



Fostering generativity in platform ecosystems: How open innovation and complexity interact to influence platform adoption

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ABSTRACT

Platform sponsors strive to govern their platform ecosystem to be generative in supplying complementary products abreast of adoption targets. A more comprehensive pool of adopters requires high value creation capacity. Leveraging the opening of borders to complementors for competing in adoption could be a winning strategy when fostering generativity. Seldom has this view been studied empirically; therefore, the present study examines the effects of supply-side openness on platform adoption and investigates generativity's role between them as a mediator. Moreover, the study explores the heterogeneity between early and late adopters in generativity's influence. We also analyze generativity in mediating the effect of openness by the moderating influence of technological complexity. Consequently, a moderated mediation analysis is employed on panel data of 8960 video games in six platforms and three regions. Results show that platforms' openness propels their adoption, and generativity mediates this effect. Specifically, this study clarifies the idea that supply-side openness, the proliferation of more open innovation strategies, enhances platforms' value generation capacity, and both enhance platform adoption. Findings also indicate that platforms' technological complexity positively moderates the mediation role of generativity, revealing that in more complex platforms, openness increases generativity more intensely.

1. Introduction

The structures of many industries have changed dramatically in recent years with the implementation of digital platforms. This evolution later became the origin of platform ecosystems (Bresnahan and Greenstein, 1999) that spread globally to many prominent businesses (Cusumano et al., 2019). Thus, in today's modern world, platforms such as digital marketplaces, smartphones, and video game consoles play an influential role in economics (Stallkamp and Schotter, 2021). In recent years, one of the platform types that has attracted the attention of researchers in this field is that of video game consoles (Cenamor, 2021; Inoue et al., 2019). Moreover, the COVID-19 pandemic caused a significant increase in sales of games and consoles (Statista, 2021), and in playing time (Barr and Copeland-Stewart, 2021), altogether intensifying their importance for academic researchers.

One of the most effective facilities causing the unique expansion of platforms is the formation of ecosystems that provide multifarious innovation. The concept of a "platform ecosystem" generally consists of a platform and its complementors (Gawer and Cusumano, 2014).

Complementors use the resources and capabilities of the owner, making their platform full of diverse and complex innovations (Jacobides et al., 2018; Nambisan et al., 2019). Platform owners, taking the governance role, orchestrate autonomous but interdependent complementors by the regulation and access control of boundary resources to create values that match user demands (De Reuver et al., 2017; Lusch and Nambisan, 2015). Platform owners also design the architecture of platforms modular enough for complementors to develop and commercialize their own complementary products (Gawer and Cusumano, 2014; Thomas et al., 2014). For instance, in the video game industry, platform owners such as Sony, Microsoft, and Nintendo provide consoles with the capability of allowing third parties such as Gameloft, Ubisoft, and Epic Games to develop and publish video games (Ozalp et al., 2018).

Extensive research on open innovation has broadly discussed how different actors coordinate in platform ecosystems to create and capture value (Altman and Tushman, 2017; Parker and Van Alstyne, 2018). In the extant literature, the degree of openness and innovation strategies are principal issues in the governance of a platform (Adner, 2006). How open a platform is at the complementor level is the overall outcome of

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the innovation strategies selected for each complementary product. Thus, it will influence the ecosystem's value creation and capture dynamics (Cenamor and Frishammar, 2021; Cennamo, 2016). Platform sponsors embrace open innovation as a major innovation strategy that helps them supply innovative complementary products regarding user needs (Adner and Kapoor, 2010; Tavalaei and Cennamo, 2020). Since they deal with heterogenic user preferences, utilizing an adequate degree of openness is a pivotal advantage for succeeding against the competition (Scholten and Scholten, 2012; Steiner et al., 2016).

Existing research addresses openness as an influential factor that directly and indirectly affects a platform's success (Eisenmann et al., 2009; Wang et al., 2020). Notable studies worked on the consequences of openness that propel users to adopt a platform, such as the advocacy of openness on the network effect (Choi et al., 2019), its effect on expanding market potentials (Ondrus et al., 2015), lessening lock-in concerns of users, and its influences on differentiating the products (Eisenmann et al., 2009). Similarly, Wang et al. (2020) argued that when demand diversity is high in platforms, supply-side openness will eventually in the platforms' success.

What needs to be studied is the effect of supply-side openness on a platform's capacity to produce diverse values as a pivotal determinant in spurring platform adoption rates. Studying this capacity provides a deeper understanding of the effects of openness on adoption rates. In fact, it accentuates the role of a within-system innovation capacity—generativity—in the openness governance of platforms. Generativity of a platform, a concept representative of a system's innovation capacity, should be aligned with users' dynamic desires (Jarvenpaa and Standaert, 2018). With the growing penetration of platforms in people's lives and the advancement of technology, the diversity of user desires earns more significance in platform ecosystems. Absorbing various innovations derived from the advancement of technology helps platforms keep their role significant as enablers of value generation, since technologies advance in responding to various needs (Dahlander et al., 2021; Versteegen et al., 2019). Hence, considering generative outcomes in a platform helps to deepen one of the conditions in which openness contributes to a platform's success (Lee and Raghu, 2014; Rossi et al., 2020). Thus, a deeper investigation into innovation capacity changes that result from platform openness will provide insights into effective openness governance.

Generativity alongside strategies also depends on the architecture (Moon and Choi, 2016). One crucial aspect of generative architecture is its technological complexity. Previous research discussed the decelerating effect of technological complexity on platform ecosystems' value creation (Cennamo, 2016; Cennamo et al., 2018). Theoretically, this effect is rooted in the high-level specialization of components in a more complex system (Baldwin and Clark, 2000; Singh, 1997). However, open innovation has been identified as a solution to overcome technological complexities since it allows the absorption of more specialized knowledge and experience from complementors (Caloghirou et al., 2004; Nambisan et al., 2019). Although previous studies mentioned the hindrance effect of complexity to value creation capacity and discussed the need for openness in this situation; however, what needs to be studied is the effectiveness of supply-side openness in recovering the loss of generativity when technologies become more complex.

The present study, therefore, investigates the influence that openness exerts on adoption through platform-level generativity. The study also addresses the aforementioned gap related to platform complexity by investigating the effectiveness of openness strategy at different levels of technological complexity. In fact, by conducting an empirical analysis, generativity's potential mediation role in the openness-adoption relationship and the moderated mediation role of complexity are examined. To examine the effect of complexity, first, we contrast the influence of openness in enhancing a platform's generativity where the technological complexities differ. Then, we investigate how these possible differences influence the mediation role of generativity. For this purpose, we conduct an empirical analysis by using panel data of six video game

consoles (in seventh and eighth generations) from 2005 to 2021 in three world regions.

Building on the literature on open innovation, we focus on the notion of platform ecosystems as semi-regulated marketplaces governed by platform owners who strive to foster complementary innovation to make it more appealing to potential users (Jacobides et al., 2018). By investigating the role of generativity between platform openness and adoption, the study elucidates one result of proper openness governance, which enhances platforms' value generation capacity and attracts more adopters. Moreover, addressing the role of technological complexity interacting with openness would broaden the understanding of the effects of platforms' architecture design and its generative governance. The study shows that in more complex platforms, openness increases generativity more intensely. Finally, in an additional analysis, generativity's role in platforms' adoption is investigated closely by considering the heterogeneity between early and late adopters. This exploration will provide insight into aligning generativity with users' dynamic desires. The results reveal that platforms' generativity is more influential for later adopters since they avoid purchasing mistakes and seek a more reliable source for their various desires.

The remaining part of this article is organized as follows. The next section reviews theories and the extant literature on the study's notions; then, we posit our hypotheses. The third section describes our method, data, and details related to empirical analyses. In the last three sections, first, we interpret the results, and then, we fulfill our study with a discussion and conclusion.

2. Theoretical background and hypothesis development

2.1. Platform ecosystems, openness, and platform adoption

The term *ecosystem* in the context of management studies refers to a group of interacting companies whose activities depend on and affect each other (Jacobides et al., 2018). The concept of business ecosystems emerged in the literature as an economic community in which companies co-evolve their capabilities around a new trajectory of innovation (Moore, 1993, 2006). Leaders or central contributors of a business ecosystem act as a central hub and exert control for maintaining a leading position to develop a robust community of contributors to value generation (Iansiti and Levien., 2004). This concept is broader than that of platform-based ecosystems (Tiwana, 2014). Platform ecosystems, however, are built on the interaction and co-creation between platform owners and third parties (Tiwana et al., 2010; Wareham et al., 2014).

In platform ecosystems, external innovators, known as complementors, participate in ecosystem innovation (Gawer and Cusumano, 2014). The core product provided by the platform owner is based on a modular architecture with a stable core surrounded by a flexible boundary (Tiwana et al., 2010). Platform ecosystems form a "hub and spoke" arrangement, with a collection of complementors connected to the central platform through shared resources and technologies that comprises technical standards, programming interfaces, and SDKs¹ (Jacobides et al., 2018). Platform sponsor orchestrates autonomous complementors by the regulation and access control over boundary resources to create values matching user demands (De Reuver et al., 2017; Lusch and Nambisan, 2015). In fact, the platform owner constitutes a suitable organizational form to enable interaction (McIntyre et al., 2021), fair competition, and co-competition of complementors with the least difficulty and cost (Adner, 2017; Gawer, 2021). Interdependent complementors maintain their interaction and collaboration with the platform and ecosystem members within the confinements of governance and regulation while striving to maximize benefits independently (Nambisan et al., 2019). Thus, the owner's strategy in resolving the tension between openness and control on the supply side of a platform is

¹ Software Development Kits.

pivotal for its success.

Scholars have broadly discussed the technology adoption rate as an essential factor in the platform's success in gaining market share (Kristensson et al., 2020; Rietveld and Eggers, 2018). Adoption decisions of users in a platform-based market are interpreted with models mainly consisting of two facets related to innovation and network externalities (Cabral, 1990; Rietveld and Eggers, 2018). Earlier adoption is induced by innovation in products and the novelty of values brought to the market (Panico and Cennamo, 2020; Rietveld and Eggers, 2018). As the platform ages, network-related factors such as installed base, network effects, and product availability gain more importance (Cenamor et al., 2013; Steiner et al., 2016). Considering drivers of adoption decisions, we discuss influences exerted on adoption rate by sponsors' openness strategy and within-system consequences of this strategy related to value generation capacity.

From the theoretical perspective, open innovation strategy requires investments to have more complementors and technology complementarities (Chesbrough and Wim Vanhaverbeke, 2006). Predominantly, openness leads to the availability of complementary goods and services, increasing firms' value offering (Chesbrough, 2003a, 2003b). Openness helps firms to offer different combinations of values with a better innovation performance from complementary resources (Laursen and Salter, 2006; Wernerfelt, 1984). Thus, platform sponsors seek more complementary products that reinforce the network effect (Cenamor et al., 2013).

In general, the openness degree of a firm is related to the number of external partners (Chen et al., 2011). Openness in platforms would increase by opening borders to third-party complementors (Gawer, 2020). Therefore, innovation strategies used for supplying complementary products determine the degree of openness on the ecosystem level (Cenamor and Frishammar, 2021). Platform's supply-side openness (Eisenmann et al., 2009) is affected by commercial and technological interactions with complementors, particularly in the video game market (Cenamor and Frishammar, 2021; Choi et al., 2019). Therefore, openness could be interpreted as convenient commercialization, interoperable interfaces, and facilitated technology integration (Benlian et al., 2015; Gawer, 2020).

Opening a platform will propel adopters by decreasing users' lock-in concerns and increasing the platform's dexterity in responding to diverse user needs (Eisenmann et al., 2009). Ondrus et al. (2015) discussed the idea that a platform that is more open to technologies will have more sizable market potential and a higher predicted adoption rate. Moreover, studies asserted that platform openness that results in more complementary products, directly and indirectly, incites platforms' adoption rate (Cenamor et al., 2013; Zhu and Iansiti, 2012).

Besides many arguments discussing how openness will influence platforms' success, some studies indicated that openness governance requires smart controls to avoid detrimental effects on the platform ecosystem. Noticeably, studies stated that uncontrolled openness would eventuate intense competition among complementors causing deterioration of their profit and motivations (Boudreau, 2012; Eisenmann et al., 2009). Excessive openness unrelated to users' demand diversity will lead to crowding out complementors' innovation incentives (McIntyre et al., 2021). Moreover, a platform with excessively open boundaries faces complementors' free-riding behavior, especially for its new entrants, diminishing complementary products' quality and user satisfaction (Cennamo and Santaló, 2019; Saadatmand et al., 2019). All these studies indicate that favorable results of openness are associated with the "right governance" and resolving the tension between access and control (Thomas and Tee, 2021).

Proper design and right governance are paramount in orchestrating value creation aiming at a platform's success (Schrieck et al., 2016). Right governance requires matching openness with the required innovation capacity according to user demands (Thomas and Tee, 2021; Wang et al., 2020). Strategically opening the boundaries of a platform will increase the value creation capability by capturing value from

complementary resources (Alexy et al., 2018). This will improve the platform's innovation performance (Barney and Clark, 2007; Wang et al., 2020). Complementors have open or controlled access to shared resources and knowledge; on the other hand, they try to compete with their own "off-platform" resources (Boudreau et al., 2021). In summary, platform owners try to govern the openness with regulation and employ boundary resources for control over complementors to maximize value capture, reduce lock-in concerns, and increase platforms' attractiveness (Alexy et al., 2018; Cutolo and Kenney, 2021). However, in practice, the right governance needs to be in place; control over complementary innovations with open boundaries is critical to gain the favorable outcomes of openness and avoid unfavorable ones.

Accordingly, one way to keep track of the right governance is to investigate what aftermaths of openness will lead to a higher attractiveness of a platform. In this study, we focused on platforms' capacity to generate diverse value. Thus, the study first posits a positive relationship between the degree of openness in platform ecosystems and their adoption rate. Then, we investigate the role of generativity between openness and platform adoption.

2.2. The role of generativity

Platforms expecting higher adoption rates must face a diverse heterogeneity of users; thus, to satisfy various desires, they need to supply diverse values. Such a generative platform is the consequence of opening boundaries to third parties cultivating heterogeneous innovation and co-creation (Cohendet et al., 2020). Ecosystems orchestrating the dynamics of value creation for comprehensive coverage of users' needs increase their acceptance (Gawer, 2020). One consequence of successfully implementing open innovation for platforms is the differentiation of products according to distinguishable segments (Eisenmann et al., 2009). Scholars addressed similar implications of this aspect as generativity in platform ecosystems.

Cennamo and Santaló (2019) defined *generativity* in platform ecosystems as "the ecosystem's capacity to foster complementary innovation from autonomous, heterogeneous firms." The significant role of generativity in platforms, especially video game consoles, has been propounded in previous studies (Nambisan et al., 2019; Wareham et al., 2014). Generativity has been identified as a factor that influences user satisfaction in an ecosystem (Cennamo and Santaló, 2019). Ecosystems adopting openness strategies that reinforce innovation creation tend to be more generative (De Reuver et al., 2017; Karhu and Ritala, 2020). In this regard, Thomas and Tee (2021) discussed generative governance in the context of information systems, pointing out that openness is an antecedent of generativity. In their study, access control over boundary resources is a significant aspect of generative governance, which indicates the influence of supply-side openness.

It is essential to notice that openness does not always result in a favorable generativity level. Inducing generativity mandates platform owners to expose their platforms' boundary resources to gain from more complementary innovation. However, platform owners' ability to reap generative appropriability matters in the tension of control and generativity. Platform owners need to foster cooperation with complementors; they can share platforms' resources and intellectual property rights (IPRs) by employing open-source licenses (Karhu and Ritala, 2020). This decision would advocate generativity; however, it will enforce considerable risks of imitation. Adopting an inbound openness strategy (outside-in) will favor the IPRs for the platform owner. Instead, when using the outbound openness strategy (inside-out), the beneficiary would be the complementors (Enkel et al., 2009; Parker and Van Alstyne, 2018).

More open platforms are more willing to give away IPRs (Altman and Tushman, 2017; Parker et al., 2016); extreme cases happen with open-source licenses (Karhu and Ritala, 2020). In practice, platform owners strive to reach an optimal degree of openness and a proper duration for keeping IPRs from developers. This privilege helps them control

competition, complementary contributions (to avoid technological risks), and the contents (Chesbrough, 2003a, 2003b), although excessive control may decline complementors' incentive to innovate (Parker and Van Alstyne, 2018). In platform ecosystems, generativity appropriability ensues when it benefits different sides: users, ecosystem members, and platform owners. Platform owners who can take more substantial risks adopt more open innovation strategies and keep IPR at an optimal duration, which leads to more generative capacity.

Through this viewpoint, openness has a two-fold effect when the ability to exploit generative outcomes exists; first, entering various complementors is a means to generate various values; second, it leads to more innovation creation tendency (Inoue, 2021; Saadatmand et al., 2019). More complementors would provide heterogeneity as they have different experiences and can perceive the world differently. Complementors as established companies of different sizes, regions, and cultures generate diversified values (Thomas and Tee, 2021). Besides, Inoue (2021) found that in platforms with higher degrees of openness, complementors' tendency to create radical innovations increases; thus, openness would trigger further innovation among existing complementors which boosts generativity (Cennamo and Santaló, 2019; Thomas and Tee, 2021).

Collectively, the above arguments articulate that one important factor promoting generativity in the level of platform ecosystems is the openness degree. Hence, we posit the following hypothesis:

Hypothesis 1. In a platform ecosystem, the increase in the degree of openness influences a positive effect on generativity.

Today, in platform-based markets, users can switch between platforms with a wide range of choices; however, switching may cost them in some markets, such as video games (McIntyre et al., 2020). The switching cost induces sponsors to work on adoption drivers actively. Generativity, an ecosystem's capacity to respond to users' heterogeneous preferences, plays an essential role in adopters' intentions (Steiner et al., 2016; Thomas and Tee, 2021). A platform harboring the capacity for providing diverse value in complementary products is more likely to affluence the potential market (Moon and Choi, 2016; Panico and Cennamo, 2020). Increasing diversity and innovation in a platform is a win-win resolution; platforms possessing higher generativity levels benefit from user satisfaction and create a favorable reputation (Cennamo and Santaló, 2019). Relatedly, consumers become attracted to a platform that provides them with a richer portfolio of product variety and more diverse technology use cases (Landsman and Stremersch, 2011; Zittrain, 2008).

Generativity increases through the contribution of various parties in responding to unanticipated changes derived from the heterogeneous desires for innovation and distinguished experience (Zittrain, 2008). In platform ecosystems, it results from the diffusion of the provided technology among heterogeneous complementors by their product development (Cennamo and Santaló, 2019) provoked by users' preferences (Panico and Cennamo, 2020). Cultivating generativity, by its nature, depends on opening the borders to various complementors since responding to such unanticipated changes requires broadened access to complementors.

However, increasing generativity limitlessly puts the entire platform ecosystem at risk of rejecting complementary products or deteriorating user satisfaction (Cennamo and Santaló, 2019; Nielsen and Hanseth, 2010). Platform owners should align generativity's usefulness with users' preferences (De Reuver et al., 2017; Gawer, 2020). Therefore, they need to exert control over platform-level generativity (Chowdhury et al., 2021). Overly varied and fragmented complementary products are less beneficial for both complementors and consumers; excessive generativity makes it difficult to capture value from complementary innovations (Gawer, 2020). Avoiding the lack of harmony between complementors and a platform's generative architecture—an unbalanced relation between architectures' innovation potential and complementors' capacity—is essential. Resolving the tension between

openness and control is crucial for approaching a generative fit (Thomas and Tee, 2021).

Platform owners, through openness, can drive generativity to reach a balance between value and desires; this will help them overcome limitations in passing their adoption trajectory. They need to orchestrate innovation to reach a capacity that matches heterogeneous user preferences (Rogers, 2003). Proportionate generativity could be ascribed as one of the consequences of proper openness governance, which attracts more adopters.

Borrowing Bass's (1969) adoption model that explains two approaches for the potential market, being innovator and imitator, we discuss the effect of generativity on platform adoption (Ondrus et al., 2015). In platform ecosystems, imitators are affected by the installed base and users of complementary products (Healey and Moe, 2016; Inoue and Tsujimoto, 2018a). Innovators tend to explore diversified experiences among complementary products (Kumar et al., 2020; Lee and O'Connor, 2003). Maintaining generativity in a platform ecosystem influences the adoption of both approaches. First, it provides a diverse portfolio of complementary products; this advantage responds to the exploration desires of innovators. Second, a rich portfolio of products responds to more heterogeneous preferences and covers various tastes; thus, the more sweeping coverage brings more users and increases imitators' further intention. In addition, imitators are later adopters who behave in a more risk-averse manner and avoid purchasing mistakes; a more generative platform is a reliable source of value that helps them relieve platform-switching concerns. In sum, all imply that platform generativity spurs its adoption rate.

As discussed earlier, the degree of supply-side openness will influence platforms' adoption rate. Altogether, the prevalence of arguments corroborates that generativity is a within-system innovation dynamic affected by platform openness and induces the adoption rate. All provide groundings for the postulation of the following hypothesis:

Hypothesis 2. In a platform ecosystem, generativity mediates the positive relationship between the degree of openness and platform adoption.

As discussed earlier, adopters in different platform stages have different approaches to exploring values and getting incentivized toward the platform (Rietveld and Eggers, 2018; Rogers, 2003). Earlier adopters tend to be more explorative and self-motivated to try new technologies and products (Prins et al., 2009); their adoption is expedited by the novelty and innovation discovered in the complementary products (Kumar et al., 2020). However, in the later stages of the platform life cycle, where the late adopters are the majority, the variety of software products becomes more important (Clements and Ohashi, 2005). Since they are risk-averse and avoid switching costs (Kumar et al., 2020), they seek a platform with a better capacity to generate value. According to this heterogeneity in adoption incentives, generativity would differently affect relatively earlier and later adopters. Thus, we supplement the analysis by considering the demand heterogeneity between earlier and later adopters to investigate generativity's role in depth.

2.3. The role of platform complexity

Rapid technological development leads platforms to the next generation, enabling its ecosystem to sustainably capture values from complementors, enhance the core functionality, and increase innovation performance (Cennamo and Santaló, 2013). With the upgrade of hardware and software, new generations of platforms with more complex technological capabilities emerge in the markets (Cennamo et al., 2018; Daim et al., 2014). In video game platforms, the competition between platform sponsors in sales of consoles resets by a generation shift. Therefore, new generations could cause different adoption patterns for each console, and sometimes the market's dominant player differs (Daim et al., 2014; Shi et al., 2014).

Cennamo et al. (2018) discussed the notion that new generations of platforms exert more complexity since they contain more interdependent components in their core technology. In detail, complexity increases by implementing more processing units in the architecture and adding more programming interfaces for developing complementary products. With higher complexity, the development of complementary products becomes more arduous (Cennamo et al., 2018; Daim et al., 2014). Accordingly, the complexity arising in the next generation decelerates value creation in the early stages of a platform's life cycle (Cennamo, 2016); hence, generativity decreases.

From the theoretical standpoint, within a system with complex technology, there are components with high levels of complementarity and co-specialization. Therefore, open innovation could be a solution since it provides access to specialized knowledge of external resources and reduces the costs of product design and development by resource sharing (Baldwin and Clark, 2000; Singh, 1997). Thus, broadened access to specialized knowledge improves firms' performance (Chesbrough, 2003a, 2003b). The new technology being concomitant with the increase in the openness and heterogeneity of complementors is a potential factor for increasing the generativity of a system (Nambisan et al., 2019).

A platform becomes more technologically complex through upgrades like increased processing units and technology advancements, such as new CPU/GPU architecture, AI-enabled hardware/software, et cetera. (Cennamo et al., 2018; Kovtun, 2021). So, there are multiple brand-new technologies and functionalities to be adopted by complementors. With low levels of openness, it is difficult for a platform to be generative as its pool of complementors is not sufficient to utilize the potential innovation capacity—the absence of generative fit (Nambisan et al., 2019; Thomas and Tee, 2021). When a platform's technological complexity is elevated, complementor-level openness facilitates increasing diversity of value creation (Adner and Kapoor, 2010; Kapoor and Agarwal, 2017). The more complementors using the new technology upgrades, the more diverse technology use cases are generated. Consequently, platform owners, when upgrading technologies and adding functionalities, should make them more malleable, modular in structure, and loosely coupled, which forms a generative architecture (Baldwin and Clark, 2000; Thomas and Tee, 2021). The platform should maintain or increase its interoperability by investing in the toolsets that facilitate product development (Anderson et al., 2014).

Moreover, since the increase in openness after the upgrade of technologies is helping a platform to reach the state of generative fit (i.e., the balance between complementors' community and platforms' architectural innovation capacity), it increases a platform's attractiveness by providing brand-new implementations of emerging technologies (Jarvenpaa and Standaert, 2018). In other words, increasing openness is a solution to mitigate the complexity barrier, which leads to platform success. Involving more third parties increases the capacity to generate value; this effect is more significant in a new complex platform, since it contains more tools to generate diverse value (Anderson et al., 2014; Sandulli et al., 2012).

Thus, regarding the previous studies, it can be inferred that with the inevitable upgrades of platforms, the dependence of generating value on the number of involved third parties is affected by the technological complexity of generations. Furthermore, the intervention of technological complexity influences generativity's effect on the adoption rate as it changes users' experiences of diverse values. Thus, the above arguments lead this study to develop the following hypothesis:

Hypothesis 3. In a platform ecosystem, the interaction of degree of openness and platform complexity positively moderates the mediation effect of generativity; in more complex platforms, openness increases generativity more intensely.

Fig. 1 shows the conceptual model that clarifies relationships among the degree of openness, generativity, platform complexity, and platform adoption.

3. Methodology

3.1. Data

This study uses data from the video console game market to test hypotheses. These platform ecosystems contain complementors in the two areas of video game development and publishing. For instance, Sony, the platform sponsor of PlayStations, controls the platform and lets complementors develop and publish their video game products (Cenamor and Frishammar, 2021). The video game industry has been a topic of high importance in empirical research due to the increase in their pervasiveness. The global value of this industry reached over \$120 billion in 2020.

We have conducted our empirical analysis using an unbalanced panel including six non-hand-held video game consoles; PlayStation 3, PlayStation 4, Xbox X360, Xbox One, Nintendo Wii, and Wii U. In the analysis, 8960 video games were involved (some were cross-platform) from November 2005 to May 2021. The main source of our data was VGChartz, a leading market research website that covers more than 59,000 game titles. It is a well-known data source in many empirical game-related articles (Cenamor and Frishammar, 2021; Song et al., 2017). From VGChartz, for each game title, we obtained records of name, console, release date, genre, game developer, and publisher. In addition, we obtained regional and monthly data for unit sales for each platform.

The second data source was Metacritic, a popular website aggregating reviews about entertainment products (Song et al., 2017). Since only one genre title existed for each game in VGChartz's dataset, we enriched game genres' data using Metacritic. We also used Metacritic for game release dates for the very few titles with missing release data on VGChartz.

Third, we collected price data of platforms from Price Charting,² a website gathering historical prices in the game market. For enriching price data, we obtained records from platform owners' corporate websites or Amazon; to reach these websites' historical data, we used the Internet Archive,³ a comprehensive web archive. Finally, the source selected for the information about population was the World Bank, and for inflation rates, we used data from the U.S. Bureau of Labor Statistics.

We conducted the observations for analysis on panel data indexed by platform, region, and time. In addition, we analyzed the data with a monthly approach and in three regions: the U.S., Europe, and Japan. Eventually, our final data set concluded in 1871 observations at the platform-region-month level.

3.2. Variables

3.2.1. Dependent variable

Based on the conceptual model, the dependent variable for this study is *Platform adoption_{pri}*. This variable represents the rate at which individuals based in a particular region select a specific platform to adopt its technology when refusing to choose other platforms (Cenamor et al., 2013; Corts and Lederman, 2009). *Platform adoption_{pri}* is the natural logarithm of the ratio of the total number of sales for platform *p* in the region *r* and month *t* divided by the *Potential market_{rt}* available for all platform sponsors in the region *r* and month *t*. The *Potential market_{rt}* would be the population of region *r* at month *t* minus the number of *Total adopters_{rt}*, which is the sum of adopters of all consoles we used for this analysis with a consideration of a decay rate. To capture the potential depreciation of old consoles, we involved a monthly decay rate of 0.85 %, according to Cenamor et al.'s (2013) weekly decay rate. The calculated indicator of *Platform adoption_{pri}* is presented below:

² www.pricecharting.com

³ <https://web.archive.org>

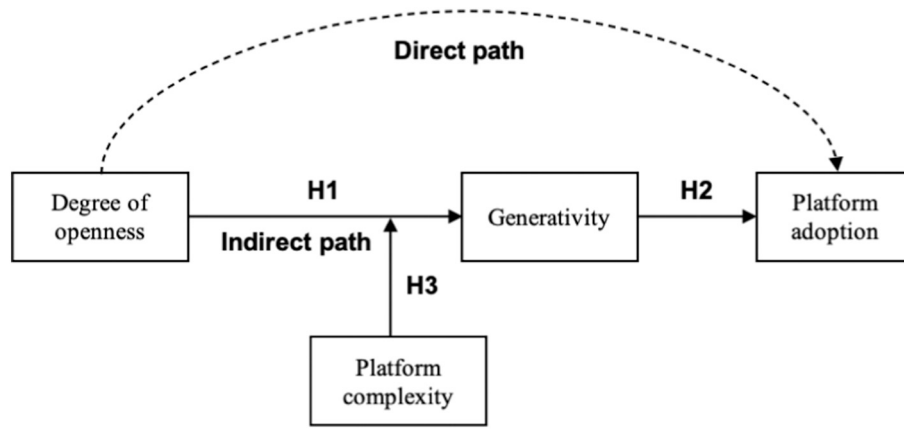


Fig. 1. The conceptual diagram and summary of hypotheses.

$$\begin{aligned} \text{Platform adoption}_{prt} &= \ln \frac{\text{Sales}_{prt}}{\text{Potential market}_{rt}} \\ &= \ln \frac{\text{Sales}_{prt}}{\text{Population}_{rt} - \text{Total adopters}_{rt}} \end{aligned} \quad (1)$$

3.2.2. Independent variable

In the literature on hardware and software development, the two principal activities that determine the degree of openness at the level of complementary products are the development and commercialization of them (Choi et al., 2019; Greul et al., 2018). Similar to Cennamo and Frishammar's (2021) debate, we assume that the degree of openness in supplying a new complementary product to a platform is higher when third parties carry out both the development and commercializing of the product (third-party strategy), rather than when only a single third party is involved (inbound or outbound strategies). Furthermore, the lowest degree will appear when a platform sponsor carries out both activities⁴ (proprietary strategy).

By considering the effect of these per-game innovation strategies in supply-side openness, we calculated the *Degree of openness*_{pt} in a platform with the sum of the numbers of third parties involved in the development and commercializing of each game released in the platform *p* and month *t* divided by the number of games released in the same month and platform. Employing this measurement, when a platform takes more open strategies (i.e., involving more complementors), the openness degree will increase up to 2. Getting more complementors involved requires opening up boundary resources, preparing interfaces for easy connection, and facilitating business-level collaborations. For instance, according to our dataset, when PS4 was announced, in the first two months, the degree of openness was closer to 1 rather than 2. It indicates that the sponsor has decided not to rely on third parties for both sides of development and publishing for all games (in around 40 % of the games, the owner has participated). In the four following months, PS4 became more open to complementors; this resulted in a degree of openness above 1.8 (in less than 10 % of the games, the owner has participated). Table A1 in Appendix A presents a concrete example from the data with the measurement of a platform's degree of openness.

3.2.3. Mediator variable

To measure *Generativity*_{pt} at the platform level, similar to the method used by Cennamo and Santaló (2019) in the context of video game platforms, we calculated the number of game titles released with diverse genre sets in platform *p* and month *t*. This method aims to capture the

monthly capacity of a platform to provide diverse technology uses in the supply of complementary products to afford various possible user preferences. In our data, every game is labeled with multiple genres; thus, we counted the number of game titles with unique combinations of genres in a specific month and platform. *Genres* describe the main features of games, such as gameplay, activity types, and content (Vargas-Iglesias, 2018). We employed this method of measurement since the diversity of the combination of genres supplied to the ecosystem could be identified as an indicator of the system's capacity to deliver diverse values. We also applied different measurements for generativity calculation to test the robustness of the results. The tables in Appendix B present a concrete example from the data and different generativity measurements used.

Since dealing with a considerable number of different genres requires some adjustments to maintain adequate accuracy, we used two methods to simplify the data of genres (Inoue and Tsujimoto, 2018b). First, we merged genres with similar connotations to avoid the rehash.⁵ Second, in any platform, we used the genres that occur in more than 0.2 % percent of total game titles published on that platform.⁶

3.2.4. Moderator variables

As the technology of hardware and software advances in new generations of video game consoles, the complexity of the platform architecture will increase (Cennamo, 2016). This study identifies the relative complexity of platforms by using a dummy variable titled *Platform complexity* that takes the value of 1 if the platform is in the eighth generation and 0 for the seventh generation (Cennamo et al., 2018). Further, we replace it with another variable in the robustness analysis to check whether the results hold.

For considering demand heterogeneity between early and late platform adopters (in Models 3a and 3b, related to additional analysis for demand heterogeneity), we have employed a variable that indicates relatively how late the adopters joined the platform. We have calculated *Platform diffusion*_{prt} for the platform *p*, in region *r* and at month *t*, with the equation below (Rietveld and Eggers, 2018):

$$\text{Platform diffusion}_{pr} = \frac{\text{Installed base}_{prt}}{\text{Installed base}_{pr}} \quad (2)$$

*Installed base*_{prt} measures the installed base of platform *p* in region *r* from the beginning to month *t*; *Installed base*_{pr} measures the total installed base of platform *p* at the end of its life cycle in region *r*. When the platform is being diffused, *Platform diffusion*_{prt} increases, indicating

⁴ Our measurements do not consider complementors who are acquired completely by platform sponsors as third parties. We count them as platform sponsors when providing a game after the time they have been acquired.

⁵ For instance, we merged "Motocross" and "Motorcycle" into a single genre titled "Motorcycle".

⁶ For example, we did not consider the genres that were used in less than three games in the platform Xbox 360.

that our observation is turning to be from later adopters.

3.2.5. Control variables

The study includes several econometrics specifications related to platform ecosystems for controlling other aspects affecting platform adoption. We controlled for the effect of a platform's duration of appearance in the regional market by Age_{prt} . This measures the amount of time platform p has been sold in region r and month t ; the age is calculated by the number of months and is represented in years (Cenamor and Frishammar, 2021). For controlling the number of platforms' users, which affects potential users' adoption decisions (Cenamor et al., 2013; Wiegand et al., 2015), this study uses $Installed\ base_{prt}$ as a control variable. This variable is calculated by the accumulative number of users that have adopted platform p in region r from the release date to month $t-1$. Considering hardware depreciation, we calculated this variable by the natural logarithm of the adjusted sum of console sales by a monthly decay rate of 0.85 % up to the month $t-1$ (Cenamor et al., 2013; Inoue, 2019). For controlling the effect of monetary sacrifice (Steiner et al., 2016; Zhu and Iansiti, 2012), the $Price_{pt}$ is included. Assuming that the regional prices are highly correlated, and according to our access to valid data, we considered $Price_{pt}$ as the USA retail price of the cheapest version of platform p in month t . We turned all prices to the value in USD in May 2021, using the Consumer Price Index. We recognized a considerable seasonality pattern in the last and first two months of most years (after that, platform ages more than 60 months; only December and January appear to maintain seasonality); accordingly, this effect is controlled by adding a dichotomous variable of *Seasonality* that takes 1 at mentioned months, otherwise 0 (Inoue, 2021). *Platform* dummies are employed to control the effects of brands, technological and marketing resources, and other platform-specific characteristics. *Year* dummies are added to control the year-specific effects, such as the pandemic in 2020 or the effects of dominant design periods. Lastly, the *Region* dummies help us capture particular impacts on adoption originating in these regions.

3.3. Model specification

We employ regression modeling to test Hypothesis 1, and for testing Hypotheses 2 and 3, we follow Hayes' (2013) bootstrapping method and Baron and Kenny's (1986) method. Using these methods, we examine *Generativity's* mediation effect and conditional process analysis for moderated mediation effect of *Platform complexity*. Also, we test moderated mediation by estimating conditional indirect effects using the approach introduced by Bollen (1987) and Sobel (1986). We employ Hayes' (2013) PROCESS macro (bootstrap samples = 5000) for these analyses (see Appendix C).

As shown in Table 2, Models 1a and 1b analyze the effects of openness and *Platform complexity* on *Generativity*; Models 2a and 2b analyze the effects of *Generativity* and *Degree of openness* on *Platform adoption*. Models 3a and 3b, as an additional analysis, analyze the effect of demand heterogeneity between early and late platform adopters by adding *Platform diffusion* and its interaction with *Generativity* to Model 2b. Considering that users' adoption decisions are made based on previous characteristics of platforms, we lagged the variables of generativity and openness by one month (Cennamo and Santaló, 2019; Inoue, 2021). Additionally, we prolonged lag times in the robustness analysis. The possible endogeneity problems that might be in place for *Generativity* and *Degree of openness* are addressed using 2SLS estimation in addition to OLS for our Models 2a and 2b. Since we are using time series (captured over months) and cross-sectional (across platforms) data, the results of OLS regression may have heteroscedasticity and autocorrelation of errors. To solve these problems, we have used robust standard errors adjusted for platform-region clusters. We also performed generalized least squares (GLS) models to bring unbiased coefficients in the results (Jeffrey M. Wooldridge, 2010). The interacting variables are mean-centered to reduce the possible multicollinearity in moderation tests.

We conducted a test calculating variance inflation factors (VIF) for checking the multicollinearity between variables; all VIFs calculated for variables are below ten, and the average of VIFs equals 1.86 for the Model 1b and 1.78 for the Model 2b. The results confirm that no major collinearity was observed in the measurements. To avoid outliers, we eliminated 32 records.⁷

3.4. Endogeneity

When investigating the effect of generativity on platform adoption, we control for the platforms' fixed effect and also the effect of an increase in the number of complementors which is reflected in degree of openness. Therefore, in our estimation, the effect of generativity is estimated within a platform by the increase in the variety of genres used in game development, independent of the increase in the openness to complementors. However, speculation about the endogeneity problem exists for the effect of openness and generativity on adoption. Notably, we are concerned that generativity is increased by the decisions of complementors to provide games with various genres under the effect of the platform's marketing activities which insinuates high adoption rates. Complementors usually become aware of the platform sponsor's marketing plans beforehand in order to get prepared (Corts and Lederman, 2009). This unobserved effect will encourage complementors to produce games with various genres since they expect various desires from more users adopting the platform. Moreover, openness could also be endogenous; the platform's investment in marketing increases both adopters and the likelihood of supply of complementary products, which leads to more third parties. The ideal way to eliminate the endogeneity problem is to design and conduct experimental research that employs endogenous variables as random treatments in Models 2a and 2b. However, this method would be difficult and massively time-consuming to address this problem in the context of platform ecosystems. Another way could be by using instrumental variables and testing our models with instrumental variable (hereafter, IV) estimation. Therefore, we instrumented $Generativity_{pt}$ by $Skillfulness_{dt}$, which measures the average of $Skillfulness_{dt}$ related to game developers who released product/s in platform p and month t . $Skillfulness_{dt}$ variable is measured by the number of unique genres in which the developer d has released games till month t (in all of the platforms of the seventh and eighth generations). $Generativity_{pt}$ and its IV have a significant correlation in our data; 0.803.

Further, we instrumented $Degree\ of\ openness_{pt}$ by $NPOC_{pt}$, new pairs of old complementors, that measure the portion of games provided by new pairs of complementors (developer-publisher) in platform p and month t , who have already contributed to games of the platform before month t . This variable indicates what percentages of games released in that month have been the result of collaboration between two complementors that have previously contributed to games provided on that platform, but where the combination of developer-publisher is new to the platform. $Degree\ of\ openness_{pt}$ and its IV have a significant correlation in our data; 0.302 (see Appendix D for more details about the IV selection). Moreover, we tested potential issues of weak IVs using Stock and Yogo's (2005) critical values, indicating that the models do not contain the weak-instrument problem.

After choosing IVs and estimating with 2SLS regression, we checked for the endogeneity of $Generativity_{pt}$ and $Degree\ of\ openness_{pt}$ using Wooldridge's (1995) robust regression-based test of endogeneity, and the results indicate that in both Models 2a and 2b, both variables were endogenous. Table D1 in Appendix D presents the first stage least squares results.

⁷ For identifying multivariate outliers, we used Mahalanobis distance based on a chi-square test with the degree of freedom of 21 (number of dependent variables). The records with $p < .001$ were eliminated.

4. Results

4.1. Main results

Table 1 contains information on Pearson correlation coefficients of the variables and their descriptive statistics. The information about Year dummies is not presented, to make the table more simplified. As presented, the correlations between variables are within acceptable limits.⁸ The first-stage results in (Appendix D) Table D1 indicate that the IVs fit the conditions for explaining both endogenous variables.

Table 2 presents the models testing our Hypotheses 1 and 2. Model 1a includes control variables and the independent variable influencing the mediator (*Generativity_{pt}*). It represents that *Degree of openness_{pt}* has a significant positive effect (OLS: $\beta = 0.191$, $p = .000$) on *Generativity_{pt}*; thus, it supports Hypothesis 1. Moreover, results from Models 1a and 1b show that control variables' effects are aligned with previous studies. In Model 1b, *Age_{prt}* has a significant negative effect on *Generativity_{pt}*, as the value generation in platforms decreases over time (Cennamo, 2016). Results significantly show that when *Seasonality* occurs, it propels *Generativity_{pt}* since it works as a stimulus for complementors to generate more value (Cennamo and Santaló, 2019). Also, all *Platform dummies* have significant influences on *Generativity_{pt}* as platforms' internal resources and strategies affect the value creation processes (Sandulli et al., 2012).

In Model 2a, the results show a significant effect of *Degree of openness_{pt}* on *Platform adoption_{prt}* (2SLS: $\beta = 0.322$, $p = .000$) in the presence of control variables; this result is a necessary outcome for testing our mediation premise in Hypothesis 2. Model 2b clarifies that *Generativity_{pt}* positively affects *Platform adoption_{prt}* with control for the effects of *Degree of openness_{pt}* (2SLS: $\beta = 0.122$, $p = .000$). Besides, in Model 2b, the effect of *Degree of openness_{pt}* on *Platform adoption_{prt}* is still significant (2SLS: $\beta = 0.246$, $p = .002$). Nevertheless, the coefficient value decreases as the generativity enters the model (2SLS: β changed from 0.322 to 0.246). Taking into account the results of Models 1a, 2a, and 2b, they meet Baron and Kenny's (1986) mediation test conditions (indirect effect using OLS models: $\beta = 0.038$, $p < .001$; indirect effect using 2SLS⁹ models: $\beta = 0.086$, $p < .05$). We also conducted a mediation test using Hayes' (2013) bootstrapping method shown in Table 3. The mediation test results show that the indirect effect of *Degree of openness_{pt}* on *Platform adoption_{prt}* through *Generativity_{pt}* is positive and significant ($b = 0.250$ and 95 % C.I. = 0.205–0.292). All the estimated indirect effects are statistically significant; thus, they all confirm our Hypothesis 2, indicating the partial mediation effect of *Generativity_{pt}*. Noticing the effect size of openness and generativity clarifies that they are substantial factors driving platform adoption. The effect size for openness ($\beta = 0.322$) is comparable to the effect for the installed base. Studies discussed the installed base as a major factor in platform adoption (Healey and Moe, 2016). A significant portion of this effect (around 24 % as β changed from 0.322 to 0.246) is carried through generativity's indirect path. Moreover, control variables added to Models 2a and 2b show influences on adoption similar to prior findings. *Installed base_{prt}* and *Seasonality* exert a significant and positive effect on *Platform adoption_{prt}* (Cenamor et al., 2013; Steiner et al., 2016). Besides, price (Cenamor et al., 2013; Steiner et al., 2016) and age influence adoption negatively. Furthermore, the represented two region dummies (Euro and USA) indicate a significant positive influence on adoption. Some platform dummies present meaningful results on platform adoption, indicating

Table 1
Descriptive statistics and Pearson correlation matrix.

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Degree of openness	1.790	0.459	1													
2. Generativity	11.080	7.817	0.33**	1												
3. Platform complexity	0.390	0.487	0.12**	0.17**	1											
4. Platform diffusion	0.394	0.322	-0.25**	-0.33**	-0.03	1										
5. Age	4.725	2.967	-0.22**	-0.27**	-0.33**	0.89**	1									
6. Installed base	15.246	2.384	-0.06**	-0.01	-0.18*	0.29**	0.41**	1								
7. Price	227.162	139.689	0.15**	0.14**	0.04	-0.72**	-0.74**	-0.39**	1							
8. Seasonality	0.220	0.414	-0.03	0.18*	0.04	-0.05*	-0.07	-0.15**	0.08**	1						
9. Region dummy: USA	0.340	0.473	-0.01	-0.01	0.00	-0.02	0.00	0.24**	0.01	0.00	1					
10. Region dummy: Euro	0.340	0.473	-0.01	-0.01	0.00	-0.03	0.01	0.13**	0.00	0.00	-0.51**	1				
11. Platform dummy: Wii	0.170	0.376	-0.25**	-0.09*	-0.36*	0.05	0.00	0.14**	-0.16**	-0.03	0.00	0.00	1			
12. Platform dummy: PS3	0.210	0.411	-0.03	-0.01	-0.41*	0.00	0.16**	0.10**	0.19**	-0.01	0.00	-0.01	-0.24**	1		
13. Platform dummy: X360	0.230	0.421	-0.06*	-0.11**	-0.43**	0.00	0.22**	-0.02	-0.08**	-0.01	0.01	0.01	-0.24**	-0.29**	1	
14. Platform dummy: Wii U	0.100	0.300	-0.06*	-0.20**	0.42**	-0.00	-0.24**	-0.16**	-0.03	0.04	0.00	0.00	-0.15**	-0.17**	-0.17**	1
15. Platform dummy: PS4	0.140	0.352	0.09**	0.32**	0.52*	-0.05*	-0.13	0.08*	0.12	-0.01	0.00	0.00	-0.19**	-0.22**	-0.14**	-0.14**

* $p < .05$ level.

** $p < .01$ level.

⁸ The high correlation coefficient between *Platform diffusion_{prt}* and *Age_{prt}* compelled us not to enter both variables in a model.

⁹ We estimated indirect effects using second-order approximation of standard errors (Sobel, 1982), the OLS for model 1a, and 2SLS estimated coefficients for Model 2b with clustered robust standard errors. When testing generativity's mediation since we do not enter *Platform complexity*, we need to add another dummy variable to capture effects of all platforms.

Table 2
Regression results.

	Model 1a				Model 1b				Model 2a				Model 2b			
	Generativity				Generativity				Platform adoption Total effect				Platform adoption Direct effect			
	OLS		GLS		OLS		GLS		OLS		2SLS		OLS		2SLS	
	β	p	β	p	β	p	β	p	β	p	β	p	β	p	β	p
Degree of openness	0.191	0.000	0.144	0.000	0.162	0.000	0.106	0.000	0.106	0.002	0.322	0.000	0.069	0.019	0.246	0.002
Generativity													0.196	0.000	0.122	0.000
Platform complexity	−0.270	0.002	−0.295	0.000	−0.391	0.000	−0.409	0.000								
Degree of openness × Platform complexity					0.268	0.053	0.261	0.000								
Age	−0.783	0.000	−0.778	0.000	−0.753	0.000	−0.753	0.000	−0.924	0.000	−0.782	0.000	−0.770	0.000	−0.721	0.000
Installed base	−0.014	0.703	−0.093	0.001	−0.001	0.957	−0.068	0.012	0.254	0.001	0.245	0.000	0.257	0.001	0.249	0.000
Price	−0.497	0.000	−0.484	0.000	−0.451	0.000	−0.440	0.000	−0.314	0.000	−0.238	0.002	−0.216	0.016	−0.195	0.019
Seasonality	0.202	0.000	0.149	0.000	0.187	0.000	0.138	0.000	0.195	0.000	0.201	0.000	0.155	0.000	0.175	0.000
Region dummy: USA	0.005	0.742	0.039	0.189	0.001	0.986	0.029	0.310	0.274	0.010	0.281	0.003	0.273	0.010	0.278	0.003
Region dummy: Euro	0.005	0.681	0.033	0.247	0.001	0.917	0.025	0.368	0.258	0.004	0.264	0.001	0.257	0.004	0.262	0.001
Platform dummy: Wii	−0.120	0.000	−0.121	0.000	−0.122	0.015	−0.128	0.000	0.188	0.130	0.233	0.028	0.170	0.160	0.211	0.051
Platform dummy: PS3	0.125	0.000	0.128	0.000	0.115	0.028	0.118	0.000	0.454	0.005	0.408	0.003	0.383	0.017	0.376	0.008
Platform dummy: X 360									0.268	0.048	0.226	0.063	0.223	0.090	0.208	0.086
Platform dummy: Wii U	−0.240	0.000	−0.238	0.000	−0.128	0.048	−0.133	0.000	−0.062	0.566	−0.029	0.779	−0.015	0.890	−0.007	0.943
Platform dummy: PS4	0.274	0.000	0.290	0.000	0.223	0.022	0.237	0.000	0.333	0.006	0.333	0.001	0.279	0.022	0.299	0.006
Year dummies	Included		Included		Included		Included		Included		Included		Included		Included	
R2	0.406		0.287		0.442		0.330		0.697		0.660		0.720		0.696	
F	62		36		68		43		208				222			
Wald Chi2											3739				4235	
Durbin-Watson	1.464		1.883		1.462		1.868		1.599		1.452		1.660		1.566	

Notes. All the OLS and 2SLS models above are reported from estimations using clustered robust standard errors.

Table 3

Mediation and moderated mediation results.

Mediator	Indirect effect using Hayes' (2013) bootstrapping method		
	b	SE	95 % CI
Generativity	0.250	0.022	[0.205–0.292]
Indirect effect using Sobel's (1982) method with 2SLS estimation and clustered robust standard errors			
Generativity	0.171	0.065	[0.044–0.298]
Conditional indirect effects using Hayes' (2013) bootstrapping method			
Platform complexity	b	SE	95 % CI
Conditions			
Generativity 0	0.145	0.021	[0.103–0.186]
Generativity 1	0.280	0.031	[0.220–0.340]
Conditional indirect effects using Bollen (1987) and Sobel's (1986) approach with 2SLS estimation and clustered robust standard errors			
Generativity 0	0.090	0.030	[0.032–0.148]
Generativity 1	0.174	0.062	[0.052–0.296]

Notes. In estimating conditional indirect effects using Bollen's (1987) and Sobel's (1986) approach, we used 2SLS estimations for model 2b and OLS estimations for model 1b; both models were estimated with clustered robust standard errors.

the potential effects of differences in their internal resources, brand awareness, and marketing activities (Cenamor et al., 2013; Sandulli et al., 2012).

To test our premise about the moderation role of *Platform complexity*, we take Models 1a and 1b into account. Model 1b indicates that the effect of *Degree of openness_{pt}* on *Generativity_{pt}* is still statistically significant (OLS: $\beta = 0.162$, $p = .000$) after entering the interaction of *Degree of openness_{pt}* and *Platform complexity*. In both models, the influence of *Platform complexity* is negative and statistically significant (Model 1a OLS: $\beta = -0.270$, $p = .002$ and Model 1b OLS: $\beta = -0.391$, $p = .000$); aligned with preceding studies, it shows that the new generation will decelerate diverse value creation in platform ecosystems (Cennamo, 2016; Thomas et al., 2014). According to our Hypothesis 3, we expected that the interaction of *Platform complexity* and *Degree of openness_{pt}* would positively influence *Generativity_{pt}*, and the GLS result in Model 1b also confirms it (OLS: $\beta = 0.268$, $p = .053$; GLS: $\beta = 0.261$, $p = .000$); it is important to notice that the OLS result is marginally significant. Finally, we conducted a moderated mediation model in Table 3 that also indicates a positive moderated mediation effect. According to the model, the indirect effect related to *Generativity_{pt}* in more complex platforms ($b = 0.280$ and 95 % C.I. = 0.220–0.340) is greater than the corresponding effect in less complex platforms ($b = 0.145$ and 95 % C.I. = 0.103–0.186). Moreover, addressing the possible endogeneity problem for degree of openness and generativity, we used the predicted values of the 2SLS analysis for testing the conditional indirect effect of *Platform complexity*. We estimated conditional indirect effects using the approach introduced by Bollen (1987) and Sobel (1986); the results were robust to these analyses. All results support our Hypothesis 3.

To epitomize the results, Fig. 2 plots the moderation effect of *Platform complexity*. It illustrates the effect caused by dichotomous conditions of *Platform complexity* in the relationship between openness and generativity. It explains that in more complex platforms, openness increases generativity with a more significant, steeper slope. The interpretation of this result is that impediments created for generativity in more technologically complex platforms can be compensated by increasing the degree of openness (Cennamo, 2016).

4.2. Analysis for demand heterogeneity

In Table 4, we present the results related to Models 3a and 3b, where we test the moderation role of *Platform diffusion_{prt}* on the effect of *Generativity_{pt}* on *Platform adoption_{prt}* to address the effect of demand heterogeneity of adopters being relatively early or late. In these two models, we included the control variables, but their results are not reported here

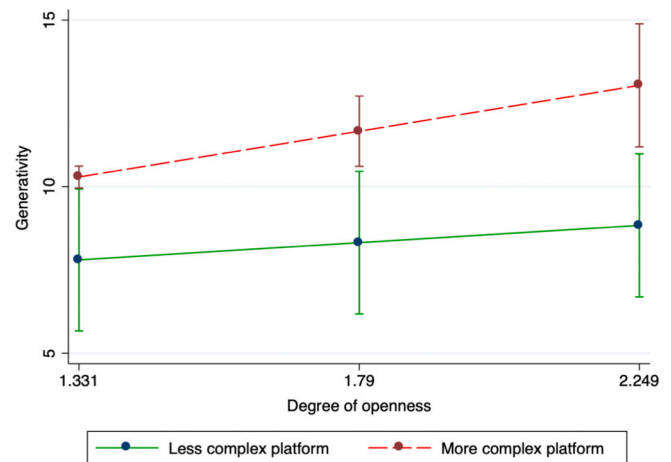


Fig. 2. Predictive margins of degree of openness contrasted in two platform complexity levels (with 95 % CI).

Table 4

Regression results for considering demand heterogeneity.

	Model 3a Platform adoption		Model 3b Platform adoption	
	2SLS		2SLS	
	β	p	β	p
Degree of openness	0.205	0.001	0.191	0.002
Generativity	0.099	0.007	0.120	0.000
Platform diffusion	-0.754	0.000	-0.713	0.000
Generativity $\times$ Platform diffusion			0.065	0.022
Control variables	Included		Included	
R ²	0.741		0.746	
Wald Chi2	5365		5531	

Notes. The results are the 2SLS estimated coefficients with clustered robust standard errors. To address the possible endogeneity problem for the interaction of generativity and platform diffusion, we instrumented it by the IV used for generativity interacted with platform diffusion.

for presentation purposes. Similar to Rietveld and Eggers' (2018) study, the results indicate that *Platform diffusion_{prt}* has a negative statistically significant effect on *Platform adoption_{prt}* (2SLS: $\beta = -0.713$, $p = .000$), and its interaction with *Generativity_{pt}* has a positive statistically significant effect on *Platform adoption_{prt}* (2SLS: $\beta = 0.065$, $p = .022$). Platform diffusion decreases adoption since earlier adopters tend to have more explorative intentions to enter a new market. The results indicate that generativity's effect on adoption differs for heterogeneous adopters and is more substantial for relatively late adopters. The platform's capacity for diverse value generation propels later adopters to join the platform more than early ones. As discussed earlier, generativity positively affects adoption for both early and late adopters. In particular, for later adopters, a platform with a greater capacity to produce diverse values is a more reliable ecosystem since they are risk-averse and seek to avoid purchasing mistakes. Early adopters are more explorative and seek more novel complementary products (Rietveld and Eggers, 2018). However, generativity is not just about novelty. Explorative (earlier) adopters are confident in joining a platform with less capacity to produce diverse value relative to the earlier adopters. Also, Clements and Ohashi (2005) discussed how the variety of software products becomes more important in the later stages of the platform life cycle.

4.3. Robustness analysis

The first step to ensure the robustness of the results is by conducting more than one test. As indicated in Table 1, the analysis for Hypothesis 1 is supported by both OLS and GLS regression models. The confirmatory

mediation tests for **Hypothesis 2** are Baron and Kenny's (1986) test and Hayes' (2013) bootstrapping method. Results related to **Hypothesis 3** are consistent in both OLS and GLS regression models, validating the moderation effect of *Platform complexity*, and conditional indirect effects in the bootstrapping model also confirm **Hypothesis 3**.

Obviously, the independent variable, *Platform adoption_{prt}*, affects the results critically. Since we identified platforms' adoption rate using the potential market, there might be some concerns because of using regions' entire population or the calculation of total adopters. Thus, we employed another measurement for platform adoption: *Sales_{prt}*. This variable is calculated by the natural logarithm of unit sales related to platform *p* in the region *r* and month *t*. After replacing it, we retested the hypotheses, and the results were robust to this change (see [Appendix E, Table E1](#)).

Next, we scrutinized the identification of generativity. We employed measurements and robustness tests similar to Cennamo and Santaló's (2019) work. Since genres describe game features such as gameplay, activity types, and content (Vargas-Iglesias, 2018), their diversification could be identified as generativity: the capacity to produce diverse value. Therefore, we enriched our game genre data to capture this capacity with a considerable resolution. Accordingly, our final data set contains on average three genres for each game. In our data, on average, there are 1490 game titles for each platform, characterized by about 80 unique genres. Thus, in calculating generativity, we can assume that (on average) we employed 80 features (genres) for 1490 game samples for each platform, to detect the number of new feature combinations published. Accordingly, how we measured generativity captures the diversity of value with a considerable resolution.

We have examined the sensitivity of the findings to different measurements of generativity. We used a second method employing only one genre for each game title using the one-genre records of VGChartz's data, and measured *Generativity_{pt}* as the number of diverse genres that appeared in provisioned games in platform *p* and month *t*. Using the third method, we involved the two most frequent genres of games in calculating generativity. This method measures the diverse genre sets but confines them to a maximum of two genres. For instance, a platform in month *t* supplied three games in the following genres: first, "Action, 3D, and Platformer"; second, "Action, 3D, and Fighting"; and third, "Action, Horror, and Survival." Our baseline measurement counts generativity as 3. The second method counts generativity as 1, and the third method counts generativity as 2. Using two additional methods, we repeated the analyses and obtained similar outcomes that supported Hypotheses 1 to 3 (see [Appendix E, Tables E2 and E3](#)).

Another step for robustness analysis was considering different lag times to test the effect of *Degree of openness_{pt}* and *Generativity_{pt}*. In addition to the main results, we increased the lag by 3 and 6 months, retested the hypotheses, and found that the results were the same. It indicates that the chronological effects of openness and generativity on adoption are valid in a time range from 1 to 6 months (see [Appendix E, Tables E4 and E5](#)).

In addition to the endogeneity of variables discussed, there was speculation about the endogeneity of some control variables in Models 2a and 2b: price and installed base. However, since, according to [Table 1](#), price and installed base correlate lowly with openness and generativity, they will hardly affect the estimation of openness and generativity to become unbiased. Thus, for reassurance, we ran a model without them and found that the results related to our hypotheses hold (see [Appendix E, Table E6](#)).

We also used another identification strategy to provide reassurance from the results related to technological complexity. For that, we scrutinized the literature on software and hardware design. In the literature, the main components affecting the performance of a game console are the CPU, GPU, and RAM (Cennamo et al., 2018; Daim et al., 2014). Also, industry reports indicate that advanced hardware complicates the development of complementary products. Complementors must deal with more processing units, adopt specialized cores and overcome

programming challenges (Cennamo et al., 2018; Kovtun, 2021; Reimer, 2005). So, capturing technological complexity would require an in-depth comparison of the three components. Nevertheless, all six consoles have different architectures. So, we tried to capture the advancement of GPUs and CPUs as an indicator of relative technological complexity among platforms by employing the data of GPUs' and CPUs' performance. We used a measurement that is comparable among different architectures and processor technologies. This measurement is calculated by the data of GFLOPS¹⁰ as an index for the performance of processing units, which is a conventional way of comparing performance between different processing units (Kogge, 2011).¹¹ We replaced the variable of *Platform complexity* with *Performance indicator_p*, the natural logarithm of the sum of GFLOPS corresponding to GPU and CPU used in platform *p*. Then we repeated the analyses of Models 1a and 1b and conditional indirect effects. The results supported **Hypothesis 3** related to technological complexity (see [Appendix E, Tables E7 and E8](#)).

For testing whether there are significant differences between regions in the effect of openness and generativity on platform adoption, we used each dummy variable of the regions as moderators of both generativity and openness in Model 2b. The results showed no significant differences between regions, and they can be generalized to the three regions. It is crucial to notice that the region dummies themselves cause significant effects on platform adoption (see [Appendix E, Table E9](#)).

5. Discussion

Within the context of platform ecosystem governance, openness management is of the highest importance. To address the influences of complementor-level openness on the adoption rate, we analyzed the direct and generativity-mediated indirect effects. Besides, we contrasted the indirect effect in two platform complexity levels to address complexity's effect contracting with openness on value creation and platform adoption. The results extend the current understanding of influences caused by the openness strategy in platforms' success in several ways. The study indicates that a more open platform accessing various complementors increases its capacity to respond to various user demands. Therefore, the value creation capacity increase, and the platform would benefit from that to target more potential users.

The results indicate that the positive effect of openness on the adoption rate is partially carried through generativity. In other words, a platform with sweeping access to external sources tends to have a higher adoption rate as a result of two major determinants: first, the abundance of complementors and their products that reduces users' lock-in concerns and the cost of complementary products (Gebregiorgis and Altmann, 2015); second, the increase in the platform's capacity to generate diverse value that attracts users by increasing the variety of complementary products (Karhu et al., 2018; Saadatmand et al., 2019).

We postulated our hypotheses based on openness' positive influence on adoption and, accordingly, the positive mediation of generativity. In a holistic view, open innovation provides access to external sources of information and capability, increasing the dexterity of platforms to respond to user needs. Widely discussed, openness propels the performance of innovation (Bogers et al., 2018; Nambisan et al., 2019) and accelerates the adoption of new technology (Eisenmann et al., 2009; Wang et al., 2020). However, it has been exhorted that the opening of borders to complementors should be limited up to a point; otherwise it will eventuate in deterioration of profits and complementors' motivation (Boudreau, 2012; Laursen and Salter, 2006). According to the literature, the positive effect of openness on adoption is in place when it harnesses network effects, reduces lock-in concerns, and provides differentiated innovations (Eisenmann et al., 2009). In this study, to

¹⁰ Giga floating point operations per second

¹¹ The table of architecture and GFLOPS related to each platform's CPU and GPU is provided in [Appendix F](#).

understand the dynamics of right governance, we focused on the role of generativity as a consequence of openness (i.e., the system's capacity to differentiate) that advocates adoption. Hence, first, we posit a positive relationship between the degree of openness in platforms and their adoption rate; second, we investigate a deeper understanding of the role of generativity in between. In fact, we assume that platform owners try to avoid excessive openness since the nature of a platform ecosystem relies on the proportionate contribution of complementors. Therefore, the effect of excessive openness would not mar the total positive effect of openness on platform adoption.

Also, generativity's overall effect on adoption is supposed to be positive, although scholars have mentioned some unfavorable effects of uncontrolled generativity, such as over-fragmented complementary products (Gawer, 2020). This is rooted in the efforts of platform owners to maintain a platform's generativity with the approach of balancing the diversity of values generated and required (Thomas and Tee, 2021). Moreover, we assumed that if openness exerts an overall positive effect on platform adoption, a part of its effect should have been carried through generativity increase since one of the favorable outcomes of openness that attracts adopters is increasing the capacity to generate diverse value. So, the present study looks at platform openness through a perspective within which confined openness leads to an overall better adoption rate, and confined generativity mediates a part of this effect toward adoption.

Furthermore, the results (of additional analysis) indicate that adopters are affected by generativity heterogeneously. Acceptance of a platform by greater generativity not only increases its adoption rate in the early stages but also in the later stages, as it reinforces the network externalities. However, the differences in the effect of generativity caused by the increase of platforms' diffusion elucidate that adopters, based on the stage they adopt the platform, get incentivized toward platforms differently. Since adopters' approaches to searching for value differ in different stages, generativity's effect is perceived differently. Later adopters value a platform with greater generativity as a reliable ecosystem with a greater capacity to provide various outputs. Thus, generativity becomes more important for later adopters, since adopting a reliable platform helps them avoid purchasing mistakes and switching costs (Kumar et al., 2020; Polites and Karahanna, 2012). This interpretation describes why the product variety in video game markets attracts adopters' attention in the later stages of the platform life cycle (Clements and Ohashi, 2005). Moreover, prior research has discussed how later adopters tend to have more initial usage of products than earlier ones (Healey and Moe, 2016; Prins et al., 2009).

The study's last finding is about digesting the effect of technological complexity on value creation. In platform ecosystems, technology enhancement increases the complexity of product development. Complementors need to deal with these technological complexities, such as new technology of processors or the increase in their numbers (Cennamo et al., 2018). Subsequently, ecosystems' generativity drops off; counterintuitively, when platform owners release more complex platforms and adopt more open innovation strategies, platforms' generativity increases toward higher levels.

Remarkably, the results deepen the understanding of generativity by indicating that technological complexity hampers the capacity to generate value, and by defining that the key strategy to overcome this hindrance is openness (Kapoor and Agarwal, 2017). This finding is aligned with previous studies revealing that adopting more open innovation strategies is more useful when the technologies are more complex and challenging (Sandulli et al., 2012). Similarly, Wang et al. (2020), discussed how knowledge complexity required for platform innovation reduces the crowding-out influence of supply-side openness. So, the performance of the openness strategy would increase in technologically advanced platforms.

6. Conclusion

The current study aimed to determine the role of openness in the success of platform ecosystems by focusing on generativity's mediation role. We also contrasted this impact in different levels of technological complexity.

The findings extend the understanding of a platform's performance related to open innovation strategies in both domains of development and commercialization. It clarifies that the increase in the use of innovation strategies involving more third parties results in a greater value-creation capacity. It then becomes a keystone to satisfy various user desires for gaining a higher adoption rate. Platform sponsors' decisions about innovation strategies determine the supply-side openness degree that influences their platform's performances. The present study designates generativity as a pivotal capacity that platform sponsors should consider when opening borders to third parties. Thus, the right openness governance requires involving external resources in development and commercialization that leads to the diverse value creation capacity, since a part of openness's effect on platform success is through the increase in generativity.

Moreover, the inevitable upgrade for new platform generations faces platform sponsors with significant challenges in maintaining the value generation capacity they were previously holding (Cennamo, 2016; Daim et al., 2014). Platform sponsors should trade off a paradoxical challenge between launching a new generation or maintaining generativity. Upgrading technology creates adoption difficulties for complementors but brings new capabilities for users; however, maintaining the previous capacity to generate value is essential because targeting higher adoption rates requires responding to more heterogeneity of preferences (Wareham et al., 2014). This study reveals that in an ecosystem with more technological complexity, openness propels generativity more intensely than the less complex platforms.

6.1. Theoretical implications

The findings contribute to open innovation literature by improving the theoretical understanding of openness governance and how it affects platform adoption with respect to generative governance. The results indicate that the proliferation of innovation strategies that open ecosystems to third-party complementors leads to a higher adoption rate. Prior research stated that the abundance of external resources being bundled with platform resources for value creation and capture leads to competitive advantage (Alexy et al., 2018; Eaton et al., 2015), and propels the acceptance rate of a platform (Eisenmann et al., 2009). The study deepens the effect of supply-side openness on adoption by capturing the degree of openness using third-party involvement in both the development and commercialization of complementary products. This way of capturing openness provides implications for the theoretical understanding of it. It could be implied that besides openness in development, open commercialization also matters in boosting the adoption rate of a platform.

Moreover, this study focuses on the effects of open governance and implies that governing a platform with a higher degree of openness will eventuate in a generative product portfolio. This part of our study contributes to the literature on generative governance and clarifies that the degree of supply-side openness positively influences generativity. This means that more technological and commercial capacity borrowed by open innovation increases the capacity of diverse value generation.

The research's focal finding reveals the mediation role of a platform's generativity between its degree of openness and adoption. The study focuses on generativity's mediation dynamics to address one consequence of the right governance. The results broaden the current understanding of the influence of openness on platforms' success; the study implies that the effect of openness (a part of it) on the adoption of a platform occurs by the increase in generativity. It provides insights beyond the conventional understanding of the effect of openness on

adoption. It clarifies that when opening boundaries to complementors, a portion of the involved third parties will work on diversifying features and values. The interpretation of this phenomenon is that the increase in involved third parties brings diverse skills and incentives that increase an ecosystem's accountability for the diversity of user preferences (Thomas and Tee, 2021; Wareham et al., 2014), which leads to higher adoption rates. In fact, this study, building on the positive effect of openness on adoption, identifies generativity as the systemic capability of platforms that mediates this relationship.

Lastly, the study focuses on the relationship between openness and generativity and finds that technological complexity in a new generation of platforms causes impediments in creating diversified values. This finding corroborates the prior studies (Cennamo et al., 2018; Yoo et al., 2010) asserting that complexity in the core technology of platforms slows down the value creation of complementors. Counterintuitively, the study indicates that when the technology is more complex, governing a platform to be more open results more effectively in generativity. In other words, in more complex platforms, openness increases generativity more intensely. One way to interpret this result is that open innovation performance becomes more significant when challenges require complex knowledge (Sandulli et al., 2012). Another way is that complex systems entail co-specialized components and functionalities that each require specialized knowledge; thus, a more open platform receives a more extensive breadth of knowledge (Baldwin and Clark, 2000).

In addition, the results make empirical contributions to the literature by employing a comprehensive data analysis using the data of six platforms involving the seventh and eighth generation of video game consoles, and three regions. The contribution of the empirical analysis can be ascribed to measuring openness with the consideration of per-game innovation strategies and generativity with different resolutions.

6.2. Managerial implications

Our study provides several managerial implications for ecosystem governance. For platform sponsors, governing platform openness is one of the toughest strategic decisions that requires a deep understanding of ecosystems' dynamics. This study presents some outcomes of openness on two user-related aspects: generativity and adoption. Specifically, platform sponsors should consider that complementor-level openness in both areas of development and publishing affects their entire adoption trajectory. This study reveals that sponsors need to think of openness strategically and align market demands with an advisable use of innovation strategies. According to the sweeping market potential that platforms tackle, sponsors deal with heterogeneous users and discursive preferences. They require architecture and sufficient external resources that their complementarity is generative enough to make them capable of responding to those preferences (Alexy et al., 2018; Thomas and Tee, 2021).

In addition, our analysis underscores that platform sponsors should govern their ecosystem to reach a capacity which is capable of generating novel and diversified values abreast of the targeted adoption rate. Also, the study suggests that these factors are sequential; first, the openness increases the platform's generativity; together, they improve the adoption rate. Noticing the sequential effects of these determinants provides insights for controlling the openness with respect to the generativity level and adoption targets.

Moreover, treating adopters as heterogeneous provides implications about how different generativity affects different adopters. Generativity at the moment of adoption appeals more to late adopters. So, platform sponsors need to pay attention to the dynamic need for generativity if they want to keep their generativity synchronous with the appetites of adopters. In this regard, platform owners need to consider governing the platform's openness and generativity, considering the platform's life cycle (Rong et al., 2013). In later stages, governing a platform to advance in generativity is more crucial. Generativity, regarded as a

system's capacity to respond to various desires, could be used as a means to give insights for platform owners to determine the conditions in which openness contributes to a platform's success; it helps balance the openness toward the need for generativity in each stage of the life cycle. Platform owners need to determine when to rely more on value capture or contribute to co-create with complementors. At a stage when generativity is more crucial, they can turn to value capture—leveraging openness in the competition regarding the influence of generativity.

Lastly, the study recommends that platform sponsors should consider that the next generations severely hamper generativity. They lose their platforms' generativity level in the new generation by complexifying the core technology. However, they have the key to recovering to the previous level; openness. Thus, the study suggests that one way to maintain value creation capacity after the complexification of the technologies is advocating interoperability of the platform's architecture at the design level and governing with the policies/procedure that facilitates complementary innovation.

6.3. Limitations and future research

This section presents several limitations of our study and provides future research suggestions. We analyzed our hypotheses employing video game data, while several platform ecosystems could be examined, and reinforce the generalizability of hypotheses. In our data, handheld consoles had significant missing points in data about genres, so we had no choice but to exempt them from the analysis. Future studies may consider the enriched data. In addition, future research may consider adopters' heterogeneity beyond the early and late segmentation and investigate their behavioral adoption intentions affected by perceived openness and generativity. We investigated the openness effects at the supply-side level and analyzed the effect of external resource adequacy on the adoption rate, while other levels could be investigated under this subject. A platform's generativity could be affected by the life cycle of the complementary products. We measured generativity triggered by the release of complementary products. Future studies might consider a more comprehensive measurement of generativity by involving complementary products' life cycles. Lastly, generativity involves different concepts (Moon and Choi, 2016; Thomas and Tee, 2021); we captured it by employing a comprehensive data set of genres. Involving and identifying different aspects of generativity in platform ecosystems could be considered in future studies.

CRediT authorship contribution statement

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- CRediT author statement: Conceptualization, Methodology, Validation, Investigation, Resources, Writing - Original draft, Writing - Review & Editing, Supervision, Project administration.

Mostafa Khoshbash

- CRediT author statement: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Resources, Writing - Original draft, Writing - Review & Editing, Visualization.

MohammadMahdi Saeedian

- CRediT author statement: Conceptualization, Validation, Writing - Original draft, Writing - Review & Editing.

Declaration of competing interest

There are no conflicts of interests.

Data availability

Data will be made available on request.

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Appendix A. In our data, Xbox One platform in December 2013 provided four games. [Table A1](#) presents the corresponding data and measurement of the *degree of openness*

Table A1

Measurement of *degree of openness*.

Game title	Publisher	Developer	Number of third parties involved
Sea Animal Games for Toddlers and Kids with Jigsaw Puzzles	Ubisoft	Mafooly	2
Peggle 2	Electronic Arts	PopCap	2
Max: The Curse of Brotherhood	Microsoft Studios	Press Play	1
Halo: Spartan Assault	Microsoft Studios	Vanguard Games	1
Degree of openness (total number of third parties involved/number of games released):			6/4 = 1.5

Appendix B. In our data, Xbox One platform in February 2014 provided five games in the following genres. [Table B1](#) presents the corresponding data and different generativity measurements used in this study

Note: Measurements show different genres/genre sets till the release of each game, and in the last row, they count different genres/genre sets as generativity of the month.

Table B1

Different measurements of *generativity*.

Game title	Genres (Metacritic)	Genres (VGChartz)	Baseline measurement	Second measurement ^a	Third measurement ^b
The LEGO Movie Videogame	Action Adventure, Fantasy	Action Adventure	{{Action Adventure, Fantasy}}	{Action Adventure}	{{Action Adventure, Fantasy}}
Rayman Legends	2D, Action, Platformer	Action	{{Action Adventure, Fantasy}, {2D, Action, Platformer}}	{Action Adventure, Action}	{{Action Adventure, Fantasy}, {2D, Action}}
Strider (2014)	Action Adventure, Fantasy	Action Adventure	{{Action Adventure, Fantasy}, {2D, Action, Platformer}}	{Action Adventure, Action}	{{Action Adventure, Fantasy}, {2D, Action}}
Thief	Action Adventure, Fantasy	Action Adventure	{{Action Adventure, Fantasy}, {2D, Action, Platformer}}	{Action Adventure, Action}	{{Action Adventure, Fantasy}, {2D, Action}}
Plants vs. Zombies	Action, Shooter, Tactical, Third-Person	Action	{{Action Adventure, Fantasy}, {2D, Action, Platformer}, {Action, Shooter, Tactical, Third-Person}}	{Action Adventure, Action}	{{Action Adventure, Fantasy}, {2D, Action}, {Action, Shooter}}
Measured generativity in February 2014, on Xbox One:			Three different genre sets	Two different genres	Three different genre sets

^a Uses VGChartz's one-genre data.

^b Uses two most frequent Metacritic's genres for each game.

Appendix C

More about [Hayes' \(2013\)](#) bootstrapping has been provided below:

[Hayes' \(2013\)](#) method uses bootstrapping technique to resample observations with replacement. Then, the indirect effect or conditional indirect effects are calculated in each new sample constructed through this resampling process. By using bootstrapped samples (e.g., 5000 samples), the analysis estimates the indirect effects. The PROCESS macro uses the "second-order" estimator to calculate the standard errors. Then, there would be 5000 estimated indirect effect coefficients that have a normal distribution. The estimated coefficients are used to construct a 95 % confidence interval for the "true value" of the indirect effect. The absence of zero within the lower and upper limits of the estimated confidence intervals (2.5th and 97.5th percentiles) supports that the estimated indirect effect calculated from the original observation sample is statistically significant.

Appendix D. First, the reason that we chose *Skillfulness_{pt}* as an IV for *Generativity_{pt}* is as follows

Developers' skillfulness is calculated using panel data of games released¹² on all platforms of the seventh and eighth generations. Each month, if a developer provides a game/s in which new genres (those that the developer never before employed) exist, its skillfulness increases by the number of new genres. *Skillfulness_{pt}* is measured by the average of developers' skillfulness in the month *t* and platform *p*.

The more skillful the developers who produce games for a platform are, the more various products are likely to be developed, which increases

¹² Records of VGChartz with enriched genres' data from Metacritics.

generativity. Thomas and Tee (2021) indicated that value creation incorporates the concept of generative outcomes. Developers' skillfulness in producing games in diverse genres could be interpreted as an influential concept that fortifies the value creation factor of generativity. The average skillfulness of developers involved in game development positively affects generativity and is likely to be unrelated to the unobserved variables that encourage both adoption and complementors' decisions for diverse value generation. The average skillfulness of game developers will not encourage prospective adopters unless they have developed various products recently, which is the path through which IV affects adoption through generativity. Adopters' decisions do not concern developers' diverse value generation skills; the only reason that they would consider this characteristic of developers is that they make diverse value, which is the generativity of platforms.

Second, the reason that we chose $NPOC_{pt}$, new pairs of old complementors, as an IV for degree of openness, is as follows:

Variable $NPOC_{pt}$ is calculated by the use of panel data of games in the six platforms of the seventh and eighth generations, platforms that we focused on. Each month, $NPOC_{pt}$ is measured by the number of games that are provided from the new combinations of developers-publisher who have provided games before in the platform, divided by the number of total games released on the platform.

According to the identification strategy used for capturing openness, the new pairs of complementors indicate that platform sponsors use open innovation strategies with diverse combinations of knowledge providers. Even though the developer and publisher have worked with the platform before, the new pair means collaboration and co-creation with new arrangements of companies that require different agreements and integration. Variable $NPOC_{pt}$ positively correlates with the degree of openness and is likely to be unrelated to the unobserved variables that encourage openness and adoption together. The reason is that complementors, when they are aware of the platform's significant marketing activities, have a strong tendency to work with the developer/publisher that has succeeded before, to exploit this opportunity and not risk a new partner.

The table below presents the first stage least squares results.

Table D1
First-Stage regression results.

Instrumental variables	First-stage model [Table 2, Model 2a]	First-stage model [Table 2, Model 2b]	
	(1) Degree of openness	(2) Degree of openness	(3) Generativity
NPOC	0.256***	0.237***	0.073 ***
Skillfulness		0.164***	0.756***
Age	−0.603***	−0.515***	−0.471***
Installed base	0.054***	0.046***	−0.034***
Price	−0.295***	−0.224***	−0.201***
Seasonality	−0.020	−0.046	0.081***
Region dummy: USA	−0.035**	−0.032**	0.014
Region dummy: Euro	−0.031**	−0.028*	0.0121
Platform dummy: Wii	−0.195***	−0.158*	0.228***
Platform dummy: PS3	0.200***	0.196**	0.372***
Platform dummy: X 360	0.177	0.195*	0.343***
Platform dummy: Wii U	−0.103***	−0.036	0.076*
Platform dummy: PS4	−0.045***	−0.090***	0.041
Year dummies	Included	Included	Included
R ²	0.258	0.273	0.724
Partial F-statistic	20	21	74
Minimum eigenvalue statistic	136	67	67
Wooldridge robust regression-based test	F (1,17) = 14.318	F (2,17) = 3.870	F (2,17) = 3.870

Notes. First-stage model (1) corresponds to 2SLS Model 2a, and first-stage models (2) and (3) correspond to 2SLS Model 2b. The effects presented are standardized coefficients. The minimum eigenvalue statistics reported for all first-Stage models are above all critical values for the weak instrument test at the 5 % significance level (Stock and Yogo, 2005). These tests reject the possible problem of weak instruments. Wooldridge's (1995) robust regression-based tests of endogeneity confirm that Degree of openness and Generativity are endogenous as in model 2a F (1,17) = 14.318 (p < .01) and in model 2b: F (1,17) = 3.870 (p < .05). These tests are adjusted for 18 clusters as we run our models with clustered covariance matrix clustered by platform-region.

* p < .1.

** p < .05.

*** p < .01.

Appendix E

All the models presented below are reported from estimations using clustered robust standard errors.

Table E1
Regression results with sales as the independent variable.

	Model 2a		Model 2b	
	Sales		Sales	
	2SLS		2SLS	
	β	p	β	p
Degree of openness	0.293	0.000	0.224	0.002
Generativity			0.112	0.000
Platform complexity				
Degree of openness × Platform complexity				
Age	−0.746	0.000	−0.690	0.000
Installed base	0.226	0.000	0.229	0.000

(continued on next page)

Table E1 (continued)

	Model 2a		Model 2b	
	Sales		Sales	
	2SLS		2SLS	
	β	p	β	p
Price	−0.216	0.024	−0.177	0.019
Seasonality	0.185	0.000	0.161	0.000
Region dummy: USA	0.427	0.000	0.424	0.000
Region dummy: Euro	0.436	0.000	0.434	0.000
Platform dummy: Wii	0.236	0.014	0.217	0.028
Platform dummy: PS3	0.400	0.001	0.370	0.004
Platform dummy: X 360	0.238	0.034	0.221	0.048
Platform dummy: Wii U	−0.024	0.796	−0.005	0.959
Platform dummy: PS4	0.306	0.001	0.275	0.006
Year dummies	Included		Included	
R2	0.715		0.744	
Wald Chi2	4765		5375	

Table E2Regression results related to our second measurement of *generativity*.

	Model 1a Generativity OLS		Model 1b Generativity OLS		Model 2b Platform Adoption 2SLS	
	β	p	β	p	β	p
Degree of openness	0.241	0.000	0.215	0.000	0.201	0.016
Generativity					0.203	0.000
Platform complexity	−0.118	0.046	−0.230	0.026		
Degree of openness × Platform complexity			0.247	0.006		
Control variables	Included		Included		Included	
R2	0.543		0.554		0.708	
F	84		87			
Wald Chi2					5593	

Table E3Regression results related to our third measurement of *generativity*.

	Model 1a Generativity OLS		Model 1b Generativity OLS		Model 2b Platform Adoption 2SLS	
	β	p	β	p	β	p
Degree of openness	0.213	0.000	0.185	0.000	0.234	0.004
Generativity					0.134	0.000
Platform complexity	−0.224	0.014	0.342	0.002		
Degree of openness × Platform complexity			0.263	0.012		
Control variables	Included		Included		Included	
R2	0.427		0.461		0.708	
F	67		74			
Wald Chi2					5593	

It is important to note that using the results of the models presented in E2, E3, and Model 2a of [Table 2](#), all three hypotheses are supported.¹³

Table E4Regression results with *degree of openness* and *generativity* lagged by 3 months.

	Model 2a Platform adoption 2SLS		Model 2b Platform adoption 2SLS	
	β	p	β	p
Degree of openness	0.183	0.000	0.117	0.013
Generativity			0.107	0.000
Control variables	Included		Included	
R2	0.690		0.709	

(continued on next page)

¹³ Using the results mentioned and the Sobel tests for mediation and conditional indirect effects.

Table E4 (continued)

	Model 2a Platform adoption 2SLS		Model 2b Platform adoption 2SLS	
	β	p	β	p
F				
Wald Chi2	3998		4296	

Table E5Regression results with *degree of openness* and generativity lagged by 6 months.

	Model 2a Platform adoption 2SLS		Model 2b Platform adoption 2SLS	
	β	p	β	p
Degree of openness	0.259	0.000	0.217	0.008
Generativity			0.032	0.047
Control variables	Included		Included	
R2	0.675		0.686	
F				
Wald Chi2	3766		3807	

Table E6Regression results with omitted *Price* and *Installed base*.

	Model E6a Platform adoption 2SLS		Model E6b Platform adoption 2SLS	
	β	p	β	p
Degree of openness	0.366	0.000	0.203	0.002
Generativity			0.1975	0.000
Control variables ^a	Included		Included	
R2	0.594		0.656	
F				
Wald Chi2	2796		3435	

^a Other than price and installed base.**Table E7**Regression results with replacing *platform complexity* by *performance indicator*.

	Model E7a Generativity OLS		Model E7b Generativity OLS	
	β	p	β	p
Degree of openness	0.191	0.000	0.146	0.000
Performance indicator	−0.575	0.002	−0.786	0.000
Degree of openness × Performance indicator			0.440	0.000
Control variables	Included		Included	
R2	0.406		0.497	
F	62		85	
Wald Chi2				

Table E8Moderated mediation results. Conditional indirect effects of degree of openness on platform adoption through generativity moderated by *performance indicator*.

	Performance indicator	b	SE	95 % CI
Generativity	2.136	0.101	0.030	[0.042–0.159]
Generativity	3.574	0.114	0.033	[0.049–0.179]
Generativity	5.013	0.127	0.037	[0.055–0.199]

Notes. In estimating conditional indirect effects using [Bollen's \(1987\)](#) and [Sobel's \(1986\)](#) approach, we used 2SLS estimations for model 2b from [Table 2](#) and OLS estimations for model E7b.

Table E9

The results related to the moderation effect of each region dummies interacting with openness and generativity's effects on platform adoption added to Model 2b.

		b	p
USA	Degree of openness × Region dummy: USA	−0.106	0.376
	Generativity × Region dummy: USA	−0.001	0.972
Euro	Degree of openness × Region dummy: Euro	−0.039	0.091
	Generativity × Region dummy: Euro	0.018	0.101
Japan	Degree of openness × Region dummy: Japan	0.231	0.070
	Generativity × Region dummy: Japan	0.019	0.082

Appendix F

Table F1

Platforms' CPU and GPU (Kovtun, 2021; Thang, 2017).^a

Console	GPU	GPU's GFLOPS	CPU	CPU's GFLOPS
Wii	ATI Hollywood (243 MHz)	12	IBM Broadway (729 MHz)	8.8
PS3	NVidia RSX (550 MHz)	230.4	IBM CELL (3.2GHz)	204.8
Xbox 360	AMD Xenos (500 MHz)	240	IBM Xenon (3.2GHz)	115.0
Wii U	ATI Latte (550 MHz)	352	IBM Espresso (1243 GHz)	14.9
PS4	AMD GPGPU 18 CU (800 MHz)	1843.2	AMD Jaguar (1.6 GHz)	102.4
Xbox One	AMD GPGPU 12 CU (853 MHz)	1310	AMD Jaguar (1.75 GHz)	112.0

^a The GPUs and CPUs' FLOPs data are gathered from the industry reports cited above and technical specifications reported by platform providers.

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