to continuously acquire new users and retain existing users to maintain sustainable user bases.

Conclusion

In this paper, we have taken an initial step to investigate the sustainability of Web3 platforms through the lens of business lifecycles and identify the critical driving forces during the two growth phases. Given the centric role of users in a platform ecosystem, our research tackles the user adoption factors that define a user base, i.e., new user count, returning users count and one-time users. We conduct a dynamic PVAR analysis of the temporal transaction data of 2,557 Web3 platforms. Our study implies that new users count and returning users count are predominant factors in driving platform growth. Especially, new users are the initial drive of user adoption. The network effects of user adoption are forming in Phase 1 and exhibit a stable pattern in Phase 2. It emphasizes the importance of new user acquisition in Phase 1, which lays the groundwork to push for sustainable network effects for a future phase. New users and returning users are equally critical for platform growth in Phase 2. The central role of new uses across these two growth phases points out the difference in platform growth between Web3 platforms and Web2 platforms where returning users are dominantly important. In addition, our finding shows that a platform's standing in Phase 1 can critically determine its subsequent sustainability. A well-operated development phase leads to platform maturity with a much higher probability.

Our study highlights the central role of users. It enhances the understanding of the growth and sustainability of Web3 platforms. In addition, our study also offers valuable practical implications. It informs entrepreneurs of how a Web3 platform would thrive along an upgrowth trajectory and helps them formulate effective business strategies toward user adoption. Certainly, our work has a few limitations. We focused on metrics related to user adoption. As an extension, a detailed examination into user base segments, such as one-time users vs. loyal users, and developers vs. consumers, may foster new streams of research.

References

Abrigo, M. R., & Love, I. (2016). Estimation of panel vector autoregression in Stata. *The Stata Journal*, *16*(3), 778-804.

Aral, S., & Walker, D. (2011). Creating social contagion through viral product design: A randomized trial of peer influence in networks. *Management science*, *57*(9), 1623-1639.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Cennamo, C., & Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets. *Strategic management journal*, *34*(11), 1331-1350.

Chen, W., Li, W., & Xie, K. (2020). Growing Entrepreneurship with Crypto Tokens. In (Vol. 7). *ICIS 2020 Proceedings*.

Choudary , **S. P.** (2022). *Web3 competitive advantage: Winning in open and decentralized ecosystems*. https://platforms.substack.com/p/web3-competitive-advantage-winning?s=r

Clements, M. T. (2004). Direct and indirect network effects: are they equivalent? *International Journal of Industrial Organization*, *22*(5), 633-645.

Cong, L. W., Li, Y., & Wang, N. (2021). Tokenomics: Dynamic adoption and valuation. *The Review of Financial Studies*, *34*(3), 1105-1155.

Fisch, C., & Momtaz, P. P. (2020). Institutional Investors and Post-ICO Performance: An Empirical Analysis of Investor Returns in Initial Coin Offerings (ICOs). *Journal of Corporate Finance*.

Fisher, G., Kotha, S., & Lahiri, A. (2016). Changing with the times: An integrated view of identity, legitimacy, and new venture life cycles. *Academy of Management Review*, *41*(3), 383-409.

Fritsch, F., Emmett, J., Friedman, E., Kranjc, R., Manski, S., Zargham, M., & Bauwens, M. (2021). Challenges and approaches to scaling the global commons. *Frontiers in blockchain*, *4*, 578721.

Fromberger, M., & Haffke, L. (2019). ICO Market Report 2018/2019–Performance Analysis of 2018's Initial Coin Offerings. *Available at SSRN*.

Gan, J., Tsoukalas, G., & Netessine, S. (2021). Initial coin offerings, speculation, and asset tokenization. *Management Science*, *67*(2), 914-931.

Gu, Z., Bapna, R., Chan, J., & Gupta, A. (2022). Measuring the impact of crowdsourcing features on mobile app user engagement and retention: a randomized field experiment. *Management Science*, *68*(2), 1297-1329.

Kim, J., & Yoo, J. (2019). Platform growth model: The four stages of growth model. *Sustainability*, *11*(20), 5562.

Li, S., Shang, J., & Slaughter, S. A. (2010). Why do software firms fail? Capabilities, competitive actions, and firm survival in the software industry from 1995 to 2007. *Information Systems Research*, *21*(3), 631-654.

Lin, Y.-K., & Maruping, L. M. (2022). Open source collaboration in digital entrepreneurship. *Organization Science*, *33*(1), 212-230.
Lyandres, E., Palazzo, B., & Rabetti, D. (2022). Initial coin offering (ico) success and post-ico performance. *Management Science*.
Mayer, K. B., & Goldstein, S. (1961). *The first two years: Problems of small firm growth and survival* (Vol. 2). Small Business Administration.
McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic management journal*, *38*(1), 141-160.
Momtaz, P. P. (2021). *Token Offerings Research Database (TORD)*.
Moore, J. F. (1993). Predators and prey: a new ecology of competition. *Harvard business review*, *71*(3), 75-86.
Murray, A., Kim, D., & Combs, J. (2022). The promise of a better Internet: What is Web 3.0 and what are we building? *Available at SSRN: https://ssrn.com/abstract=4082462*.
Parker, G., Alstyne, M. V., & Jiang, X. (2017). Platform ecosystems: how developers invert the firm. *MIS Quarterly*, *41*(1), 255-266.
Petitjean, F., Ketterlin, A., & Gançarski, P. (2011). A global averaging method for dynamic time warping, with applications to clustering. *Pattern recognition*, *44*(3), 678-693.
Petitjean, J., Grivel, E., Diversi, R., & Guidorzi, R. (2010). A recursive errors-in-variables method for tracking time varying autoregressive parameters from noisy observations. 2010 18th European Signal Processing Conference,
Reynolds, P. D. (1987). New firms: Societal contribution versus survival potential. *Journal of business venturing*, *2*(3), 231-246.
Sangaralingam, K., Pervin, N., Ramasubbu, N., Datta, A., & Dutta, K. (2012). Takeoff and sustained success of apps in hypercompetitive mobile platform ecosystems: an empirical analysis. *ICIS 2012 Proceedings*.
Sayyed-Alikhani, A., Chica, M., & Mohammadi, A. (2021). An agent-based system for modeling users' acquisition and retention in startup apps. *Expert Systems with Applications*, *176*, 114861.
Song, P., Xue, L., Rai, A., & Zhang, C. (2018). The ecosystem of software platform: A study of asymmetric cross-side network effects and platform governance. *Mis Quarterly*, *42*(1), 121-142.
Stummer, C., Kundisch, D., & Decker, R. (2018). Platform launch strategies. *Business & Information Systems Engineering*, *60*(2), 167-173.
Suarez, F. F., & Kirtley, J. (2012). Dethroning an established platform. *MIT Sloan Management Review*, *53*(4), 35-41.
Subramanian, H., Mitra, S., & Ransbotham, S. (2021). Capturing value in platform business models that rely on user-generated content. *Organization Science*, *32*(3), 804-823.
Thies, F., Wessel, M., & Benlian, A. (2018). Network effects on crowdfunding platforms: Exploring the implications of relaxing input control. *Information Systems Journal*, *28*(6), 1239-1262.
Tönnissen, S., Beinke, J. H., & Teuteberg, F. (2020). Understanding token-based ecosystems–a taxonomy of blockchain-based business models of start-ups. *Electronic Markets*, *30*(2), 307-323.
von Briel, F., & Davidsson, P. (2019). Digital platforms and network effects: using digital nudges for growth hacking. ICIS 2019 Proceedings,
Wang, Y.-Y., Guo, C., Susarla, A., & Sambamurthy, V. (2021). Online to offline: the impact of social media on offline sales in the automobile industry. *Information Systems Research*, *32*(2), 582-604.
Zhu, K., Kraemer, K. L., Gurbaxani, V., & Xu, S. X. (2006). Migration to open-standard interorganizational systems: Network effects, switching costs, and path dependency. *MIS Quarterly*, 515-539.