Higher-Order Externalities in Multi-Platform Ecosystems

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Abstract

Platforms have become pivotal business models and involve a different logic than traditional pipeline business models. Important factors for understanding their emergence and growth are externalities such as network effects and complementarities. At present, these concepts are focused on the effects on a single platform, but with the diffusion of platforms and their maturity, platforms are increasingly linked to each other. This interconnection of multiple platforms towards multi-platform ecosystems poses two key challenges. First, their networked structure exceeds traditional analytical approaches that are based on dyadic relationships. Second, individual choices drive externalities in these ecosystems, giving rise to emergent structures. To address these issues, the present research proposes a network science-based methodology that augments existing approaches to understand and visualize ecosystems ("ecosystem intelligence"). It presents a network conceptualization that captures the structure of multi-platform ecosystems and proposes a method for data collection and detailed network modeling. Among the main findings are three new types of externalities referred to as higher-order externalities. These include remote externalities that indicate value creation across platforms, transitive externalities representing chains between platforms, and polyadic externalities capturing value creation in n-ary relationships. They contribute to the understanding and management of the intricacies of multi-platform ecosystems, which can open new avenues in ecosystem intelligence.

Keywords: Multi-platform ecosystem, network science, network effects, complementarities, ecosystem modeling and analysis

1. Introduction

The evolution of digital platforms has profoundly transformed contemporary business ecosystems. As illustrated by the dominance of platform-operating companies in the list of the most valuable US firms (Cusumano et al., 2020), there has been a profound shift towards platform-centric business models. Large ecosystems not only evolved around general purpose platforms from Amazon and Google, but are also considered by banks, retailers, automotive companies and others. These ecosystems are fueled by externalities (Jacobides et al., 2018) such as network effects (Katz & Shapiro, 1994) and complementarities (Economides, 1996). With the diffusion and maturity of platforms, these effects are no longer limited to a single platform. For example, ChatGPT integrates information from the KAYAK and other platforms via a plugin (Teubner et al., 2023). Likewise, Amazon Alexa synergizes platforms such as the Amazon marketplace with its other platforms (Schmidt et al., 2022). This interconnectivity pattern shall be termed as multi-platform integration and refers to cohesively incorporating resources, information, and services from various platforms towards a new whole.

Multi-platforms exhibit two key characteristics: On the one hand, the network structure embraces diverse platforms, actors, and interdependencies (Zhang & Williamson, 2021). On the other hand, multi-platform ecosystems are emergent systems (McAfee, 2006) composed of independent platforms that evolve separately. Their structure is shaped by independent decisions rather than a central plan driven by one platform provider. Much of the existing literature on platforms remains anchored in exploring isolated, single platforms and the dyadic relationships between entities within those ecosystems. These studies often fall short of addressing the complexities of multi-platform environments (Au et al., 2019; Klimmek et al., 2021; Schreieck et al., 2023; Staykova & Damsgaard, 2015). Given these shortcomings, this research proposes a novel methodology like network science suited to the network structure and emergence of multi-platform ecosystems that recognizes externalities as the core driver of multi-platform growth (Börner et al., 2007; Brandes et al., 2013). This leads to the following research question:

RQ: What are externalities in multi-platform ecosystems?

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This paper is structured into seven sections to answer this research question: Section 2 delves into the background of platforms, externalities, and ecosystems. Section 3 outlines an interdisciplinary framework and analytical toolkit to model and interpret complex networked systems based on network science (Börner et al., 2007; Brandes et al., 2013). Section 4 presents a network model, illustrating its potential with a case study of the ChatGPT platform. Section 5 employs an analysis to interpret and apply our model to the Amazon Alexa platform. Section 6 provides a discussion of our results. Section 7 concludes by distilling our primary insights and sketching potential avenues for future research.

2. Research Background

This section lays the groundwork by exploring the prevailing literature on digital platforms, ecosystems and multi-platform ecosystems.

2.1 Platforms

Platforms can be differentiated into innovation and transaction platforms (Gawer, 2014). Rooted in product development, innovation platforms are characterized by a core functionality developed by the platform owner. This functionality is subsequently encapsulated and made accessible through clearly defined interfaces, often characterized as boundary resources (Ghazawneh & Henfridsson, 2013). Third-party developers capitalize on this core function to produce modules (Baldwin & Clark, 2000). A registry lists all available modules on digital innovation platforms and makes them accessible for search. Transaction platforms derive from two- or multi-sided markets (Hagiu & Wright, 2015; Rochet & Tirole, 2003). Their main aim is to facilitate transactions between different actor groups and enable access to previously untapped resources (McAfee & Brynjolfsson, 2017). Hybrid platforms marry the attributes of both innovation and transaction platforms (Cusumano et al., 2020). For example, Apple's App Store (Cusumano, 2010) offers a consolidated space for third-party developers to create and sell applications based on Apple's operating systems.

2.2 Ecosystems

Around platforms, ecosystems arise that comprise various stakeholders, including operators, users, developers, partners, and more (Jacobides et al., 2018). The expansion of ecosystems is primarily fueled by externalities (Jacobides et al., 2018). They encompass network effects, where the platform's value increases with the number of users (Katz & Shapiro, 1994) and complementarities, where the latter enhance value through additional modules, e.g., the number of apps that add to a smartphone's value (Economides, 1996). Central to ecosystem intelligence is the endeavor to discern the intricate relationships fostered by externalities among ecosystem constituents (Basole, 2021). Notably, much of the prevailing literature on ecosystems has operated on the premise of a singular platform model.

2.3 Multi-Platform Ecosystems

Due to the prevalence of the singular platform model, the concept of multi-platform ecosystems is still in its infancy. Although several research activities point toward multi-platform ecosystems, they are still dominated by an underlying single-platform perspective. For example, Schreieck et al. (2023) propose integration strategies tailored for pairs of platforms that do not scale. Similarly, the concept of auxiliary platforms presented by Au et al. (2019) emphasizes hierarchical relationships rather than networked interactions. Another approach, the notion of "platform constellations" by Staykova and Damsgaard (2015), considers multiple platforms but restricts this to those owned by a single entity. Klimmek et al. (2021) posit a hierarchical framework, which conflicts with the more egalitarian nature often observed in multi-platform ecosystems. The interaction of several platforms in innovation ecosystems was considered by (Su et al., 2018) and various dimensions of platform complexity by (Alt, 2021). Zhang & Williamson (2021) unveiled that multi-platform ecosystems foster externalities across multiple platforms. Kwak et al. (2018) investigated complementarities between platforms in innovation ecosystems. The new entry of competitors into a multi-platform ecosystem was analyzed by Mohamed et al. (2023). They postulate that ecosystems based on multiple platforms have a superior value proposition to their standalone counterparts. Lavikka et al. (2021) offered a comprehensive case study delineating the inception and design blueprint of a multi-platform ecosystem within the sphere of the circular economy. Furthermore, there are modeling approaches for multi-platform ecosystems, such as those proposed by Tian et al. (2008), Pauli (2020), Wecht et al. (2021), and Vorbohle and Gottschalk (2021). However, these approaches do not consider multi-platform ecosystems' emergent nature. While some approaches address important concerns in multi-platform ecosystems, they fail to thoroughly analyze these systems. Instead, they use elements meant for individual platforms and overlook the challenges of multi-platform environments.

3. Method for Exploring Multi-Platform Ecosystems

Many existing techniques for studying platforms and ecosystems face shortcomings when applied to multi-platform ecosystems. Methods focusing on single platforms overlook the distributed value creation due to the network orientation and emergent structures that arise across interconnected platforms (Vargo et al., 2023). Approaches centered on dyadic relationships fail to capture cascading effects and higher-order externalities stemming from complex interactions between multiple entities (Mohamed et al., 2023). To study multi-platform ecosystems, network structure and emergence are considered important characteristics, and network science as a suitable methodology.

3.1 Network Structure and Emergence

Multi-platform ecosystems have a network structure beyond single platforms' dyadic relationships, employing a hub-and-spoke architecture (Mohamed et al., 2023; Zhang & Williamson, 2021). A dense network of connections weaves many entities and relationships within multi-platform ecosystems. This encompasses interactions with multiple platform providers and diverse actor groups, such as users, developers, third-party integrators, and more (Gawer, 2014). Value emerges at numerous junctures (Hein et al., 2020). In multi-platform ecosystems, power and control are more evenly dispersed than in more single-platform ecosystems where influence is mainly with one or a few dominating entities (Hurni et al., 2022).

The complex network structure of multi-platform ecosystems is closely related to the concept of emergence. While the initiator of the multi-platform may establish rules and requirements, the decision to create modules ultimately lies with the developers and other actors involved. These decisions are influenced by externalities (Jacobides et al., 2018), resulting in many individual choices and actions. As a result, multi-platform ecosystems are considered emergent systems (McAfee, 2006), characterized by organic and sometimes unpredictable growth. New functionalities are born out of individual choices rather than a centralized strategy. Thus, understanding multi-platform ecosystems requires continuously collecting and analyzing data from individual decisions rather than relying on a blueprint. The platform actors adapt to technological changes, market needs, or user preferences, introducing or updating modules (Chen et al., 2021).

3.2 Network Science for Multi-Platform Ecosystems

Whereas prevailing techniques analyze ecosystems in isolation, network science retains connectivity information to trace propagation through the broader network. Changes in one platform can thus be shown to affect related platforms, even without direct links between them. This reflects the distributed nature of value creation across emergent multi-platform ecosystems. A network perspective allows for studying ecosystems as dynamic webs of relationships rather than isolated nodes. It provides quantitative tools to analyze complexity metrics, centralities, clusters, and higher-order externalities that influence the ecosystem. This systems-level thinking enabled by modeling platforms as networks matches the complexity of the real-world environments under study. Due to the role of network structure and emergent patterns in multi-platform ecosystems, our research adopts a three-step methodology inspired by network science to delve into the intricacies of these platforms and ecosystems. This methodology comprises three steps based on the foundational work of Brandes et al. (2013), as shown in Figure 1.

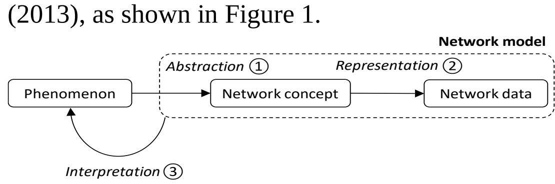

Figure 1: Network science models inspired by Brandes et al. (2013)

Network concept: In the first step, the multi-platform is considered as a phenomenon to be abstracted. Within the multi-platform ecosystem context, entities and their interplay are conceptualized as graphs. For example, platforms and modules are represented as nodes, while the relationships, specifically the assignment of modules to platforms, appear as edges. The network concept embraces all types of nodes and edges relevant for describing the multi-platform.

Network model: The network concept is used to structure data available on the multi-platform to represent it. This means that heterogeneous data from multiple sources is reformatted and reorganized to fit the graph model that has been abstracted to conceptualize the multi-platform.

Interpretation: We formulate assumptions that establish links between network elements based on network science principles. During the interpretation phase, the network model is decoded and translated into the language of the original network environment. It is important to use strong theoretical support during this phase to ensure that conclusions are aligned accurately with the studied ecosystem.

This methodological framework provides a holistic and nuanced understanding of multi-platform ecosystems that captures their complex interactions and emergent behaviors. Based on the network science methodology the following uses graph-based modeling with the nodes and edges mapping real-world objects like platforms, modules, and actors into a network model. This abstraction can encode the convoluted relationships and interdependencies that are hallmarks of multi-platform ecosystems. The expectation is that graph structure data reveals insights obscured by the single platform lens of existing approaches of platform research.

4. Network Model of Multi-Platform Ecosystems

The following section develops the network model of multi-platform ecosystems, which consists of the network concept and the collection of network data. An example of the ChatGPT platform explains this model.

4.1 Network Concept

The network concept of multi-platforms is created through abstraction (1), as shown in Figure 2. First, multi-platforms comprise a network of platforms (Alt, 2021). These innovation, transaction, or hybrid platforms maintain their distinct identities while functioning as a component in the multi-platform. The platforms coexist as distinct, independent entities within the same multi-platform. Multi-platforms are dynamic, with their structure evolving due to the entry and exit of diverse platforms.

Gateway modules enable the network structure of multi-platforms, as shown in Figure 2.

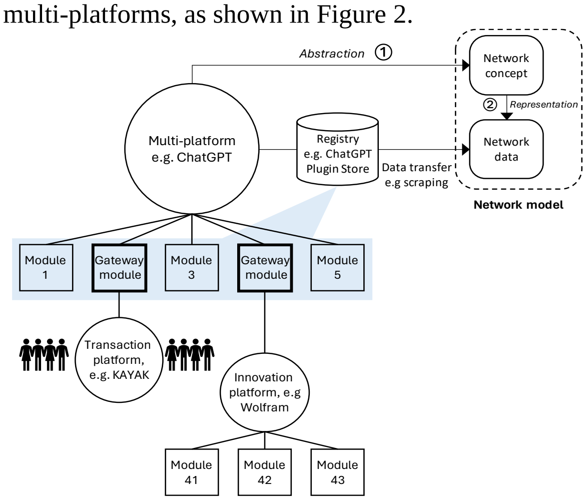

Figure 2: Creating a network model of multi-platform ecosystems

They integrate other platforms, such as innovation and transaction platforms, making their resources and services appear genuine. Gateway modules serve a pivotal role in the functionality of multi-platforms. Gateway modules also act as a bridge, providing the actors or users of the multi-platform with transparent access to both external transaction and innovation platforms.

For example, a gateway module on ChatGPT (Teubner et al., 2023) makes the KAYAK platform and its resources available. Gateway modules may even facilitate access to further multi-platforms, thus enabling the creation of a dynamically growing (or shrinking) network of platforms.

In essence, the gateway module streamlines the process, ensuring that interactions, transactions, and innovative pursuits are not confined to the boundaries of a single platform. Instead, it offers a seamless avenue for actors to engage with and leverage resources and opportunities from a wider network of platforms. Reflecting the importance of gateway modules for forming network-like structures, the registry enables the emergence of multi-platforms. Gateway modules are registered in a registry as same as the other modules. As (gateway-)modules may be added, modified, and removed during runtime by independent developers, the functionality available on the multi-platform also changes. In this way, the registry is the key mechanism on multi-platforms to enable emergence. Its role in providing network data will be described in the next section.

To represent the network concept, we employ a graph model comprising distinct node types to encapsulate their inherent complexity. The gateway modules have a special node type to reflect their importance. We formalize these as follows:

Let G be the graph that represents a multi-platform ecosystem.
Then, G = (V, E) where:
V is the set of all nodes, defined as:
V = {v | v is in (M, I, T, H, Mo, Ga, A)}
Where:
M = {m | m is a multi-platform}
I = {i | i is an innovation platform}
T = {t | t is a transactional platform}
H = {h | h is a hybrid platform}
Mo = {mo | mo is a module}
Ga = {ga | ga is a gateway module}
A = {a | a is an actor group}
E is the set of all edges, representing relationships or interactions between the nodes:
E = {e | e is in ((V x V), Ne, Co)}

Each edge connects two nodes defined by the pair (vi, vj), where both vi and vj are in V.
He is a subset of E, defined as:
Ne = {ne | ne is in (V x V) and ne represents a network effect}

Co is another subset of E, defined as:
Co = {co | co is in (V x V) and co represents a complementarity}

The graph accounts for four types of platforms as distinct nodes: multi, innovation, transactional, and hybrid. Each type contributes unique attributes to the ecosystem. The graph encompasses actor groups as a distinct node type. They interact with all platforms and play diverse roles in an ecosystem, such as developers or end-users, and their interactions help shape the platform dynamics. Each edge in *Ne* denotes a network effect, a phenomenon wherein the value of a platform increases as more participants or users join. Each edge in *Co* represents a complementarity in which two or more platform components enhance each other's value when used or consumed together.

The idea of gateway modules emphasizes the potential of integrating diverse platforms, resulting in seamless interaction between transactional, innovative, and hybrid platforms. In summary, we expect that replicating this intricate structure provides a distinctive perspective for understanding the inherent intricacies of multi-platform interactions.

4.2 Network Data

The primary source of network data is the registry (2) of the multi-platform, as shown in Figure 2. The data collected from the registry describing platforms, modules, and actor groups is mapped onto nodes and their interactions onto edges as defined in the network concept. Often, the registry also contains usage data and user reviews. For example, the Alexa registry (the Alexa skill shop), contains information on skills jointly used, reviews, and ratings of skills (Schmidt et al., 2022). These data are important to determine externalities, as they help to spot value creation between multiple modules and actor groups.

If the platform owner prohibits direct access to registry data, web scraping (Landers et al., 2016) may be used to obtain the data (Boegershausen et al., 2022). Previous research shows that data from the Alexa registry can be obtained in this way. Missing data may be replaced by proxies (Brynjolfsson, 2000; Schmidt et al., 2023b). The network data is restructured according to the network concept and, together, they build the network model. The network model systematically represents a multi-platform ecosystem, facilitating a comprehensive understanding of the network dynamics.

4.3 ChatGPT Network Model

To illustrate our findings, we created a network model of the ChatGPT assistant platform (Schmidt et al., 2023a). We have collected the data on ChatGPT to analyze it as a multi-platform ecosystem. The registry on ChatGPT is called the plugin store and contains the modules, aka plugins, available on the ChatGPT multi-platform. We scraped the data on 8/22/2023 and obtained a list of 920 plug-ins, each with a title, brief description, and categorization. The analysis revealed a total of 30 distinct categories of plugins available. To allow a deeper analysis, we focus on the findings in the "Travel & Accommodation" category, as shown in Figure 3. We have analyzed the gathered data, specifically identifying which ChatGPT plugins function as gateway modules. This comprised the review of the descriptions of each plugin, paying particular attention to any mention of platforms.

To enhance our analysis, we took the initiative to further break down the categories into subcategories twice. As an illustration, under the "Travel & Accommodation" category, there is a subcategory referred to as "Travel Booking", which, in turn, features subcategories such as "Flight Services." The third-level subcategories include plugins shown as boxes in Figure 3. If the plugin is a gateway module, the name of the integrated platform is displayed. For instance, the "Flight Services" subcategory showcases gateway plugins to different platforms, like KAYAK, Skyscanner, and trip.com. Our research based on the network model indicates that many ChatGPT plugins serve as gateway modules. Further research will investigate the distribution of categories in greater detail.

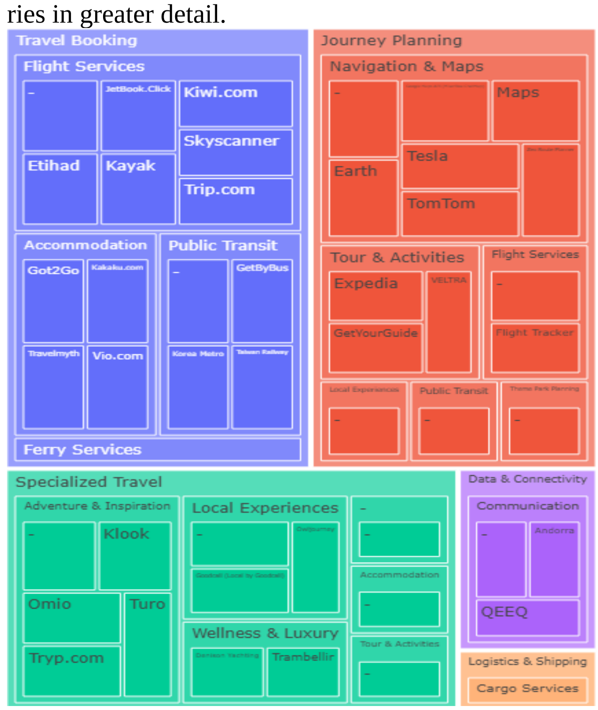

Figure 3: ChatGPT gateway modules: "Travel & Accomodation"

5. Emergent Structures and Externalities in Multi-Platform Ecosystems

The network model serves to delve into the unique externalities manifest in multi-platform ecosystems. Such ecosystems often exhibit emergent structures that give rise to unexpected externalities. As platforms and modules become increasingly interconnected, they frequently generate unanticipated value, creating a complex web of interactions. For example, a module initially designed for a specific function on one platform may interact synergistically with a module from an entirely different platform, revealing emergent structures' rich potential and complexity. These externalities are not just dyadic but result from the interplay among multiple platforms, modules, or actor groups. Unlike conventional externalities, which involve direct interactions between two entities, these "higher-order" externalities involve intricate interactions among three or more entities, resulting in cascading effects that can alter the value or impact of individual elements within the ecosystem.

We investigated various analytical methods to identify and categorize these externalities, including network motif analysis, centrality measures, community detection, and graph embedding techniques (Maharaj, 2018; Pržulj, 2007). While motifs may not always capture the local nuances of an ecosystem's network structure (Kashtan & Alon, 2005), centrality measures, despite highlighting node importance, can neglect critical local interactions essential for understanding externalities (Börner et al., 2007). Although useful for identifying dense clusters of nodes, community detection methods may overlook specific community architectures (Fortunato, 2010). Additionally, while invaluable for machine learning applications, graph embedding could distort the local network structure (Cai et al., 2018).

To gain a more nuanced understanding of these externalities, graphlet analysis (Maharaj, 2018) was chosen to examine network effects and complementarities specifically. Graphlets are small, interconnected subgraphs within a larger network that capture the fine-grained details of localized interactions (Pržulj, 2007). These graphlets, categorized by increasing complexity as G0, G1, G2, and so on, allowed us to identify various forms of externalities based on their interconnection patterns. For example, a graphlet with numerous interconnections indicates a strong network effect, whereas a graphlet featuring a central platform or module connected to multiple nodes suggests clear complementarities. We uncovered how externalities are distributed throughout the ecosystem by incorporating these observations into our broader network analysis.

Our in-depth analysis sheds light on three unique types of higher-order externalities specific to multi-platform ecosystems. The subsequent section will explore the complexities of these externalities and examine their characteristics and impact on intricate ecosystems. By identifying higher-order externalities, we aim to pave the way for innovative ecosystem strategies and better decision-making in multi-platform ecosystems.

We investigated the complementarities of Alexa's multi-platform ecosystem to validate our theoretical findings. We had to omit the presentation of the network effects due to space constraints. Alexa was chosen because usage data has been available since 2016, and prior research describes how to identify network effects and complementarities on the Alexa platform using proxies (Schmidt et al., 2023b). A detailed process for data collection on the Alexa platform has already been described in detail (Schmidt et al., 2022). It combines web scraping with proxies (Brynjolfsson & Smith, 2000). Web scraping has the advantage that the collected data are behavioral and not influenced by the participants (Landers et al., 2016). Furthermore, even large datasets can be collected repeatedly due to automation, considering the evolving nature of multiplatform-ecosystems due to their emergent structures.

5.1 Remote Externalities

We define remote externalities as those with participating entities distributed to different platforms. There are both remote network effects and remote complementarities. They are found through G0 graphlets, characterized by two nodes connected by an undirected edge (Pržulj, 2007). Such patterns depict the binary relationship between entities, whether distinct actor groups or separate modules. Nodes symbolize disparate actor groups or modules existing on separate platforms, whereas the connecting edge signifies their interaction.

Remote network effects arise when the value of a user group on one platform is impacted by the number or activity of users on a different platform. For example, if an online gaming platform (Platform A) supports gameplay streaming and a separate social media platform (Platform B) lets users discuss these streams, as Platform B grows, Platform A becomes more valuable to gamers due to a larger potential audience. This interplay demonstrates a remote network effect between users of both platforms.

G0 graphlets also enable us to elucidate **remote complementarities** by exemplifying the relationship between two modules operating on different platforms. The level of joint usage of such modules can indicate supermodular complementarities in consumption (Jacobides et al., 2018). The results of the Alexa multi-platform are presented in Figure 4. It shows a heatmap of the relative strength of remote complementarities between different Alexa categories containing external platforms. Since the Alexa ecosystem encompasses many categories (Schmidt et al., 2022), we focused on identifying the categories of skills with the highest level of joint usage on the platform. For example, there are relatively strong complementarities between streaming platforms in the music and audio category and platforms in the news category.

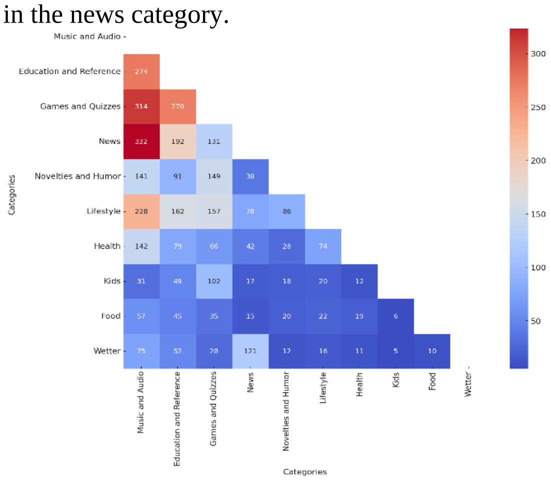

Figure 4: Relative strength of remote complementarities of category in Alexa

5.2 Transitive Externalities

We define transitive externalities as those that occur when one entity exhibits externalities with two other entities: one directly and the other indirectly through the second entity. G1 graphlets (Pržulj, 2007), composed of three nodes linked by two edges, effectively illuminate these types of externalities by representing the three entities as nodes and their sequential externalities as edges. Such transitive externalities entail a sequence of interactions across multiple platforms, potentially giving rise to network effects or complementarities between platforms that otherwise would not interact directly.

Transitive network effects arise when the relationship between two actor groups indirectly influences a third group, even though no direct link exists between the first and third parties. For instance, if Platform A provides course content, it may prompt students to discuss and share resources on Platform B. Subsequently, as courses conclude, students might turn to Platform C to resell their textbooks. In this scenario, even without a direct connection between Platforms A and C, an increase in enrollments on Platform A could lead to a surge in textbook resales on Platform C, facilitated by interactions on Platform B**.**

Transitive complementarities arise when one module's value or utility is indirectly enhanced through the interaction of two other modules. Their idea is comparable to transitive network effects but focuses on complementarities instead. The transitive externalities within the Alexa multi-platform ecosystem are illustrated in Figure 5, which displays the graphlets with the strongest transitive complementarities.

Our approach involved searching for G1 graphlets demonstrating strong complementarities in the Alexa network model. The "Music and Audio" category, which contains many external platforms, is the starting point for two transitive complementarities: "Education and Reference" -> "Kids" and "Games and Quizzes" -> "Kids". These transitive complementarities intersect with other categories, such as "Education and Reference" -> "Lifestyle" -> "Health".

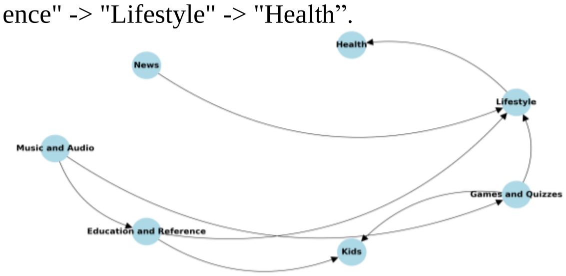

Figure 5: Transitive complementarities in Alexa

5.3 Polyadic Externalities

Polyadic externalities involve scenarios where three or more entities are fully interconnected through externalities. These can range from basic ternary externalities to more complex quaternary forms and beyond. The G2 graphlet (Pržulj, 2007) effectively captures ternary relationships by fully interconnecting all entities through externalities, forming a closed triad. Three edges link three nodes. These nodes could represent different actor groups or modules within platform ecosystems, while the edges symbolize their interactions.

Polyadic network effects refer to the phenomenon in which the value for a particular group of users or actors increases due to the simultaneous interaction of three or more distinct groups. The G2 graphlets illustrate ternary network effects, depicting three actor groups (or platforms) and their reciprocal interactions. For example, users log their workouts and track their physical progress on Platform A. These users share their fitness journeys and inspire others on Platform B. As users become more health-conscious, they seek healthier meals, driving them to Platform C for personalized meal plans. Here, a ternary network effect emerges among the three platforms. The more people use the fitness app (Platform A), the more health-focused content is generated on the social media platform (Platform B), which in turn increases the demand for the meal planning platform (Platform C).

Polyadic complementarities arise when the value of a module is enhanced by the interaction of three or more distinct modules, extending beyond the traditional binary complementarities. G2 graphlets can effectively capture ternary complementarities within platform ecosystems. We investigated the occurrence of ternary complementarities in the Alexa multi-platform ecosystem by searching for G2 graphlets in the Alexa network model, as shown in Figure 6. The results of the analysis are presented in the following graph. It comprises overlapping G2 graphlets. Some nodes appear in multiple ternary complementarities. Understanding such ternary complementarities can be valuable for platform owners or developers. For instance, they might bundle or recommend skills, design crossover promotions, or identify areas for new skill development.

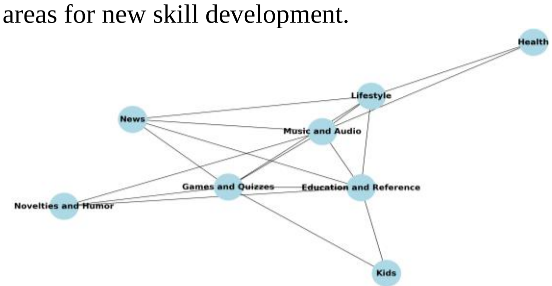

Figure 6: Ternary externalities in Alexa

6. Discussion and Limitations

This research introduces a network science approach, offering a wider lens than single-platform approaches to understand and analyze multi-platform ecosystems. Building on established studies (see section 2.3), our work expands the existing body of knowledge by shifting the focus from isolated platforms to interconnected, networked multi-platform ecosystems. The adopted methodology aligns with recent findings that suggest dyadic approaches fall short of capturing the emergent complexities of multi-platform ecosystems (Vargo et al., 2023). The graph-oriented model represents multi-platform ecosystems, where nodes and edges symbolize entities like platforms, modules, and actor groups and their relationships, such as network effects and complementarities. Our analysis reveals the crucial role of gateway modules in shaping multi-platform ecosystems, as exemplified by their presence in the ChatGPT platform. We also demonstrate how registries enable emergence in multi-platform ecosystems, citing evidence from Alexa's platform data.

These insights contribute to developing more effective strategies and tools for multi-platform ecosystem management. For example, the analysis of the Alexa platform yielded a range of higher-order externalities, such as remote, transitive, and polyadic externalities, unique to multi-platform ecosystems. By capturing how these externalities unfold across multiple platforms, we offer a methodology for understanding how changes propagate even between platforms lacking direct connections. This allows us to build more comprehensive theoretical models of multi-platform ecosystems. Our work substantiates the idea of higher-order externalities, suggested by Zhang & Williamson (2021), as factors behind the superior performance and value creation in multi-platform ecosystems.

Contrary to existing approaches that often model multi-platform ecosystems through centralized or top-down structures (Au et al., 2019; Klimmek et al., 2021; Schreieck et al., 2023; Staykova & Damsgaard, 2015), our method differs by leveraging network science. This perspective allows to represent multi-platform ecosystems as a networked structure of independent platforms that can vary in extent and complexity. Unlike systems that presuppose a high-level blueprint, this approach recognizes each platform as a sovereign entity capable of making its own decisions.

The platforms may enter or leave the multi-platform ecosystem based solely on their strategic imperatives. This flexibility enriches the model by depicting the multi-platform ecosystem as a dynamic and evolving entity shaped by its constituent platforms' collective yet independent decisions. There is no need for a higher-level plan to govern these decisions; rather, the ecosystem emerges naturally from the actions and reactions of its members.

Another benefit of the present approach is its reliance on direct, observable data to represent these decisions, which avoids the biases that may creep into models based on assumptions or indirect measurements. The data collection process is streamlined and can be easily automated, requiring minimal effort for execution. This simplicity and efficiency enable high-frequency data acquisition, ensuring the network model is continuously updated to reflect real-time changes in the multi-platform ecosystems.

For researchers, our research provides nuanced insights into ecosystem structures by identifying and describing higher-order externalities. In particular, it is possible to characterize multi-platform ecosystems in a much more precise way than before. These data-driven ecosystem profiles enable academic comparison and longitudinal tracking. For practitioners and managers, the approach serves as a strategic asset. It allows for anticipating the impacts of ecosystem alterations, such as the addition or removal of platforms, thereby enabling proactive and informed decision-making. For example, the addition of platforms both increases potential externalities but also increases the risk of competition. Our methodology facilitates effective resource deployment and ecosystem management by identifying key nodes, dependencies, bottlenecks, and inefficiencies.

However, this research has some limitations. First, our network model is relatively simplistic and may not capture all intricate dynamics. Future work could enrich the model by adding node and edge attributes. Second, we based our findings on two case studies within the conversational AI domain; a broader empirical base would add robustness. Improved data collection could enhance the fidelity of these representations. Third, investigating real-world ecosystems using network science implies simplifications that could miss subtle details. Alternative approaches should be investigated. Fourth, the static graphlet analysis overlooks temporal dynamics, an area future research could explore. Finally, while we theoretically derived types of higher-order externalities, empirical validation on a larger scale would lend more rigor to these concepts.

7. Conclusion and Future Research

Multi-platform ecosystems are characterized by their intricate network structures and the phenomenon of emergence. Both aspects have traditionally posed significant challenges in the realm of ecosystem intelligence. Our research employs a network science approach to dissect and understand these complex systems. In doing so, we have unearthed what we call the "dark matter" of these ecosystems - higher-order externalities that have hitherto remained obscure. This finding contributes to ecosystem intelligence, which often falls short of capturing the unique complexities inherent in multi-platform settings. Thus, our findings offer a valuable roadmap for navigating and strategically managing these intricate ecosystems.

Looking ahead, there are several avenues for future research. Extending the methodology to a wider array of case studies could bolster its validation. Advanced graphlets could provide a more nuanced portrayal of higher-order externalities. Incorporating diverse data types, such as user behavior patterns and economic metrics, can yield a more holistic understanding of these ecosystems. Multiple perspectives, e.g., depicting network effects or complementarities, enrich the analysis. Employing dynamic network analysis could show how ecosystems evolve, an important dimension currently missing from our work.

In summary, the study of data-network effects represents an intriguing and largely unexplored field for investigation. On the one hand, the presented research lays the foundation for a more expansive theoretical framework for understanding multi-platform ecosystems. It highlights these systems' inherent challenges, offering actionable insights for more strategic ecosystem management. On the other hand, more sophisticated solutions and tools for mastering ecosystem challenges may emerge, such as ecosystem intelligence. They will complement existing approaches and help businesses in world where platforms are increasingly intertwined and dynamic.

8. References

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