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The role of platform ecosystem configuration toward performance bifurcation

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ABSTRACT

The prevalence of digital ecosystems and platforms underscores the need for a deeper understanding of the factors that influence performance variations within these platforms. This study introduced a multidimensional model to examine the platform ecosystem characteristics that affect performance outcomes. To this end, it adopted the Lotka-Volterra complex system theory. The model was simplified into a one-dimensional framework, enabling the examination and prediction of the relationship between performance bifurcation and configurations of platform characteristics. This study provides practical insights and implications that extend beyond academia. The results reveal that high network threshold values indicate robust platform performance, suggesting resilience against collapse. Additionally, increasing the network effect influences platform performance by shifting competition strength toward prominent tipping-point locations, which is considered a desirable regime. The results further confirm that competition dampens a platform's exponential growth; however, cross-network effects enhance it. These insights have significant implications for investors, offering a practical vision that can inform managers' strategic decision-making. These findings provide a solid foundation for developing informed strategies to enhance platform performance. In a world in which digital ecosystems play a pivotal role, the implications of this study empower stakeholders to make data-driven decisions, fostering success in a dynamic and competitive digital business environment.

Introduction

The concept of platform ecosystems has become crucial in the current era. These ecosystems are characterized by fast digital transformation and increasing interdependence (Duan et al., 2022). Encompassing various stakeholders, such as platform owners, developers, and users, they have become vital conduits for innovation, economic growth, and value creation (Duan et al., 2023). Understanding the dynamics within platform ecosystems, particularly how their inherent characteristics and configurations shape performance outcomes, is of paramount importance. The architecture of a platform ecosystem depicts how its production can be organized (Baldwin et al., 2000). Thus, platform ecosystem configurations substantially influence their comprehensive dynamics, performance, stability, and susceptibility to collapse (Loudahi & Khurshid, 2022; Morris et al., 2021).

Over the past few decades, platform ecosystems have become crucial players in the modern economy. Platform ecosystems have replaced traditional models in the software industry and beyond (Duan et al., 2021). As economic and social transactions move to the Internet, platform ecosystems have emerged as enablers of exchange between different groups of agents in many areas. This phenomenon goes beyond the use of traditional models to evaluate the platform performance. Belleflamme and Peitz (2021), Loux et al. (2020), and Van Alstyne et al. (2016) used traditional financial theory to examine platform performance. The configuration of a platform ecosystem forms an extensive and complex network of dynamic interconnections between users and characteristics. This configuration makes it challenging to evaluate the performance using only traditional theoretical models.

In the past, conventional theories have been employed to analyze platform performance. However, limited consideration has been given to the interaction between platform ecosystem characteristics and operational performance during evaluation. Platform ecosystem structuring is the prevailing approach for addressing intricate network challenges (Innocenti et al., 2020; Mysachenko et al., 2020).

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Although these methods predominantly concentrate on innovating and enhancing platform products and services, they often overlook valuable information embedded within the platform's characteristic topology. The networking and diverse operations of these entities have long inspired observers; however, comprehending the mechanisms underpinning their diversity, bifurcation, tipping points, and operational performance remains a formidable challenge (Bascompte & Stouffer, 2009; Brose et al., 2006; Loreau, 2010). Their theoretical exploration frequently hinges on extensive numerical simulations as modeling techniques.

This study reveals the configuration of the platform ecosystem characteristics that permit intricate cross-network interactions. Despite superficial differences in the platform ecosystem (Ye et al., 2023), they can be understood within a unified framework and discerned by only a handful of parameters, as Lotka-Volterra complexity theory advocates. Complex structures do not necessarily require complex dynamics (Barbier et al., 2018; Duan et al., 2023). This study demonstrates that the different modes exhibit comparable collective qualities in the context of platform ecosystem configuration characteristics. These traits were recorded using parameter attributes.

This study fills a gap in the literature by focusing on complex networks and the emergence of platform ecosystems. First, we identify individual characteristics from Barbier et al. (2018) and group them into various modes to form a community to examine the emergence of the characteristic mode in platform interactions. Second, we develop a new model by accumulating the characteristics' modes within the generalized Lotka-Volterra dynamics theory framework to show the influence of the interaction among the platform characteristics and the operations performance. Previous studies, such as Jacobides et al. (2018), failed to identify such influence. In contrast, we formulate a simplified method suitable for diverse complex platform systems. This method uncovers pertinent structures within these systems (Jia et al., 2021), allowing the evaluation of previous simplified theories that have proven helpful in platform ecosystem management. Finally, this study offers insight into platform characteristic configurations and a prediction of any platform's platform bifurcation point (and, thus, the critical transition point).

The novelty of this study lies in its attempt to uncover the intricacies of platform ecosystems and their impact on performance outcomes. Unlike Barbier et al. (2018) and previous studies focused on complexities in ecology, this study aims to provide fresh perspectives on the complex relationship between the characteristics that form the configuration of these ecosystems and the phenomenon of performance bifurcation. This approach goes beyond static snapshots and analyzes how changes in ecosystem characteristics over time influence performance divergence. Peltoniemi and Vuori (2004) proposed that a business ecosystem could be understood as an intricate system characterized by self-organization, emergence, co-evolution, and adaptation. Nonetheless, this study concentrates on the intrinsic growth rate, competition, and cross-network effects. It embraces a multifaceted approach to demonstrate that the platform ecosystem does not recognize a one-size-fits-all solution for performance.

Furthermore, it seeks to unravel how innovative models can reshape performance outcomes. This study adds to the current body of knowledge and provides valuable insights for platform owners, governments, and ecosystem participants to navigate the volatile digital environment. Platform ecosystems stimulate economic transformation and innovation. From a micro perspective, using an ego network lens indicates that a company's actions and achievements significantly influence its connections with partners and their relationships (Zaheer et al., 2010). This approach offers an in-depth view of specific firms and highlights the importance of an individual firm within an innovation ecosystem. Nevertheless, these perspectives fail to provide a comprehensive understanding of the platform ecosystem's performance because they overlook the inherent structure of the platform when analyzing its overall effectiveness. This study distinguishes itself by transcending conventional methodologies and approaches for examining platform performance. Most platform performance studies tend to be retrospective, analyzing past performance data without considering the ecosystem's ability to adapt to unforeseen disruptions. This new perspective enriches the current understanding of platform dynamics and provides valuable insights for researchers and stakeholders in these ecosystems.

The remainder of this paper is structured as follows. Section 2 explores the relevant literature and identifies potential shortcomings. Section 3 focuses on developing models to represent the theoretical linkages and simulations of the empirical outcomes. Section 4 examines and evaluates the findings, and Section 5 concludes and offers recommendations for further research.

Literature review

The developed model contributes to the existing platform ecosystem literature by advancing the understanding of diverse domains. Gawer and Cusumano (2014) identify specific platform types and practices that are crucial for effective leadership, shedding light on managing competition and fostering innovation. In addition, Ghazawneh and Henfridsson (2013) generate specialized constructs to comprehend stakeholder actions in third-party development, including self-resourcing, regulation-based security, diversity resourcing, and sovereignty. Gawer (2021) extends their research by providing a nuanced understanding of stakeholder dynamics. The scope of The Jia et al. (2021) is expanded by conducting an ideal experiment to explore the diverse evolutionary trajectories of platform business models in different environments, focusing specifically on China's Tencent and Alibaba. Öberg and Alexander (2019) emphasize openness in various dimensions, link it to knowledge management outcomes, and offer practical insights for firms in selecting mechanisms.

Furthermore, Van Alstyne et al. (2016) investigate network effects as a driving force for successful platforms, emphasizing the crucial understanding of when external forces contribute to or detract from value. Moreover, they underscore the pivotal role of open governance in allowing entities beyond the owner to shape trade rules and reward-sharing dynamics on the platform. This comprehensive review synthesizes these contributions and highlights the interconnected insights that advance the current understanding of platform ecosystems. By synthesizing existing scholarly works, this literature review aims to shed light on the various mechanisms that can shape platform performance in ecosystems. This study delves into the empirical and theoretical research within these domains, encompassing definitions, network effects and their characteristics, competition and associated features, ecology, and platform strategies and designs. This comprehensive exploration aims to elucidate how diverse configurations influence performance and contribute to performance bifurcation within platform ecosystems. Existing literature on platform definition defines platforms within ecosystems as the aggregation of access channels or interfaces that address the challenges encountered by entities within the ecosystem (Iansiti & Levien, 2004). Hence, their study provides a comprehensive overview of platform ecosystems, history, and current state. The authors argue that platform ecosystems are transforming the economy and provide practical advice to firms that want to participate in these ecosystems.

Moreover, some studies have suggested that platform ecosystems are dynamic and evolving. Kietzmann et al. (2011) show that thriving platform ecosystems can adapt to changing market conditions and user requirements. This adaptation requires continuous innovation and the ability to integrate new technologies and services. Platforms have been found to offer corporations significant innovation opportunities (Chatterjee, 2013). A platform system represents a fresh and powerful organizational strategy employed across various industries to facilitate innovation and business transactions (Duan et al., 2024). Consequently, the pursuit of innovative platforms has emerged as the most effective strategy for attaining enduring revenue streams. The literature also explains how competition can lead to the emergence of new and innovative platforms, but it can also create fragmentation and decrease overall network effects.

According to existing literature, the cross-network effect is a crucial driver of platform ecosystem performance. Platform ecosystems are pivotal in contemporary business dynamics, as they foster innovation and value creation (Adner, 2017; Rochet & Tirole, 2003). Exploring the significance of these networks, their constituent elements, and the specific roles undertaken by each participant is crucial for comprehending the collective value generated by collaborative networks and the community (Reynolds et al., 2023). Network effects, encompassing direct and cross-network effects, heavily influence platform success (Rangaswamy et al., 2020; Van et al., 2016). Research has extensively covered these effects, emphasizing their positive impact on user adoption and engagement within a platform (Farrell & Klemperer, 2007; Kretschmer et al., 2022). It is imperative to distinguish between the direct effects occurring within the platform and the cross-network effects that extend beyond influencing interactions between different networks (Van et al., 2016).

Noteworthy studies have explicitly focused on cross-network effects, shedding light on how interactions between diverse networks impact overall platform performance (Gawer & Cusumano, 2014; Rochet & Tirole, 2006). The reviewed literature contributes substantially to understanding the cross-network effects on platform ecosystem performance, with implications for future research directions and industry practices (Parker et al., 2017; Rietveld & Schilling, 2021). Rochet and Tirole (2004) find that network effects can potentially establish a dynamic in which a single dominant platform emerges as the winner-take-all platform and captures the most market share. Another study argues that network effects are insufficient for platform ecosystem success (Hagiu & Wright, 2019). The authors suggest that firms create strong value propositions, design effective mechanisms, and foster network effects through ecosystem orchestration. Their study provides a valuable framework for understanding the factors driving platform ecosystem performance. However, they omit the core characteristics of the platform when evaluating its performance.

The relevant literature cites the concept of competition characteristics in platform ecosystems. Understanding the impact of competition on platform ecosystem performance is crucial for navigating dynamic markets. Competition within platform ecosystems is garnering increasing attention (Jacobides, 2020; Yoffie et al., 2019). Scholars have explored how platform rivalry affects user adoption, value creation, and overall ecosystem performance (Bourreau & Perrot, 2020). Different forms of competition, including direct platform-to-platform and indirect competition through complementary goods or services, contribute to the complexity of platform ecosystems (Eisenmann et al., 2011; Gawer & Cusumano, 2014). Competition can catalyze innovation within platform ecosystems and competitiveness derived from acquired external knowledge to foster innovative strategies for improving performance (Li et al., 2023). Platform operators employ various strategies to navigate the competition and enhance ecosystem performance (Farrell & Klemperer, 2007). These strategies may involve pricing, service differentiation, and partnerships to strengthen the platform's position in the face of rivalry (Helfat & Raubitschek, 2018; Teece, 2018). Competition can affect user experiences and choices within platform ecosystems (Rothe et al., 2018). Research has explored how competition influences user preferences, loyalty, and the overall attractiveness of platforms (Cennamo & Santalo, 2013). Several studies examine the influence of regulatory frameworks on competition and ecosystem performance (Kira et al., 2021).

Similarly, platform governance also influences competition in ecosystems. Platform governance plays a pivotal role in shaping the competitive landscapes within ecosystems. This study also explores the impact of platform governance on ecosystem performance. In addition, we examine the existing literature, highlighting the significance of effective governance as another essential determinant of platform ecosystem performance. Governance mechanisms, such as rules, standards, and certification processes, help establish trust and reduce transaction costs between different actors. Van et al. (2016) show that platform governance significantly affects digital platform performance. This result draws attention to the effect of platform governance on firm performance. It is widely recognized that a strategy for platform performance involves creating value by facilitating interactions between various affiliated users in a two-sided market, as highlighted by Rochet and Tirole (2004). This growth is likely to persist and thrive due to network effects and value creation Evans et al., 2006 and Guo et al. (2022).

Other studies suggest that a well-designed platform ecosystem strategy can significantly improve performance. If it is well-designed, a platform's success largely depends on how well it can facilitate interactions between different actors (Gawer & Cusumano, 2014). The results further reveal that effective platform ecosystem design requires careful consideration of the actors involved, their interactions, and the rules and governance mechanisms that govern their behavior. Van Alstyne et al. (2016) contend that effective platform ecosystem design requires careful consideration of the actors involved, their interactions, and the rules and governance mechanisms that govern their behavior.

Furthermore, several platforms have incorporated ecological approaches into their frameworks, and a considerable portion has neglected to include the advanced modeling of platform ecosystems. Barbier et al. (2018) develop a comprehensive method for integrating components in complex ecological networks, focusing on precise simulations of these sophisticated systems. They show that a substantial fraction of the possible results exhibited characteristic features that remained unchanged despite adjustments in the modeling choices. There are shortcomings in the existing literature on platform ecosystem relationships and performance. Many researchers neglect the relationship between platform characteristics and performance. Jia et al. (2021) provide an overview of platform ecosystems, key concepts, and applications. They discuss the challenges of managing platform ecosystems and identify the critical success factors that could help firms achieve better performance outcomes. The study concludes by outlining the implications of platform ecosystems for business strategies and management. Most studies exclude the mathematical models and simulation studies required to analyze the mechanisms of the platform ecosystem. Their diversity, complexity, and stability research has built a theoretical e-commerce and platform ecosystem framework. Nevertheless, a thorough assessment of platform performance has not been conducted.

This study bridges this gap in research by comprehensively considering various ecosystem characteristics to form various configurations. It recognizes that platforms are not just technological entities but also social environments; hence, understanding user behavior is crucial for comprehending performance divergence (Khurshid et al., 2024). This approach allows for a more nuanced understanding of how these elements interact to influence performance. This study recognizes that every platform environment may require unique configurations. This approach acknowledges the individuality of platform ecosystems in the adopted Lotka-Volterra (LV) model and how innovative configuration models can reshape performance outcomes. This approach facilitates a broader perspective and enables researchers and stakeholders to gain insights by identifying the commonalities and distinctions across various ecosystems. This forward-looking perspective goes beyond traditional performance analysis and emphasizes the ability of ecosystems to withstand unforeseen challenges and disruptions, thus addressing a critical gap in platform research. Furthermore, this study moves beyond traditional and often-siloed methods of examining platform performance. It connects the various

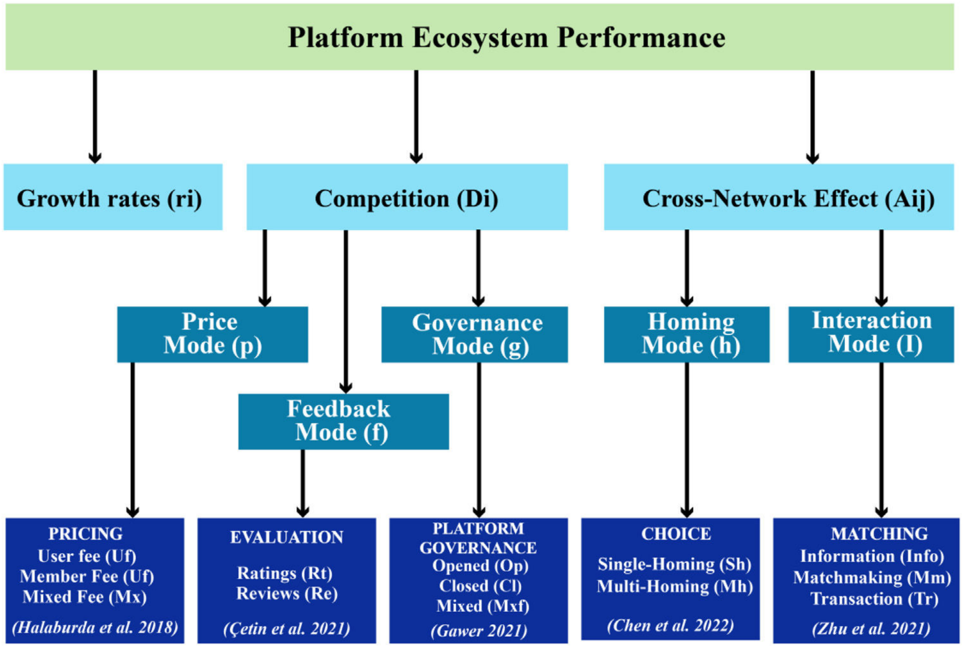

Fig. 1. Characteristics that influence platform performance.
Fig. 1 shows platform performance and its relationship with the competition and network effect characteristics. It indicates that platform performance is a function of intrinsic growth rate, competition, and network effect. In addition, competition is a function of price, feedback, and governance mode characteristics. The network effect is a function of homing and interaction mode characteristics (Çetin et al., 2021; Chen et al., 2022; Gawer, 2021; Halaburda et al., 2018; Zhu et al., 2021)

elements of platform ecosystems, considers the role of human behavior, offers a comparative and dynamic perspective, and emphasizes the importance of ecosystem resilience. Doing so, it contributes to a holistic body of knowledge in this sector by providing a more thorough and relevant understanding of platform ecosystems and their impact on performance outcomes.

Multidimensional model

This study embraces complex systems theory (Barbier et al., 2018; Duan et al., 2023). This theoretical approach emphasizes nonlinear systems, networks, and adaptive behaviors. Therefore, this study devises a novel system model to serve as a performance metric for a platform ecosystem, employing the Lotka-Volterra model approach to condense it from multiple dimensions into a single dimension and emerging phenomena (Bento et al., 2020). The reason for reducing the model is to improve empirical results' efficiency and trustworthiness, as Laurence et al. (2019) proposed. The detailed model formulation process is included in the Supplementary Material for reference. We simulated the reduced-dimensional model using MATLAB and Mathematica software tools to provide valuable insights and predict the platform's performance over time. The model was simulated to test complex networks, and the simulated results were analyzed and compared to a real-world case of the platform ecosystem for an accurate evaluation of our model.

Model formulation

This study employs several parameters to describe the platform ecosystem. We set the values for the basic form of the platform ecosystem to create a configuration. The qualitative characteristic parameters were set to quantitative values to describe the platform ecosystem *(Table S2, supplementary information)*. This study considers a model for a platform ecosystem within the context of a generalized Lotka-Volterra dynamic model. The proposed model encompasses elements such as N_i, r_i, and D_i representing platform agents, intrinsic growth rate, and competition, respectively. Q, E, and H set the functional responses, and A_{ij} is established as interaction coefficients, which are indicative of the network effect. Eq. (1) is based on Barbier et al. (2018) LV model:

$$\frac{d}{dt}N_i = N_i\left(r_i - D_iN_i - f\left(\sum_{j=1}^{s}A_{ij}N_i\right)\right). \tag{1}$$

We embraced the proposed model structure by incorporating the characteristic parameters into the original parameters of the Lotka-Volterra model. Consequently, the original parameters were expressed as characteristic parameters' functions, as Table S1 *(supplementary information)* outlined. We describe this approach and its mathematical depiction in Fig. 1 as (r_i, D_i, A_{ij})=$\Big(y(r), z(p, f, g), d(h, I)\Big)$.

N_i represents the performance or throughput of the platform sector at node i at time t, assuming that each platform sector is interconnected with other sectors. The platform sectors are akin to nodes within the network, and the business inflows are represented as edges, as illustrated in Equation (2); $\frac{d}{dt}N_i$ denotes the change in performance over time, and r_i is the intrinsic growth rate of the platform. We set K_i as the carrying capacity to limit the inherent growth rate of the system. According to the probabilistic model used for this platform, we set the growth rate term as follows:

$$\frac{dN_i}{dt} = r_iN_i\left(1 - \frac{N_i}{k_i}\right) \tag{2}$$

We assume that other external factors affect the platform. We consider this impact as a competition effect (D_i). We include the competition term into the model, expressed as:

$$\frac{dN_i}{dt} = r_iN_i\left(1 - \frac{N_i}{k_i}\right) - N_i\sum_{j=1}^{n}DN_j. \tag{3}$$

We assume that the interaction strength influences the competition of a platform (β_{ij}) in terms of price, feedback, or governance mode. This algorithm can be accomplished by adopting feedback, price, and governance modes, incorporating them as effort variables, and integrating them into Eq. (4) to formulate the harvesting model

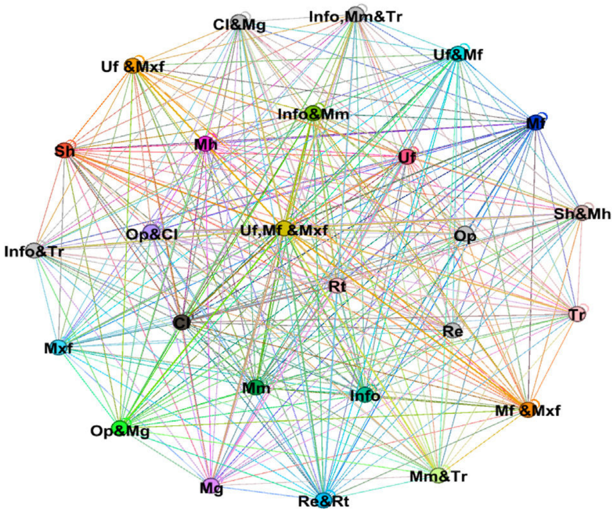

Fig. 2. Interconnectedness of Characteristics.

(Malik et al., 2021) (please refer to the Supplementary Information for the detailed steps). We express this model as:

$$D_i = N_i\sum_{i=1}^{n}\beta_{ij}^{(p)}N_j + N_i\sum_{i=1}^{n}\beta_{ij}^{(f)}N_j + N_i\sum_{i=1}^{n}\beta_{ij}^{(g)}N_j, \tag{4}$$

where,

$$\beta_{ij} = \begin{cases} 1 \ \textit{if competition} \\ 0 \ \textit{if no competition} \end{cases}$$

.

As stated earlier, D_i is influenced by price, feedback, and governance modes. We include these aspects in Eq. (4), and we obtain the following:

$$\frac{dN_i}{dt} = r_iN_i\left(1-\frac{N_i}{k_i}\right) - \left(\sum_{j=1}^{n}N_i\sum_{i=1}^{n}\beta_{ij}^{(p)}N_j + N_i\sum_{i=1}^{n}\beta_{ij}^{(f)}N_j + N_i\sum_{i=1}^{n}\beta_{ij}^{(g)}N_j\right). \tag{5}$$

Fig. 2 illustrates the interconnections between the platforms (nodes) that shape the platform ecosystem's topological architecture (A_{ij}).

The operation of the complete platform ecosystem hinges on this topological architecture, which governs the connections among platform sectors. The system topology architecture is a scaled connectivity matrix that encapsulates the mutualistic interactions among the nodes (platforms), as elaborated in Agha Mohammad et al. (2021).

The cross-network effect (A_{ij}) is introduced as an interaction term in the equation that captures the mutualistic interactions between users. This addition has a positive influence on the platform's performance. Mutualism allows the users of platforms to benefit from interconnectivity (Xu et al., 2017). Thus, the growth of one user is mutually beneficial to other connected users. These interactions affect the platform's value; hence, we further develop Eq. (6) by incorporating A_{ij} as the cross-network effect:

$$\frac{dN_i}{dt} = r_iN_i\left(1-\frac{N_i}{k_i}\right) - N_i\sum_{j=1}^{n}DN_j + d\left(N_i\sum_{j=1}^{n}A_{ij}N_j\right) \tag{6}$$

We assume that the homing and interaction modes influence the cross-network. In general, A_{ij} is the strength of the mutualism or interaction. This is the per capita effect of users on the per capita network effect, namely, the configuration of the multihoming home and the interaction mode. We set the mutualistic strength of the platform to:

$$A_{ij} = C_{ij}\frac{\propto_o(h,\ I)}{L_i^e} \tag{7}$$

L_i is the number of interactions among users who benefit from the interactions, and e is the strength of the trade-off modulating the strength and degree of interactions. When $e = 0$, there is no trade-off; however, when $e = 1$, a trade-off emerges. The parameter $\propto_o$ depends on the degree of multihoming mode and interaction mode. It quantifies the strength of the mutualistic interactions. C_{ij} is the coefficient of the interaction between suppliers i and j on a platform. We express A_{ij} as;

$$\sum_{j=1}^{n}A_{ij}N_iN_j = \sum_{j=1}^{n}\frac{a_o(\mathrm{h},\ \mathrm{I})}{L_i^e}N_iN_j. \tag{8}$$

For simplicity, the structure of this topology is expanded using a saturation functional response and an interaction strength parameter. We clarify the meaning of the usual saturation half-rate (*Following supplementary information*) by incorporating it into the general model for the platform:

$$\frac{dN_i}{dt} = r_iN_i\left(1-\frac{N_i}{k_i}\right) - N_i\sum_{j=1}^{n}DN_j + \sum_{j=1}^{n}A_{ij}\frac{N_iN_j}{Q+E_iN_i+H_jN_j}, \tag{9}$$

where Q, E_i and H_i are parameters that quantify the rate of the saturation functional response $f(N_i)=\frac{A_iN_i}{Q+E_iN_i+H_jN_j}$.

Model reduction

Eq. (9) represents a multidimensional platform network model in which each characteristic is configured into its operational characteristics. Multidimensionality increases both computational demands and unpredictability. Nonetheless, these challenges can be mitigated through the dimensionality reduction of the model (Xu et al., 2017). The supplementary information provides a comprehensive account of the steps involved in the dimension reduction process, culminating in the creation of a reduced model:

$$\frac{dN_{eff}}{dt} = N_{eff}\left[r_{eff}\left(1-\frac{N_{eff}}{K}\right)\right] - \beta_{eff}^{(x)}(N_{eff})^2 + \frac{\langle A\rangle (N_{eff})^2}{Q+(E+H)N_{eff}}. \tag{10}$$

In Eq. (10), N_{eff} denotes the aggregated effective average platform bifurcation performance across all users within the characteristic configuration network. K represents the performance capacity; r_{eff} stands for the effective intrinsic growth rate term, β_{eff} is the effective competition variable influencing price, feedback, and governance mode, and $\langle A\rangle$ is the effective mutualistic strength for sellers and consumers (platform users).

Simulation, results, and analysis

The study's results show the dynamic nature of the platform's performance depending on the empirical outcomes of various combinations of configurations. Overall, the system shows bifurcation or critical transition points for performance N_c. The platform undergoes a dynamic critical transition, resulting in system bifurcation at the point where the blue line meets the red line, called the bifurcation point. The system undergoes chaotic behavior at this point, resulting in the platform's collapse. The findings indicate that, irrespective of the specific parameter values (K, D, and r), when $N_{eff}\geq 0$, platform performance always displays two stable states of equilibrium (i.e., $\frac{\partial N}{\partial t} < 0$, when a state is stable Z at $N_{eff} > 0$ and stable state X at $N_{eff} = 0$), and it is unstable when $Y > 0$(that is, $\frac{\partial N}{\partial t} > 0$). The positioning of the critical points is contingent upon the influence of the network effect A_{ij} and competition effect D_i of each platform configuration. This result indicates that network effects and competition significantly affect platform performance (Tan et al., 2020).

Effect of network effect on the platform ecosystem bifurcation

Fig. 3 shows the bifurcation platform performance of the 14 platform configurations. The system demonstrates a solitary, stable condition for $N > N_c$ (performance threshold) that occurs at $N_{eff} > 0$, which is preferred (bold line), and an unstable state, which is undesired (dotted line), when $N_{eff} = 0$. The performance function exhibits a solitary stable condition at $N_{eff} < 0$, which is unsolvable and leads to erratic behavior. Platform configuration A_{eff} affects platform performance bifurcations when the network effect increases with time. In this study, the platform performance and its threshold values β_c are determined entirely by the platform configuration of the model in Eq. (10). The platform network effects A_{ij} determine the platform configuration-specific states along platform performance function $f(\beta_{eff}, N_{eff})$. Fig. 3 shows that a system for $\beta_{eff} < \beta_c$ always shows two states of equilibrium, the stable state Z and the unstable X. When $\beta_{eff} > \beta_c$, the system exhibits chaotic behavior.

These results are obtained from 14 configurations with varying interaction strength values (A_{eff}) and divided into three categories for clarity and precision (higher, average, and lower threshold values β_c). The configurations with higher threshold values are 10, 12, and 13, with β_c 47.29 for configuration 12 and 41.38 for configuration 10 and 13, respectively. The configurations with average threshold values are configurations 1, 2, 5, and 14, with β_c equal to 30.14, 31.07, 31.9, and 34.88, respectively. The configurations with the lower threshold values are configurations 3, 4, 6, 7, 8, and 9 with β_c equal to 28.42, 26.07, 12.36, 23.61, 11.4, and 10.39, respectively.

The results show that configuration 12, with a threshold value $\beta_c = 47.29$ and a high interaction strength of $A_{eff} = 9.02$, is the most robust configuration with a solitary, stable condition Z at the interval $0 \leq \beta_c < 47.29$, followed by configurations 10 and 13 with the same threshold values regime $0 \leq \beta_c < 41.38$ and A_{eff} equal *to* 6.6. This result indicates that configurations 12 and 13 tend to perform well within the interaction strength regime in the platform ecosystem at $N_c \geq 0.52$ and $N_c \geq 0.51$, respectively. Since the configurations tend to withstand any shock or perturbation at these critical transitions, the platforms will yield high performance with time when the interaction strength increases.

The results show how integrating services such as Facebook Messenger, Instagram, and WhatsApp creates a synergistic effect, encouraging users to engage in multiple platform facets. Users seamlessly transition between platforms, amplifying overall network effects and fostering a sense of interconnectedness. A case study on Facebook exemplifies how strategic emphasis on cross-network effects can significantly elevate platform performance. By seamlessly integrating

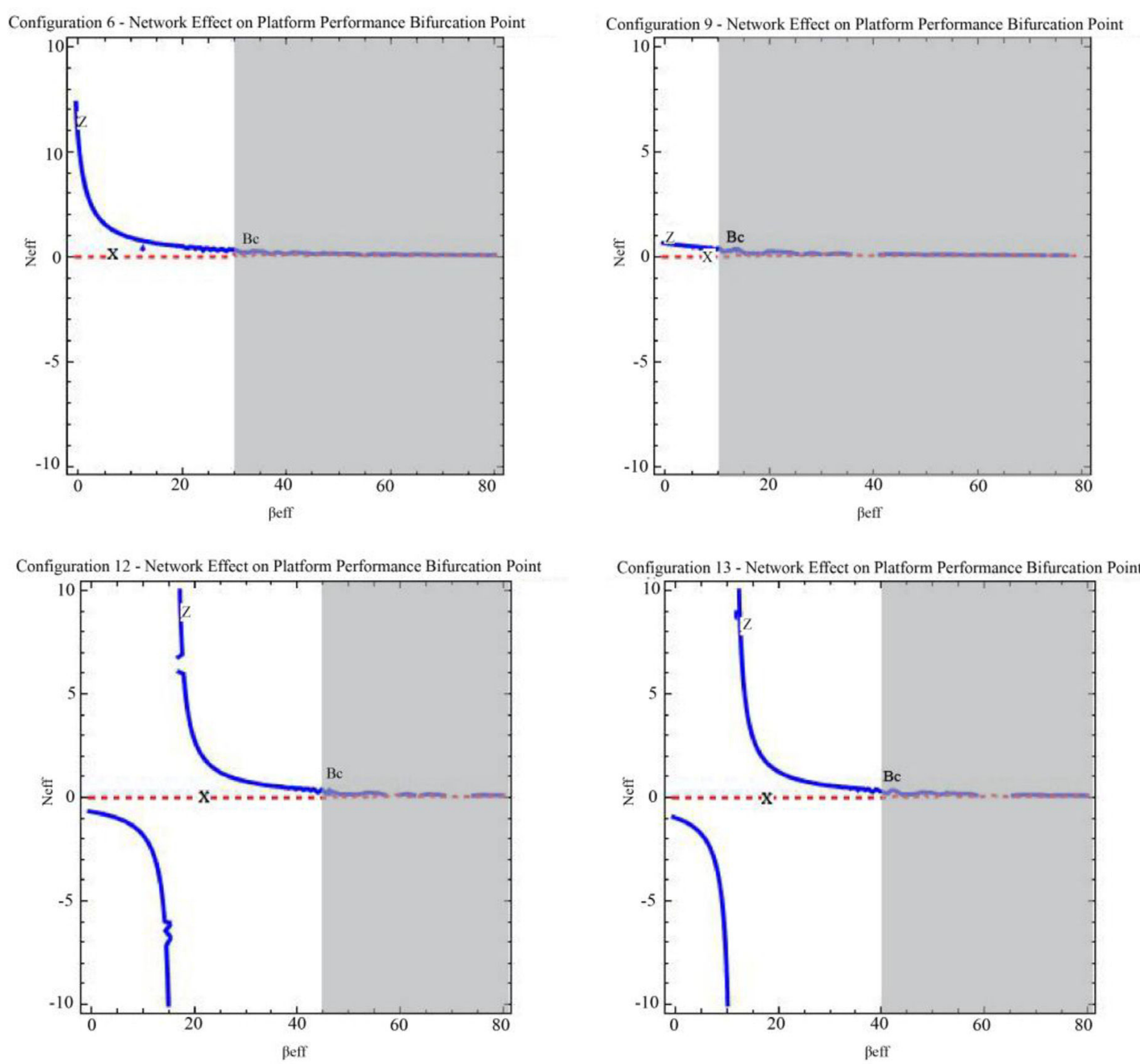

Fig. 3. Influence of cross-network effect configurations on the bifurcation points.

services and fostering an interconnected ecosystem, Facebook enhances user engagement, achieves sustained growth, and increases monetization opportunities. This case underscores the importance of cross-network effects in the success of platform ecosystems and their direct correlation with higher overall platform performance. Furthermore, both platforms experience disrupted behaviors when the interaction strength exceeds the threshold values. Configurations 6, 8, and 9 are the most vulnerable platform ecosystems, with a single stable state H at an interval of $0 \le \beta_c < 12.36$. The results indicate that, at $\beta_c \ge 12.36$, the platform can undergo total collapse.

Platforms such as Friendster and MySpace have faced a significant decline in user engagement. In 2011, Friendster shut down as MySpace transformed, losing its dominant position in social networking. The case study of Friendster and MySpace underscores the importance of sustaining interaction strength and leveraging cross-network effects for platform longevity. Failure to innovate contributes to a decline in user engagement and eventual demise. This is a cautionary tale for platforms seeking enduring success in the dynamic digital landscape.

Effect of competition on the platform ecosystem bifurcation

Competition negatively affects platforms, and the results reveal that when competition is high, a platform must attain a very high threshold value to perform well. However, when the competition threshold value is low, with the smallest operational measure in place, the platform can withstand for a long time and yield higher performance. Fig. 4 shows the bifurcation platform performances of the 18 platform configurations. The system exhibits a solitary stable state when $N > N_c$ (performance threshold) that occurs at $N_{eff} > 0$, which is the preferred state (bold line), and an unstable state that is undesired (dotted line) when $N_{eff} = 0$. A performance function with a single stable state at $N_{eff} < 0$ is unsolvable, leading to erratic behavior. Over time, platform configuration D_i (competition) affects platform performance bifurcations when competition increases. Platform network effects D_i determine the platform configuration-specific states along the platform performance function $f(A_{eff}, N_{eff})$. Fig. 4 shows that $A_{eff} < A_c$ always indicates two states of equilibrium: stable and unstable (Z and X). When $A_{eff} > A_c$, the system exhibits chaotic behavior.

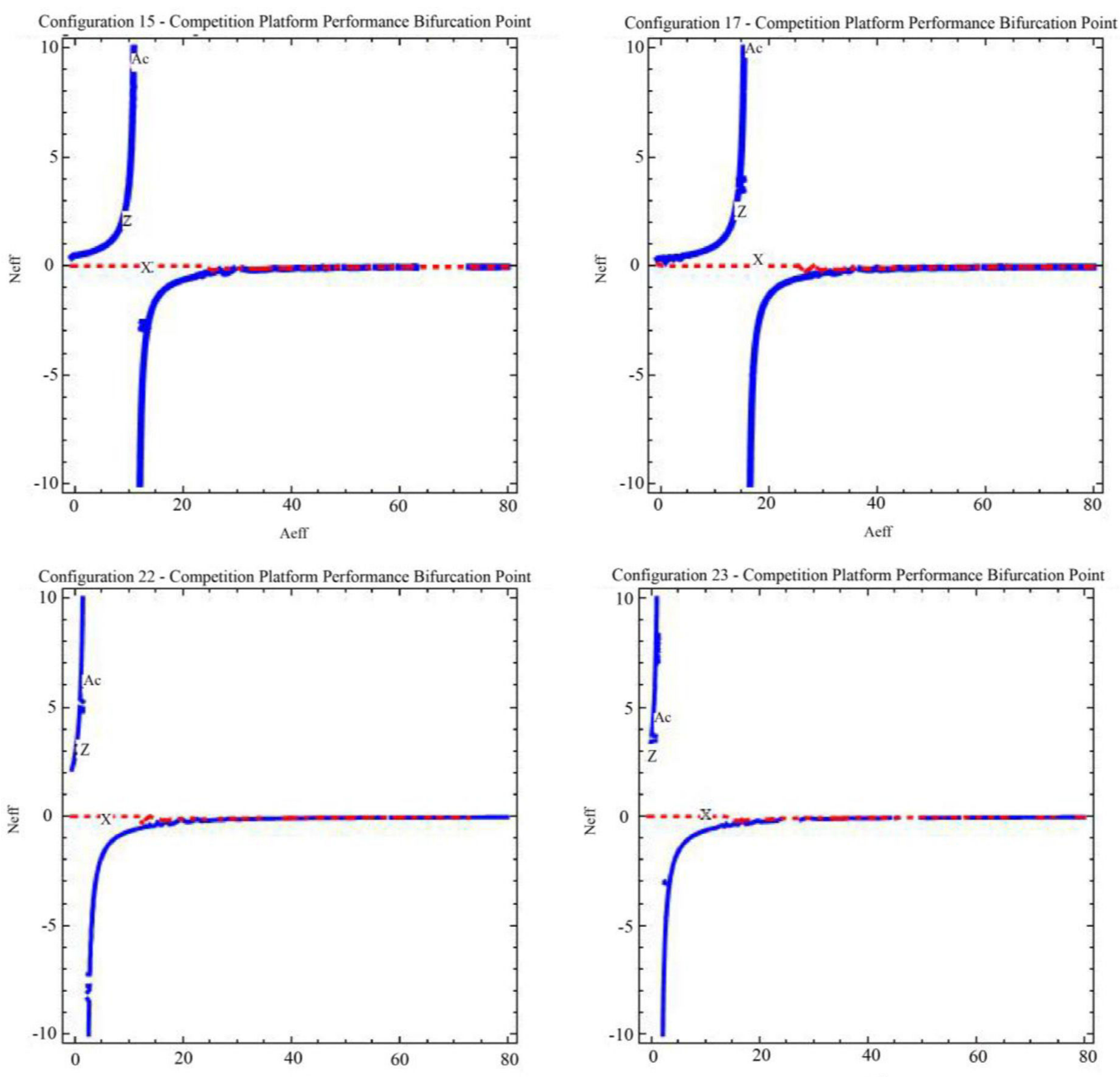

Fig. 4. Influence of competition configurations on the platform bifurcation points with different competition strengths.

The results in Fig. 4 were obtained from nine configurations varying with competition strength values (β_{eff}). The results were then divided into three categories based on clarity and precision (higher, average, and lower threshold values, A_c). The configurations with higher threshold values are Configurations 15–17, with A_c equal to 12.04, 12.62, and 16.39, respectively. The configurations with the average threshold values are configurations 18–20, with A_c equal to 6.81, 7.39, and 5.65, respectively. Moreover, the configurations with lower threshold values are 2–123, with A_c equal to 2.75, 1.55, and 0.43, respectively.

The results in Fig. 4 show that the system's behavior is asymptotically bifurcated at varying critical transitions of the competitive effect strength. These results reveal that configuration 23 is asymptotically bifurcated and has the strongest network effect (B_{eff} asymptote) $A_c = 0.43$ at stable state Z, in the range $0 \le \beta_c < 9.02$, followed by configurations 22 and 21, with the threshold values regime $0 \le \beta_c < 1.55$ and B_{eff} equal to 2.1 and 3. This result indicates that configuration 23 performs well within the platform ecosystem's competition regime at $N_c \ge 4.6$. Since the configurations have a high tendency to withstand any shock or perturbation at these critical transitions, this result implies that the platforms will yield high performance over time when there is less competition.

As a case study, we explore Microsoft Windows's performance evolution during periods of less intense competition, from 1990 to 2005 and from 2005 to 2015. The windows show stability and optimized performance in a less competitive landscape. This platform adds user-centric features by reducing competition. In response to renewed competition in 2015–2022, Microsoft adapted by introducing Windows 10, emphasizing modernization and innovation. This case highlights the platform's ability to optimize stability and adjust to changing dynamics when faced with renewed competition.

Both platforms experience disruptive behavior when the value of competitive strength is high. This result implies that the configuration is asymptotically stable at the minimal interaction strength and, thus, the most robust configuration. The lowest competitive strength results in high resiliency. Configuration 17 exhibits a higher threshold competition value; it is the least resiliency platform ecosystem at a stable state H within the interval $0 \le A_c < 30$. The results show that when $A_c \ge 30$, the platform may undergo total collapse. This result further confirms that the increased degree of competition increases the value of A_c asymptote, thus making the system struggle much longer and reaching a large threshold to attain a stable state. For instance, the intense competition between the ride-hailing giants Uber and Lyft has negatively affected the platform ecosystem, leading to a fragmented and divergent user experience. Uber and Lyft have emerged as the primary players in the ride-hailing industry, competing fiercely to capture market shares. The ensuing competition has affected their strategies, pricing models, and overall ecosystem development. The case of Uber and Lyft highlights the negative effects of competition on platform ecosystem bifurcation in the ride-hailing industry. Intense competition erodes driver earnings and fragments user experience, particularly in price wars. This case underscores the importance of strategic competition to avoid negative consequences for drivers and riders within a ride-hailing ecosystem. The remaining configurations are bifurcated at different critical transitions depending on the degree of competition strength changes, as summarized in Table S4 *(supplementary information)*.

Influence of competition configuration on platform tipping point location

The term tipping point in platform ecosystem management refers to the point at which a platform reaches a critical threshold of change, beyond which a significant and often irreversible shift occurs. In other words, it is the point at which a slight change in the platform can disproportionately impact the entire system. Identifying and understanding tipping points is essential for predicting and mitigating potential risks and impacts in various systems and processes.

We utilized the MATLAB software tool to execute the tipping-point function in Equation (12) for the cross-network effect configuration. This study examines the impact of competition on the tipping point of platform ecosystem performance. The study's findings demonstrate the influence of competition on platform performance. At $\beta_{eff} > 0$, the system experiences a collapse when the level of competition increases. The platform experiences a loss of stability to the point of no return β_C, as depicted in Fig. 3. This dynamic critical transition occurs when the system bifurcates at a specific point where the stable state (no shadow) meets the unstable state (shadow area), namely, the tipping point P(Fig. 5). At this threshold, the system exhibits erratic behavior (the platform performance collapses).

Fig. 5 shows the tipping points of configurations 1–14. This result demonstrates the effect of competition on platform performance tipping points. The platform exhibits a high tolerance at higher values of network effect configurations. Conversely, the impact of competition is not significant at extreme values, resulting in the tipping points being situated at greater values than in previous configurations. The cross-network effect configurations significantly influence tipping point locations. These findings further reveal that configuration 12 experiences the highest tipping point location with $\beta_c = 47.29\%$ when $A_{eff} = 9.02$, followed by configurations 10 and 13, with $\beta_c = 41.38\%$ when $A_{eff} = 6.6$. When $A_{eff} = 0$, at configuration 6, the platform ecosystem experiences a tipping point value β_c =12.36% when no interaction strength or network effect exists. Some negative network effects affect the platform ecosystem's tipping points. Configurations 4 and 7–9 yield threshold values β_c of 26.09, 23.61, 11.4, and 10.39, respectively.

By curating the configurations of all the characteristics, we obtained the platform tipping point location, with a value of $\beta_c = 47.29\%$ as an average tipping point of the platform; at this threshold value, the platform may thrive and perform well in the ecosystem. This result implies that the highest-performing ecosystem is configuration 12, and the least-performing platform is configuration 9. These findings indicate that performance tends to decrease across all platform system configurations as competition intensifies. Conversely, performance improves when the competition subsides, as shown in Fig. 5.

Influence of the competition configuration on the platform ecosystem performance

The impact of competition configuration and the competition interaction strength of price, feedback, and governance modes on platform ecosystem performance is examined in Fig. 6. The various values of the configurations are listed in Table S2 *(supplementary information)*, and the relevant critical transition values are summarized in Tables S3 and S4 (*supplementary information)*. When competition exists, the ecosystem's value can decrease due to fragmentation and price or cost increases for participants (Boudreau & Jeppesen, 2015); as a result, the platform experiences different operational performances. In addition, competition can affect the level of participation and investment in each group of characteristics, affecting the value created by the platform ecosystem (Rochet & Tirole, 2004).

Fig. 6 depicts the variation in configurations under the effect of competition extending from various characteristics indicated as configurations. Configuration 23, with a competition strength of 0.012 %, achieves a high performance of 14.8 billion dollars, followed by configuration 22, with a competition strength of 0.021 %, yielding 14 billion dollars. In configuration 22, the results show that a slight increase in competition leads to a decrease in performance, as indicated by the blue-crossed line in Fig. 6. The results consistently show that as competition strength increases, platform performance

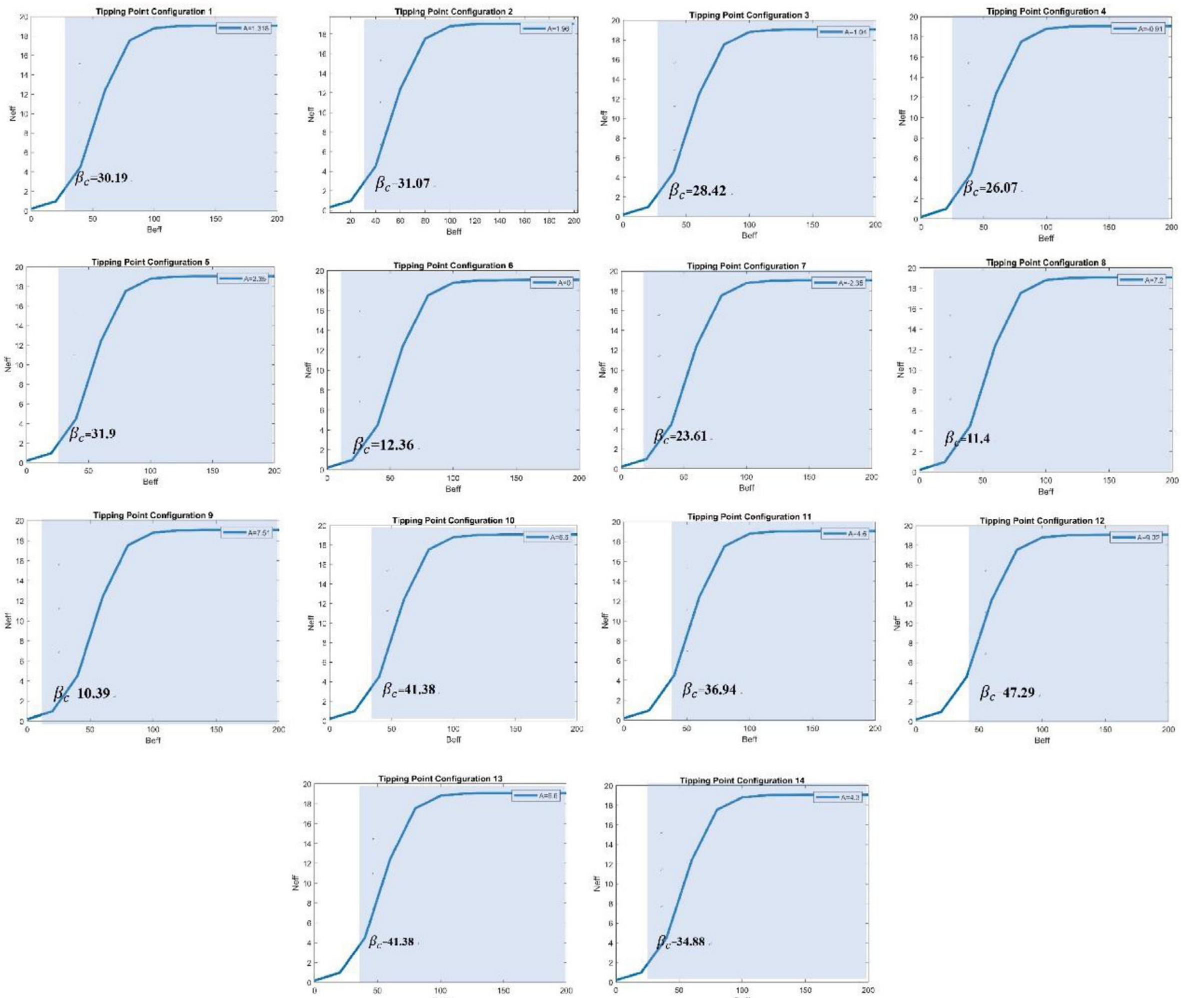

Fig. 5. Effect of competition on the platform performance tipping point.

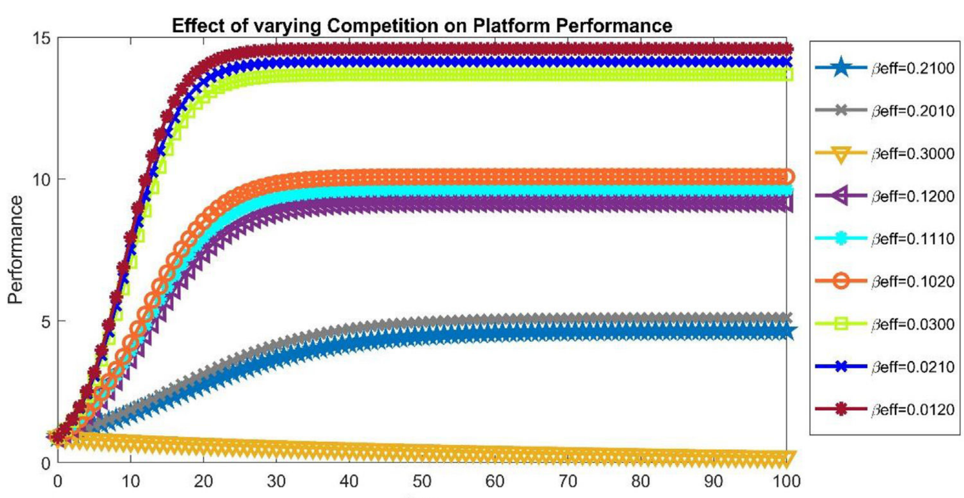

Fig. 6. Influence of the competition configuration on the platform ecosystem performance (billion dollars).

decreases (as shown in configurations 15−22). Competition strength varies in configurations 15−21, with β_{eff} of 0.21 %, 0.201 %, 0.3 %, 0.12 %, 0.111 %, 0.102 %, and 0.03 %, respectively. Performance also decreases in varying order from 14.8 billion dollars to less than a billion dollars, as shown in Fig. 6. In configuration 17, labeled gold, we observe a drastic decrease in system performance when the competition value is 0.3 %. The performance is at 0.86 billion dollars, yielding a persistent reduction over time, causing a collapse.

The results show that competition is a catalyst for examining or predicting a platform ecosystem's performance. It is vital to determine the level at which the platform can improve its performance or collapse. As competition strength increases, the platform's

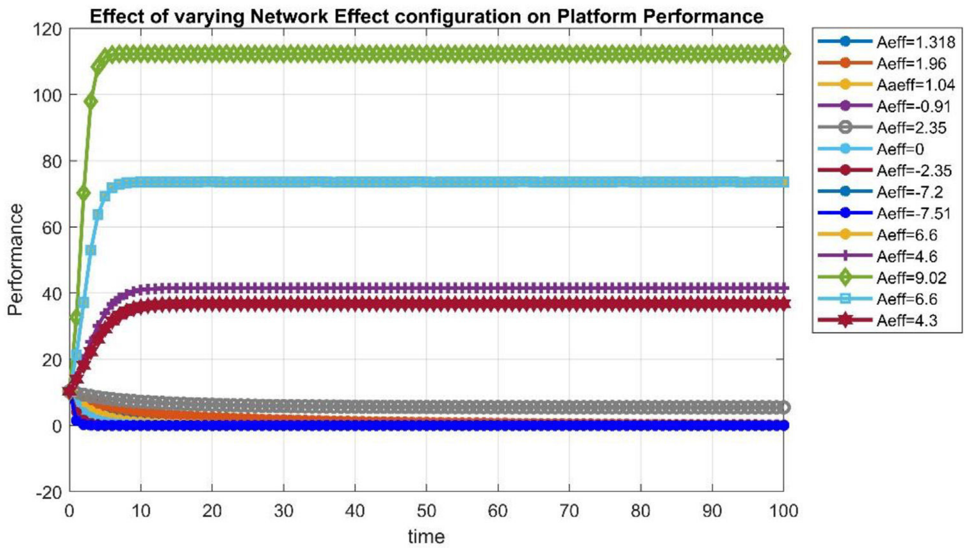

Fig. 7. Influence of the cross-network effect configuration on the platform ecosystem performance.

performance decreases, and the platform yields higher performance as competition strength decreases.

Influence of the cross-network effect configuration on the platform ecosystem performance

Fig. 7 shows the platform performance in the 14 configurations under the influence of the cross-network effect. The results reveal that an increase in network effects is generally perceived as a catalyst that facilitates performance increases in the platform ecosystem. The results are related to real case studies, as discussed in Section 5, and indicate the significant influence of the cross-network effect on platform performance. It is further argued that the various configurations generate different performance levels, as shown in Fig. 7. Moreover, we observe a variation in the configuration over time under the mediation of cross-network effects. Configuration 9 (red line) experiences the lowest platform performance, declining at *Neff* = \$0.03*b* and then collapsing, with a negative interaction strength of −7.51 %. A positive network effect affects the platform's performance. The greater the network effect, the higher the performance, and the lower the network effect, the lower the performance. Thus, platform performance initially grows on a very small scale and then collapses over time.

The results show a high network effect $A_{eff} = 9.02\%$ for configuration 12, which has the leading performing configuration, with N_{eff} of \$112 billion, followed by configurations 11 and 13, with a network effect of 6.6 % and N_{eff} of \$73.29 billion. As the network effect increases by a small margin of 6.6 % to 9.02 %, performance increases drastically from \$73.29 billion to \$112 billion. This result confirms that one primary reason a platform such as Tinder is a great success is its ability to create a positive network effect. Tinder's match-making capabilities are a critical factor in its success and have contributed to its market value. In 2021, Match Group, which owns Tinder, reported a revenue of \$2.4 billion, 17 % increase compared with the previous year. The company's market value also increased significantly, with the Match Group's stock price rising by over 300 % since its initial public offering (IPO) in 2015. Tinder's network effect, through its match-making algorithm, significantly affects its success and platform performance. Through its ability to match all users swiftly, this positive network effect has helped Tinder grow rapidly, with over 66 million active users by 2020.

Furthermore, in Configuration 1, at a network interaction strength effect of $A_{eff} = 1.31\%$, the system performance yields \$4.8 billion. This result implies that the configuration of the network effect has a highly significant impact on the platform performance. Similarly, the results relate to an article by Forbes highlighting Airbnb's success, which states that the success of Airbnb's homing mode network effect strategy is reflected in its platform performance. Since its launch in 2008, Airbnb has grown rapidly, with over 4 million hosts and 800 million guest arrivals as of 2021. Hence, Airbnb's valuation grew rapidly, from \$1.3 billion in 2011 to over \$100 billion in 2021 (Statista Research Department, 2022).

Discussion

As shown by the configurations mentioned above, some platforms yield negative cross-networks that affect the tipping point (Fig. 5). As more users join the platform or complementary products or services become available, the platform can experience a negative cross-network effect, decreasing platform value (Rochet & Tirole, 2004). For example, suppose that a messaging app becomes crowded with users. In this scenario, it might be challenging to identify essential messages, decreasing the platform's value. The simulation results in Fig. 3 show that configurations 4, 7, and 9 yield a negative cross-network effect that affects their bifurcation point. The higher the negative cross-network effect, the lower the platform performance. Recent case studies support these simulation results. In the early 2000s, MySpace was the dominant social networking platform, with millions of users and a thriving ecosystem of third-party apps and services.

However, Facebook was launched in 2004 and slowly chipped away from MySpace's user base. One key factor contributing to Facebook's success was the negative cross-network effect experienced by MySpace. As spam, fake profiles, and low-quality content flooded MySpace, it became increasingly difficult for users to find and connect with people they knew and cared about. This result explains why, in the proposed characteristics, we state information as part of the interaction mode needed to evaluate platform performance (Eq. (9)). The phenomena mentioned above led to a decline in engagement as users spent less time on the platform and began to look for alternatives. Ultimately, MySpace was acquired by News Corp in 2005; however, its relevance and user engagement continued to decline. In contrast, Facebook has become one of the world's most successful and dominant platforms, with approximately 2.7 billion monthly active users as of 2021, owing to its positive network effect, as shown in Fig. 7.

Concerning positive network effects, Figs. 3 and 4 reveal that a higher cross-network effect corresponds to a higher threshold value and, hence, enhanced performance. Configuration 12, with high network values, yields higher performance, and this maps to a case study on the Alibaba platform tipping point by Gao et al. (2021). Their study examines the tipping phenomenon and network effects on Alibaba's e-commerce platforms. The authors found that platform tipping played a significant role in the growth of Tmall.com and that network effects were the key drivers of this tipping, as shown in Fig. 5. Specifically, the authors showed that, as the number of Tmall.com users increased, the platform became more attractive to merchants and consumers, leading to a virtuous growth cycle. The authors also found evidence of the "superstar" effect, in which a few top-performing merchants accounted for a disproportionate share of sales on the platform.

Moreover, our results are consistent with those of Cennamo and Santalo (2013). They posit that the configuration of competition characteristics within a platform ecosystem significantly affects bifurcation performance, as illustrated in Fig. 4. Case studies substantiate their arguments. As previously mentioned, it is worth noting that platform governance and pricing can influence competition among platforms, thus affecting bifurcation performance. For instance, Apple continued to dominate with premium pricing and a closed ecosystem, whereas Google struggled to gain market share. At the lower end, Android dominated with its wide range of affordable devices, whereas Apple struggled to compete. Again, in 2011, Uber and Lyft together had a market share of more than 99 %, while in 2020, as competition increased, the top four riding platforms (Uber, Lyft, Bird, and Lime) had a combined market share of 99 %, squeezing Uber and Lyft's market share, in line with our results in Fig. 6.

Another case study that supports our results is the case of PinduoDuo pricing (Eq. (6)), which impacts Alibaba's bifurcation performance. Pinduoduo allows users to purchase products in groups at discounted prices. The platform quickly gained popularity in China, particularly in smaller cities and rural areas, and began to compete directly with Alibaba's flagship platform, Taobao. Pinduoduo's user base has grown, drawing customers away from Taobao and other Alibaba-owned platforms. In response, Alibaba launched its social e-commerce platform Taoxiaopu to erode PinduoDuo's market share. However, this move was unsuccessful, and Alibaba eventually shut down Taoxiaopu. The emergence of PinduoDuo as a major competitor highlighted the importance of the platform bifurcation point for Alibaba, as the company was forced to adapt to changing market conditions to remain competitive, as shown in Fig. 4.

Our findings indicate that platform characteristics have important implications for both platform operators and policymakers. Platform operators must understand the existence and timing of tipping points, which can help them make strategic decisions regarding platform growth and expansion investments. Concerning policymakers, our study provides insights into the potential for cross-network effects to create barriers to entry and reduce competition in online marketplaces to boost platform performance. The study's results highlight the importance of understanding the dynamics of competition and network effects in complex systems and the potential for small changes in the configuration of platform characteristics to significantly affect platform performance.

Conclusion and future research

Conclusion

This study demonstrates that the configuration of platform ecosystem characteristics influences platform bifurcation performance through mutualism. However, the relationship between platform ecosystems and their performance bifurcation characteristics has not been thoroughly investigated. This study is novel in subjecting the results to rigorous testing from various perspectives, bolstering its validity and robustness. A platform ecosystem is more likely to hit a point of no return when platforms are not tightly interconnected (fragile configuration structures). This study is the first to develop a network model to examine the platform ecosystem bifurcation performance. However, it aligns with prior research emphasizing the importance of network effects, platform governance, match-making, pricing, feedback, and platform homing modes in shaping platform performance. The confirmation of these attributes as crucial determinants resonates with seminal works by Van Alstyne et al. (2016), which provide a robust foundation for understanding platform ecosystem dynamics. A positive cross-network characteristic configuration significantly enhances the platform ecosystem's performance, consistent with Saadatmand et al. (2019). This study reveals that configuration 12, characterized by a threshold value $\beta_c = 47.29$ and a high interaction strength of $A_{eff} = 9.02$, demonstrates the greatest robustness, maintaining a solitary, stable condition. Configurations 10 and 13 also exhibit strong performances within specific interaction strength regimes. Conversely, configurations 6, 8, and 9 are identified as the most vulnerable, with a single stable state H observed at $0 \le \beta_c < 12.36$. Notably, these results suggest that a total collapse of the platform is likely when $\beta_c \ge 12.36$, indicating that platforms exhibit high performance as the interaction strength increases.

The study's findings indicate that increased competition brings the platform to a critical point of no return, negatively affecting its overall performance. This result aligns with Bakos and Halaburda (2020), who contend that in a platform market in which both sides engage in multihoming, strategic interdependence between the two sides may decrease or vanish. Configurations 22 and 21 follow closely with threshold values within the range $0 \le \beta_c < 1.55$ and β_{eff} of 2.1 and 3, respectively. Configuration 23, within the competition regime, demonstrates a strong likelihood of performing well in the platform ecosystem at $N_c \ge 4.6$. Conversely, configuration 17, with a higher threshold competition value, is identified as the least resilient platform ecosystem at a stable state H within the interval $0 \le A_c < 30$. Notably, these results suggest that the platform is prone to total collapse when $A_c \ge 30$. This result aligns with Guo et al. (2022), suggesting that increased competition may lead to market fragmentation. In contrast, Huang et al. (2023) advocate for government promotion of competition between platforms and the taxi industry, a perspective we disagree with.

Our research provides valuable insights into the dynamics of platform ecosystems and their impact on evolution. Hence, it has the potential to guide managers in identifying the pivotal elements influencing the success or failure of a platform ecosystem. The insights gained by analyzing the role of platform ecosystem configurations in performance bifurcation can also positively impact industries and entrepreneurs. The knowledge of robust configurations fosters innovation and growth, potentially attracting investments and promoting economic sustainability. Conversely, awareness of vulnerable configurations allows proactive measures to prevent potential economic downturns and safeguard the interests of businesses and individuals reliant on platform ecosystems. This understanding may contribute to the overall stability and resilience of the business landscape, thereby benefiting society (Wenqi et al., 2022).

Managers can devise strategies for developing robust platform ecosystems when they possess knowledge of the principal drivers and characteristic configurations. Furthermore, our model, rooted in the Lotka-Volterra complex system theory, integrates bifurcation and tipping-point analyses, shedding light on regulatory and policymaking strategies. The findings of this study contribute to the academic understanding of platform ecosystems by highlighting the configurations that lead to robust performance outcomes. These insights can guide future research and encourage scholars to delve deeper into the mechanisms influencing platform stability and collapse. Additionally, this study underscores the importance of considering robust and vulnerable configurations to provide a foundation for developing more nuanced theories and models in platform ecosystem research. It identifies circumstances that foster strong performance and conditions that trigger tipping points, improves the understanding of ecosystem evolution, and encourages managers to craft robust configuration structures for optimal platform performance.

Future works

This study captures essential platform ecosystem characteristics. However, there is scope for capturing and configuring other characteristics. Future research should be conducted using more empirical data for depth verification. Second, future research should examine the role of platform characteristics in configuring market value. Finally, exploring the key features capable of causing platform ecosystems to collapse is essential and may be a subject of future investigation.

Declaration of competing interest

The authors declare that they have no known competing conflict of interests that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Wenqi Duan: Conceptualization, Project administration, Supervision. **Akwer Eva:** Methodology, Visualization, Writing – original draft. **Larbi Andrews:** Software, Validation, Writing – review & editing. **Yuan Liu:** Formal analysis, Investigation, Writing – review & editing.

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