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The Impact of Control and Innovation Capabilities on Performance in a Platform Ecosystem: An Assessment of Chinese Firms

Qiaohong Pan[1] · Wenping Luo[2] · Benjamin Ohene Kwapong Baffoe[3]

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Abstract
Attracting considerable attention in both academia and industry, control in a digital platform ecosystem continues to serve as an important mechanism for innovation. However, the relationship between control, innovation capabilities, and performance is unclear. Probing further on this gap, survey data of 386 Chinese platform enterprises and a partial least square structural equation model (PLS-SEM) were employed to empirically analyze the impact and effects found in a platform ecosystem. The analyzed results support the proposed hypotheses; thus, outcome and informal control factors positively impact incremental innovation capability, while behavior control in a platform ecosystem significantly impacts radical innovation capability. The results also show that the influence of incremental innovation capability on financial performance is significant, and the influence of radical innovation capability on market performance is favorable. This study provides insight for platform managers to make platform ecosystem control mechanisms consistent with their innovation to improve performance.

Keywords Platform ecosystem · Platform ecosystem control · Innovation capability · PLS-SEM · Chinese firms

Introduction

Platform ecosystems grounded in digital technology are increasingly becoming a key venue for business and innovative activities in industries and sectors (Kretschmer et al., 2020). Reiterated by Leoni and Parker (2019), such interactions

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✉ Wenping Luo
wluo@shmtu.edu.cn

[1] Logistics and E-commerce College, Zhejiang Wanli University, Ningbo 315100, China

[2] School of Economics and Management, Shanghai Maritime University, Shanghai 201306, China

[3] Shanghai Beiye New Brother Supply Chain Management Co., Ltd., Shanghai, China

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or complementary among actors in platforms have facilitated transactional activities and innovations prompting cost-sharing and risk diversification. Despite numerous advantages obtained from the platform ecosystem, their characteristics and novelty differences identified in the platform have attributed to the increase in investment and information transfer risk (Bouncken & Kraus, 2013; Foerderer et al., 2019; Mikalef et al., 2020). Additionally, the availability and editable nature of digital innovation in the platform is impossible to regulate and anticipate because creativity cannot be automatically turned into positive benefits (Henfridsson et al., 2014). To maintain the platform ecosystem's competitive edge, radical and incremental innovation capabilities are seen as primary elements in its development (Julián & Camison, 2015; Subramaniam & Youndt, 2005). Radical innovation capability involves turning to different technology paths when providing new products and services, while incremental innovation capability expands existing products and services based on existing technology paths (Benner & Tushman, 2002; Benner & Tushman, 2001; Jansen et al., 2006). Although the innovation capability model can be independently used, existing works of literature have advocated for the use of two combined and distinct innovation models to positively improve organizational performance from a long-term and short-term perspective (Božič & Dimovski, 2019; Rialti et al., 2019; Soto-Acosta et al., 2015). Such design and control realization can be achieved by the platform owner.

Platform owners are essential to the success of an ecosystem platform. However, the inability of platform owners to directly control participant activities may lead to opportunistic behavior and frequent violations. Thus, without any restrictions and management for complementors, they may harm and disrupt the innovation interests of the platform (Wareham et al., 2014). Hence, the importance of platform ownership in a platform ecosystem has received widespread attention. Reiterated on its significance, Schmeiss et al. (2019) indicated that their function not only offers platform architecture but also regulates the involvement of numerous complementors scattered around proximity or other areas of the world through a value creation process. In essence, the control mechanisms designed by the platform owners have become a substantial measure of platform ecosystem success (Božič & Dimovski, 2019; Velu, 2015).

The existing control literature is based mostly on the traditional principal–agent relationship; nevertheless, the connection between a platform owner and its complementors under the platform ecosystem is more complex and diverse (Leoni & Parker, 2019). On the one hand, when platform owners exert too much control over complementors, they risk losing complementors such as third-party developers, stifling the expansion and development of platform ecosystems. When platform owners, on the other hand, disregard any kind of control, the platform environment becomes varied and fragmented, making it harder for complementors to extract benefits from innovation (Schmeiss et al., 2019). Works of literature on platform ecosystems have been extensively designed with a control mechanism based on a form of coordination, rather than just safeguarding the interests of the platform owners themselves (Tiwana, 2010). For example, Foerderer et al. (2014) posited that the impact of relational and architectural have an influence on platform generativity, while Den Hartigh et al. (2016) depicted the link between control patterns, platform flexibility, and technological development phases. Furthermore, Leoni and Parker (2019) highlighted that platform owners generally employ formal controls to oversee the value generation process, but the relative responsibilities of formal and informal controls must be considered further. Therefore, this study uses both formal and informal controls, as well as distinguishes between two types of formal controls, namely, outcome and behavior controls.

The foregoing discussion lays the foundation for further research but lacks a more in-depth exploration of the relationship between control, innovation capabilities, and performance. Although several studies have mainly focused on qualitative descriptions of control, the present study sought to extend previous research by using quantitative analysis methods to explore the influence of different control factors on innovation and performance in the context of platform ecosystems (Foerderer et al., 2014; Grunwald-Delitz et al., 2019; Leoni & Parker, 2019). In addition, innovation capabilities are linked to new knowledge acquisition and platform development, although of different types and degrees. Incremental innovation capabilities distill products and improve efficiency, whereas radical innovation capabilities develop new features and are associated with flexibility in the digital platform ecosystem (Jansen et al., 2009). However, previous research on innovation had mainly explored platform innovation from a single perspective, ignoring the different effects of incremental and radical innovation capabilities on the platform (Velu, 2015; Yoo et al., 2012). As such, despite the literature having explored the link between control and performance or innovation and performance, the impact of control and innovation on performance remains a mystery (Stouthuysen et al., 2017).

In addressing this issue, this study examines how controls impact innovation capabilities and organizational performance via the lens of organizational control theory. Specifically, we examine how outcome, behavior, and informal controls affect incremental and radical innovation capabilities, and thereby improve firm market and financial performance, using data from 386 Chinese firms by partial least square structural equation modeling (PLS-SEM). Overall, our findings deepen the research on platform ecosystem controls and guide innovative practices of platform firms.

The rest of the paper is structured as follows. In the next section, we proceed to hypothesize the effect of these associations. In sequence, we introduce the research design and methodology used in this study and then conduct hypothesis testing. Finally, we discuss the results and give suggestions for future research.

Literature Review and Hypotheses

The shift from a traditional to a modern principal–agent platform control relationship has shown to be a viable solution to platform ecosystem issues. This has been prompted because of the proliferation of advanced technology and networking of complementary companies to a primary platform ecosystem that has resulted in a more complicated and diversified platform ecosystem. It is noted that, when a platform company exercises too much control over participants, there arises the risk of losing platform participants (such as third-party developers) on the system, thereby stifling the evolutionary capabilities of the platform. Conversely, where there is no control in the platform ecosystem, the platform becomes diverse and fragmented, making it difficult for companies to obtain value from innovation. Addressing such concerns, Foerderer et al. (2014) indicated that value from innovation is obtained from how the platform is coordinated and controlled. Nonetheless, they reiterated that such normally are done based on the primary company's interests. Additionally, Leoni and Parker (2019) in their assertion pointed out that platform companies mainly use formal control as a mechanism to manage users to maintain platform companies' control over the value creation process. As a result, the necessity of assessing the relative role of formal control and informal control is essential, and this study seeks to do that (Bouncken & Kraus, 2013; Cennamo & Santalo, 2019).

The literature cited above provides the groundwork for future research, but it does not address the following three elements of the link between control, innovation, and performance: (1) lack of attention to the control mechanisms implemented by platform companies. Also, previous qualitative or quantitative research primarily focuses on the effect of platform control; innovation and performance are still relatively few. (2) The existing works of literature explore platform innovation from a single perspective, ignoring the key role of innovation capabilities to platform success. (3) Previous studies have focused on the relationship between control and performance or innovation and performance, but have not yet discussed the relationship between control, innovation capabilities, and performance. Therefore, this research takes platform companies as the research object to explore how the control mechanism affects innovation capabilities, thereby improving organizational performance.

Control Mechanisms and Innovative Capabilities

Outcome controls refer to setting-specific outcome goals for complementors, such as sales volume, product delivery time, and cost to monitor their completion (Stouthuysen et al., 2017). This implies that the supplements themselves decide how to achieve these goals. In this way, outcome controls may be regarded as a decentralized control paradigm, allowing multiple complementors to jointly contribute to the ecosystem through autonomous collaboration, therefore providing a flexible and simple environment for modular innovation, such as Google and IBM (Den Hartigh et al., 2016). Accordingly, outcome controls help complementors focus on achieving goals and delivering platform innovation by clearly articulating and accurately measuring expected outcomes (Foerderer et al., 2014).

Although outcome controls positively benefit both incremental and radical innovation capabilities, it is hypothesized that outcome controls have a more positive effect on incremental innovation capability than on radical innovation capability. Outcome controls reduce costs by setting precise targets and easing supervision of complementary activities without requiring a significant effort in scheduling complimentary activities (Schmeiss et al., 2019). Outcome controls' autonomy is compatible with the platform ecosystem and is more likely to facilitate the sharing of information required for the development of some preexisting products and services by complementors, facilitating the acquisition of incremental innovation capabilities (Božič & Dimovski, 2019). In addition, innovation activities on platforms increasingly tend to be horizontal, applying the same knowledge and technology across multiple products or platforms. The emphasis on outcome controls has positive, proximate, and predictable rewards that favor the enhancement and expansion of current technologies and paradigms (Aarikka-Stenroos & Ritala, 2017), therefore minimizing uncertainty hazards. However, radical innovation capabilities develop in unanticipated areas. To achieve superior performance, firms may focus more on incremental innovation capabilities than on radical innovation capabilities. Based on these arguments, we propose the following hypotheses:

H1a: outcome controls have a positive association with radical innovation capability.
H1b: outcome controls have a positive association with incremental innovation capability.
H1c: outcome controls have a stronger effect on incremental innovation capability than on radical innovation capability.

Behavioral controls refer to the supervision of the process of actual production (Kirsch, 2004), not only through (prior) review, (dis)approval, or co-modification of the procedures and methods recommended by complementors but also by monitoring the behavior of complementors (Gawer, 2014). Notably, the emphasis on behavioral control to coordinate the sharing of data and procedures across organizational boundaries is necessary because the emergence of platform ecosystems blurs traditional firm boundaries, and innovation in platform ecosystems relies on the joint participation of two or more complementors (Shi et al., 2020). To ensure innovation within and across organizational boundaries, platform owners monitor the activities of complementors throughout the process through behavioral controls and reconfigure roles, rules, and regulations. For example, through transparent and irreversible transaction, ledgers track the details of interactions at all times (Rialti et al., 2019). Thus, behavioral controls can guide platform activities in a timely and accurate manner to facilitate platform innovation.

The hypothesis here is that outcome controls have a more positive effect on incremental innovation capabilities than on radical innovation capabilities. Radical innovation capability multiplies the risk of opportunistic behavior because it involves the exchange of complex, sensitive, and tacit knowledge (Andriopoulos & Lewis, 2009). Behavioral controls are critical to reducing uncertainty by effectively adjusting complementary player behavior, such as data monitoring throughout the process, thereby increasing development capacity. Furthermore, radical innovation capability adopts new information or develops new knowledge reorganizations from existing knowledge, pursues new systems and processes, and attracts new customers through new distribution channels (Fink et al., 2017; Jansen et al., 2009). Behavioral controls are redirected in time to enhance the dynamics of innovation activities as well as reduce losses. Based on these arguments, we propose the following hypotheses:

H2a: behavior controls have a positive association with radical innovation capability.

H2b: behavior controls have a positive association with incremental innovation capability.
H2c: behavior controls have a stronger effect on radical innovation capability than on incremental innovation capability.

Consistent with prior studies, informal controls of the platform ecosystem rely on a common understanding of appropriate behaviors among platform members and a high degree of commitment to these socially prescribed norms and values. It strengthens mutual understanding and trust and reduces information asymmetry among complementors (Gawer, 2014). According to research, informal controls may be utilized to augment rather than replace formal controls, which have a beneficial influence on innovative activities (Shi et al., 2020). Firstly, informal controls enhance the participation of complementors, such as determining cooperative tasks and responsibilities, sharing production plans, business adjustment plans, and mutual needs (Hartigh et al., 2016). Secondly, informal controls reduce the uncertainty associated with trust-induced friction in cooperation and contribute to good, shared expectations. Moreover, informal controls can better comprehend the requirements of complementors and make timely adjustments through flexibility and information exchange norms. For instance, joint action improves platform collaboration. Although informal controls can enhance trust between the parties, the outcome is determined by the interaction of the parties involved and cannot be predicted, making it more favorable to the accomplishment of shared interest goals that impact predictability. Based on these arguments, we propose the following hypotheses:

H3a: informal controls have a positive association with radical innovation capability.
H3b: informal controls have a positive association with incremental innovation capability.
H3c: informal controls have a stronger effect on incremental innovation capability than on radical innovation capability.

Innovative Capabilities and Performance

Although the main goal of innovation is to achieve and improve performance (Božič & Dimovski, 2019; Damanpour et al., 2009), the uncertainty of innovation activities leads to inconsistent empirical findings in the literature on the relationship between different innovation activities and company performance. Overall, mainstream research evidence shows that there is a positive correlation between innovation and firm performance (Gawer, 2014).

Radical innovation capability to gain new knowledge, find new technologies, and launch new business processes is associated with the unpredictability of ultimate outcomes, long-term nature, and a high degree of autonomy (Fink et al., 2017; Jansen et al., 2009). As a result, it enables companies to dominate the market with new standards while retaining the “pioneer” advantage, avoiding the influence of the “lock-in” effect and capability traps. A platform ecosystem made up of multiple complementors is more responsive to the external environment and more proactive in creating new technologies and delivering new goods or services with enhanced advanced functionalities. Platform owners reshape the competitive landscape by opening new fields or transferring to different ones, driving higher revenues, profits, and market share. Under the effect of the platform network, when the new market gains recognition and reaches a certain amount of usage, the market expansion speed may increase rapidly and reap huge returns (Azar & Ciabuschi, 2017). Furthermore, the platform boosts performance by improving the capacity to adapt to changing client demands and preferences (Andriopoulos & Lewis, 2009; Fink et al., 2017). However, several resources invested in the early stage and a high degree of uncertainty in radical innovation may lead to high risks, resulting in a slower overall return on income. Based on these arguments, we propose the following hypotheses:

H4a: radical innovation capability has a positive association with market performance.
H4b: radical innovation capability has a positive association with financial performance.
H4c: radical innovation capability has a stronger effect on market performance than on financial performance.

Previous studies have pointed out that incremental innovation capability is based on current knowledge and techniques and established decisions to maximize the profits of existing businesses, involving reliable income, high control, efficiency, and short-term success (Božič & Dimovski, 2019; Fink et al., 2017). In the platform ecosystem, the importance of incremental innovation capability may be overshadowed by radical innovation capability due to the network effects and rapid evolution of platforms (Jacobides et al., 2018). However, the acquisition of incremental innovation capability is essential, especially when accompanied by the emergence of more competitive platforms. If the customer demand in the existing market is neglected and new areas are expanded, the platform may be overextended and fail. And upgrading in existing markets can reduce costs and make the platform more rewarding in the short term. Therefore, through using the existing knowledge, incremental innovation improves existing customers' steady growth in market share and revenue and ensures operational efficiency. Based on these arguments, we propose the following hypotheses:

H5a: incremental innovation capability has a positive association with market performance.
H5b: incremental innovation capability has a positive association with financial performance.
H5c: incremental innovation capability has a stronger effect on financial performance than on market performance.

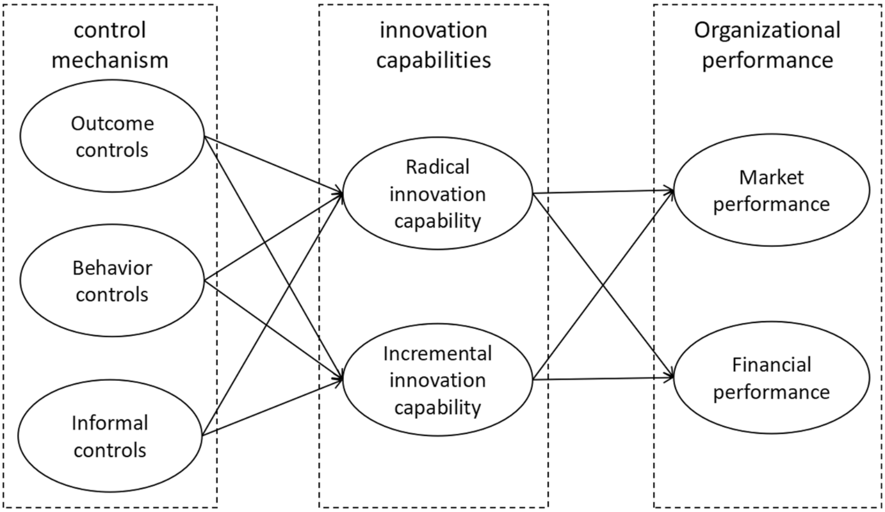

Fig. 1 Research model

Conceptual Model

Based on the literature review, this study illustrates a conceptual model, as presented in Fig. 1. The illustration reflects the hypothetical relationship between control, innovation capabilities, and performance based on the platform ecosystem. The premise of this model is that platform owners design control mechanisms to manage the platform, with which different control mechanisms influence the development of incremental and radical innovation capabilities, thereby leading to an improvement in the market and financial performance.

Method

Sample and Data Collection

Using objective data collected through an online survey, the study was conducted from July to September 2020. Ensuring that the study was reliable and valid, all instruments, data collection, and processing were done according to academic ethics. Thus, 10 managers from different Chinese platform firms and five scholars were invited for an interview and pre-testing of the questionnaire to ensure that there were no respondents burden, content validity, logic, and errors in questions designed for the target respondents (Rogelberg & Stanton, 2007). The questionnaires were adjusted and corrected from the feedback of interviewees and academic experts. The questionnaire was then collected on the website of Credamo.com after it was uploaded for the following reasons: first, Credamo is a professional data platform with more than 1.5 million respondents. The sample database can provide large-scale data collection services and has been recognized by international top journals in many fields, such as psychology, management, and sociology (Jin et al., 2020). Second, the data platform meets the demand of survey quality control, sample feature set, and answer setting. Purposive sampling method was employed to get the management understanding of platform controls from the decision-makers (Tongco, 2006). Thus, considering the small number of platform companies, making our unit of analysis respondents in the management position in companies involved in the internet platform business. Although the purposive sampling method is a non-random selection method, it has been proven to be reliable and robust for objective data analysis (Patton, 2015; Topp et al., 2004). A sample of 500 questionnaires was distributed to respondents. In the end, a total of 386 valid questionnaires were received. Table 1 shows the demographic information of respondents.

Table 1 Demographics of respondents

Demographic characteristics	Category	Frequency	Percentage (%)
Gender	Male	235	60.881
	Female	151	39.119
Age	21–30	143	37.047
	31–40	185	47.927
	41–50	42	10.881
	≥51	16	4.145
Years of experience	1–5	72	18.653
	6–10	150	38.860
	11–15	119	30.829
	16–20	27	6.995
	≥21	18	4.663
No. of employees	1–10	19	4.922
	11–50	49	12.694
	51–250	173	44.819
	≥251	145	37.565
Industry	Real estate, renting, and business activities	13	3.368
	Construction	19	4.922
	Transport, storage, and communication	35	9.067
	Education	10	2.591
	Financial intermediation	34	8.808
	Wholesale and retail trade	42	10.881
	ICT and Telecommunications	114	29.534
	Manufacturing	85	22.021
	Hotels and restaurants	28	7.254
	Other	6	1.554

Source: by authors

Measurement of Instruments

Seven constructs were used in the study, thus, three constructs under control factors (outcome controls, behavior controls, and informal controls); two constructs under innovation capabilities factors (radical innovation capability and incremental innovation capability); and two constructs under performance factors (market performance and financial performance). All scale items used a seven-point Likert scale, which ranged from 1 = "strongly disagree" to 7 = "strongly agree."

Control Factors

The factors were operationalized as three first-order latent constructs: outcome controls (OC), behavior controls (BC), and informal controls (IC), which were adapted and modified from the works of Stouthuysen et al. (2017), Kristal et al. (2010), and Grunwald-Delitz et al. (2019) to suit the study's scope. Outcome controls (OC) were defined as a measure that monitors the completion of results, while behavioral controls (BC) were defined as an evaluation and modification of platform processes via the monitoring behavior of participants. More so, informal controls (IC) were defined as a different socialization mechanism that promotes shared beliefs, norms, and values among participants.

Innovation Capability Factors

Using the research measurement instruments from Fink et al. (2017) and Jansen et al. (2009), innovation capabilities were designed as two first-order latent constructs (thus, incremental innovation capability (IIC) and radical innovation capability (RIC)). In this study, incremental innovation capability (IIC) was expressed as an incremental improvement in the ability to use existing knowledge, markets, and products or services, while radical innovation capability (RIC) was defined as the ability to explore new markets, products, or services.

Performance Factors

Performance constructs were derived from the work of Wamba et al. (2017), using a first-order latent construct to illustrate market performance (MP) and financial performance (FP) latent constructs. Based on the research study, market performance (MP) was defined as the market development of a firm, while financial performance (FP) was defined as the development returns of a firm.

Analytical Methods

The partial least square-structural equation modeling (PLS-SEM) multivariate statistics tool is widely known for its ability to analyze both formative and reflective measurement constructs, Also, known for its objective analysis of psychometric data using a small sample size. Not only does it use a small sample size, but it is also robust for checking moderation and quadratic effect of data received (Hair et al., 2019). In this study, the PLS path modeling was analyzed using SmartPLS 3.0 software (Ringle & Sarstedt, 2016).

As indicated in the rule of thumb for PLS-SEM on the required sample size for analysis, a ten times rule for the multiple pointed path arrow towards a targeted latent construct is employed (J. F. Hair et al., 2013). Nonetheless, Hair et. al. (2013) indicated that for an object calculation of the sample size for the analysis, the use of a G* Power analysis is another means for finding an effect based on the required sample size used. Based on their advice, we employed G* power analysis to calculate objectively the right sample size for this study. Thus, using an F-test linear multiple regression statistical test, a value of 0.05, power $(1-\beta)=0.90$, and a medium effect size of $f^2=0.15$, coupled with seven predictors were used. In all, a required sample size of 130 is needed for the analysis; nonetheless, our obtained sample size of 386 objectively meets the requirements for the PLS-SEM analysis.

Results

Hypothesis testing was performed by evaluating measurement (measurement validity and reliability) and structural models (relationship of measurement assumptions) (Hair et al., 2019). To test the path coefficient, the PLS algorithm was used for path analysis, the maximum number of iterations was 300, and the stop criterion was 7. In addition, a basic bootstrap test of 5000 samples with a significance level of 0.05, bias-corrected and accelerated (BCa) bootstrap, and two-tailed test types were used to test the significance of the beta coefficient (β) and t-values.

Measurement Model

The model was evaluated according to the criteria provided by Hair et al. (2019). The assessment of the measurement model included both reliability and validity components (Dijkstra & Henseler, 2015; Henseler et al., 2015). As indicated in Table 2, the standard metric loadings were greater than 0.708, indicating that all individual item reliability is acceptable. Also, the internal consistency reliability of all three reliability indicators, thus, Cronbach's alpha (α), rho (ρA), and CR exceeded the recommended minimum threshold of 0.7, indicating that all constructs are reliable. For the convergent validity, the results values of AVE (average variance extracted) for all constructs in the model exceeded the minimum significance threshold of 0.5, indicating that each construct measure had adequate convergent validity. More so, the discriminant validity analysis results found in Table 3 show that all HTMT (heterotrait–monotrait) indices were below the recommended minimum threshold of 0.85 or 0.90 (Henseler et al., 2015). In a nutshell, the analysis for the reflective measurement constructs all met the threshold requirements to proceed with the analysis of the structural measurement construct.

In this study, attention was paid to controlling for common method variance both before and after data collection, since the independent and dependent variables

Table 2 Significant results for reflective measurement indicators

Indicators	Mean	Loadings	SD
Result controls (OC): Cronbach's $\alpha = 0.894$, rho_A = 0.898, CR = 0.934, AVE = 0.825			
OC1: we set up specific performance appraisals for complementors	4.904	0.911	0.012
OC2: we set rewards for complementors that are linked to the completion of the set goals	4.933	0.906	0.014
OC3: we are linking participants' rewards to their achievement of set goals	4.922	0.907	0.016
Behavior controls (BC): Cronbach's $\alpha = 0.872$, rho_A = 0.878, CR = 0.922, AVE = 0.797			
BC1: we will modify the product or service development process if necessary	4.987	0.880	0.018
BC2: we evaluate the methods and processes used by complementors to accomplish specific tasks	5.034	0.924	0.009
BC3: we provide complementors with formal feedback on the results of their activities and behaviors to promote appropriate changes	5.023	0.874	0.019
Informal controls (IC): Cronbach's $\alpha = 0.875$, rho_A = 0.880, CR = 0.923, AVE = 0.799			
IC1: we choose complementors through the common culture and values	4.785	0.892	0.012
IC2: we attach great importance to joint meetings and the active participation of complementors to understand the goals, values, and norms of both parties	4.858	0.906	0.013
IC3: when new opportunities and challenges arise, we work with complementors to formulate new common goals	4.785	0.883	0.018
Radical innovation capability (RIC): Cronbach's $\alpha = 0.855$, rho_A = 0.858, CR = 0.902, AVE = 0.698			
RIC1: we introduce new technologies, products, and services	5.256	0.821	0.021
RIC2: we develop new commercial products or services	4.995	0.799	0.023
RIC3: we look for new opportunities in new markets	5.225	0.842	0.019
RIC4: we fundamentally change existing product or service expertise	5.078	0.879	0.014
Incremental innovation capability (IIC): Cronbach's $\alpha = 0.899$, rho_A = 0.903, CR = 0.930, AVE = 0.768			
IIC1: We improve existing products or services	5.073	0.877	0.017
IIC2: We expand the scale of existing markets	5.098	0.858	0.018
IIC3: We provide expansion services for existing customers	5.098	0.897	0.012
IIC4: We enhance our expertise in existing products or services	5.106	0.872	0.020

Table 2 (continued)

Indicators	Mean	Loadings	SD
Market performance (MP): Cronbach's $\alpha = 0.884$, rho_A = 0.885, CR = 0.920, AVE = 0.741			
MP1: we are entering new markets fast	5.049	0.845	0.019
MP2: we introduce new products or services to the market fast	5.036	0.863	0.017
MP3: we have a high success rate in new products or services	5.114	0.872	0.014
MP4: we have a high market share	5.026	0.863	0.016
Financial performance (FP): Cronbach's $\alpha = 0.898$, rho_A = 0.899, CR = 0.929, AVE = 0.765			
FP1: we have a high customer retention rate	5.407	0.885	0.012
FP2: we have a high sales performance	5.425	0.866	0.013
FP3: we have a high return on investment	5.472	0.864	0.016
FP4: we have a good overall financial performance	5.464	0.884	0.013

Source: by authors

Table 3 Differential validity analysis

Constructs	BC	FP	IC	IIC	MP	OC	RIC
BC	**0.893**	0.422	0.421	0.463	0.620	0.470	0.605
FP	0.376	**0.875**	0.519	0.654	0.509	0.419	0.418
IC	0.371	0.462	**0.894**	0.547	0.450	0.538	0.489
IIC	0.412	0.590	0.488	**0.876**	0.536	0.578	0.496
MP	0.545	0.454	0.398	0.481	**0.861**	0.483	0.705
OC	0.419	0.377	0.479	0.522	0.432	**0.908**	0.559
RIC	0.524	0.368	0.424	0.438	0.614	0.491	**0.836**

Values in bold (diagonal elements) show the square root of AVE. Below the diagonal is the corresponding correlation coefficient. Above the diagonal is the HTMT coefficient

Source: by authors

were collected from the same respondents at the same time (Podsakoff et al., 2003). Before data collection, the questionnaire items were first presented clearly and concisely by using previously established scales. Second, participants were assured that there were no correct or incorrect answers and that their responses would remain anonymous. Third, the scales were pre-tested to eliminate ambiguous items from the questionnaire. After data collection, the degree of common method bias was assessed using two different methods. First, we performed Harman's single-way test to determine if one factor explained most of the variance (Podsakoff et al., 2016). A total of 7 factors were extracted, explaining 77.212% of the total variation. The proportion of the first factor in all explanatory variables was 41.463%, which was lower than the recommended threshold of 50%, indicating that there was no common method bias in the data of this study (Podsakoff et al., 2003). Second, the full covariance assessment showed VIF values in the range between 1.237 and 1.422 for all factor levels, which is below the recommended threshold of 3.3. Therefore, it seems unlikely that common method bias threatens the validity of this study.

Structural Model

Assessing the internal model variance inflation factors (VIF), the obtained results were all below the minimum threshold of 3, indicating the absence of multicollinearity. Then a post-hoc power analysis ($N=386$, $\alpha=0.05$, $f^2=0.15$, no. predictors $=7$) was conducted indicating that the study recorded a 99.9% statistical confidence of detecting a significant effect of FP with a moderate explanatory power of 36.3% ($R^2=0.363$) and a medium accuracy power of 27.4% ($Q^2=0.274$); MP with a moderate explanatory power of 43.3% ($R^2=0.433$) and a medium accuracy power of 31.3% ($Q^2=0.313$); IIC with a moderate explanatory power of 37.1% ($R^2=0.371$) and a medium accuracy power of 27.9% ($Q^2=0.279$); RIC with a moderate explanatory power of 38.5% ($R^2=0.385$) and a medium accuracy power of 26.0% ($Q^2=0.260$). The results of the full model calculation showed that the data fit well with the model. In addition, the SRMR (standardized root mean square residual) value of 0.043 was less than the threshold of 0.08, confirming the overall model fit of the PLS path model.

More so, we estimated the standardized path coefficient and significance for each hypothesis and the data results support the original hypothesis, shown in Table 4 and Fig. 2. First, the results indicated that outcome controls had significant positive effects on radical innovation capability ($\beta = 0.264^{***}$, $p < 0.001$) and incremental innovation capability ($\beta = 0.318^{***}$, $p < 0.001$), thus supporting H1a and H1b, respectively. A *t*-test comparison of their path coefficients showed that outcome controls had a greater impact on incremental innovation capability than on radical innovation capability ($t = 5.282$, $p < 0.001$), thus supporting H1c. H1c was further confirmed by the effect size (f^2). It allows for comparison between different hypotheses and assesses whether the predictor variable has a substantial effect on the R^2 of the dependent variable. An effect size (f^2) values of 0.02 = small, 0.15 = medium, and 0.35 = large were used (Chin, 1998). The results indicated that f^2(OC → IIC) = 0.113 was greater than f^2 (OC → RIC) = 0.08, thus supporting H1c.

Second, behavior controls significant positive affected radical innovation capability ($\beta = 0.352^{***}$, $p < 0.001$) and incremental innovation capability ($\beta = 0.179^{**}$, $p < 0.001$), thus supporting H2a and H2b. A *t*-test comparison of their path coefficients showed that behavioral controls had a stronger effect on radical innovation capability than on incremental innovation capability ($t = 5.740$, $p < 0.001$), thus supporting H2c. Further, as f^2(BC → RIC) = 0.158 was greater than f^2 (BC → IIC) = 0.040, thereby supporting H2c.

Third, informal controls significant positive affected radical innovation capability ($\beta = 0.167^{**}$, $p < 0.001$) and incremental innovation capability ($\beta = 0.270^{***}$, $p < 0.001$), thereby supporting H3a and H3b. A comparison of *t*-tests on their path coefficients showed that behavior controls had a stronger effect on radical innovation capability than on incremental innovation capability ($t = 4.291$, $p < 0.001$) and that f^2 (IC → IIC) = 0.085 was greater than f^2 (IC → RIC) = 0.034, thereby supporting H3c.

Fourth, radical innovation capability significant positive affected market performance ($\beta = 0.499^{***}$, $p < 0.001$) and financial performance ($\beta = 0.136^{**}$, $p < 0.001$), thus supporting H4a and H4b. A comparison of *t*-tests on their path coefficients showed that radical innovation capability had a stronger effect on market performance than on financial performance ($t = 8.087$, $p < 0.001$), while f^2(RIC → MP) = 0.355 was greater than f^2(RIC → FP) = 0.023, thus supporting H4c.

Finally, incremental innovation capability significant positive affected market performance (0.263^{**}, $p < 0.001$) and financial performance ($\beta = 0.531^{***}$, $p < 0.001$), thus supporting H4a and H4b. A comparison of *t*-tests on their path coefficients showed that incremental innovation capability had a stronger effect on financial performance than on market performance ($t = 9.647$, $p < 0.001$), while f^2 (IIC → FP) = 0.358 was greater than f^2 (IIC → MP) = 0.098, thus supporting H5c.

Detecting Unobserved Heterogeneity Using Finite Mixture PLS Approach

In the context of PLS-SEM, this research checked whether the results of the aggregated data were unbiased. Finite mixture PLS (FIMIX-PLS) was used to detect

Table 4 Results of structural model analysis

Hypothesis	Path	Path coefficient	Standard deviation	*T* statistics	95% BCa confidence	Effect size (f^2)	Result
H1a	OC → RIC	0.264***	0.056	4.743	(0.154,0.371)	0.080	Accepted
H1b	OC → IIC	0.318***	0.060	5.282	(0.198,0.431)	0.113	Accepted
H2a	BC → RIC	0.352***	0.061	5.740	(0.225,0.464)	0.158	Accepted
H2b	BC → IIC	0.179**	0.063	2.845	(0.051,0.300)	0.040	Accepted
H3a	IC → RIC	0.167**	0.050	3.324	(0.075,0.271)	0.034	Accepted
H3b	IC → IIC	0.270***	0.063	4.291	(0.149,0.393)	0.085	Accepted
H4a	RIC → MP	0.499***	0.062	8.087	(0.382,0.621)	0.355	Accepted
H4b	RIC → FP	0.136**	0.050	2.716	(0.044,0.242)	0.023	Accepted
H5a	IIC → MP	0.263**	0.077	3.415	(0.113,0.408)	0.098	Accepted
H5b	IIC → FP	0.531***	0.055	9.647	(0.415,0.631)	0.358	Accepted
		SRMR = 0.043	R^2 for FP = 0.363	R^2 for MP = 0.433	R^2 for IIC = 0.371	R^2 for RIC = 0.385	
			Q^2 for FP = 0.274	Q^2 for MP = 0.313	Q^2 for IIC = 0.279	Q^2 for RIC = 0.260	

these symbols***p-value < 0.001 and**p-value < 0.01 were used to indicate the significance of the construct

Source: by authors

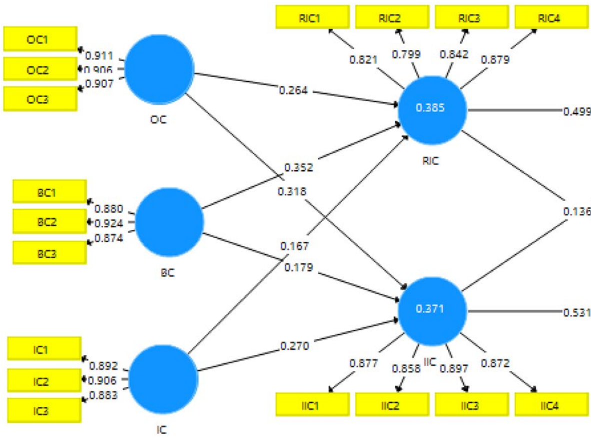

Fig. 2 Structural model results

unobserved heterogeneity in the survey data (Joseph F. Hair et al., 2016; Matthews et al., 1989). According to Hair et al. (2015), a minimum R^2 of 0.25 and a significance level of 0.05, from three maximum numbers of the arrow pointing to a construct (IC and RC), a calculated minimum sample size of 37 would be obtained. The theoretical upper bound for the maximum integer obtained by dividing the sample size (386) by the minimum sample size (37) was 10 (Joseph F. Hair et al., 2016). After running the FIMIX-PLS algorithm 10 times for segments 1–10, the appropriate target solution was identified from appropriate segmentation by the Akaike Information Criterion (AIC), modified AIC with factor 3 (AIC 3), Modified AIC with Factor 4 (AIC4), Consistent AIC (CAIC), Bayesian Information Criterion (BIC), Minimum Description Length with Factor 5 (MDL5), and normed Entropy Statistics (EN) (Matthews et al., 1989; Msa et al., 2022).

As shown in Table 5, ACI_3 and CAIC, as well as AIC_4 and BIC, present different segments. The literature indicated that AIC overestimates the correct number of segments, while MDL_5 underestimates the number of segments (Matthews et al., 1989). AIC was in a ten-segment solution, indicating that the correct number was significantly lower than this number. MDL_5 was in a one-segment solution, indicating that two or more segments were recommended. Thus, the correct number of segments is probably between two and ten. However, the EN value of the two and three-segment solution was lower than 0.5, indicating that the separation of the two segments was not well implemented. Furthermore, the relative fragment sizes suggested that the selection of more than three fragments was not justified due to the minimum sample size limitation (see Table 6). Therefore, the data set used in this study was valid, acceptable, and generalizable.

Table 5 Information criteria by segment by FIMIX-PLS

Criteria	1	2	3	4	5	6	7	8	9	10
AIC	3649.669	3558.371	3513.619	3495.560	3385.239	3386.941	3387.877	3342.025	3353.665	**3298.955**
AIC3	3663.669	3587.371	3557.619	3554.560	3459.239	3475.941	3491.877	3461.025	3487.665	**3447.955**
AIC4	3677.669	3616.371	3601.619	3613.560	**3533.239**	3564.941	3595.877	3580.025	3621.665	3596.955
BIC	3705.051	**3673.090**	3687.676	3728.954	3677.971	3739.010	3799.284	3812.770	3883.747	3888.375
CAIC	3719.051	**3702.090**	3731.676	3787.954	3751.971	3828.010	3903.284	3931.770	4017.747	4037.375
MDL5	**4038.577**	4363.967	4735.903	5134.532	5440.899	5859.288	6276.912	6647.749	7076.076	7438.054
EN		0.402	0.434	0.557	0.641	0.650	0.703	0.715	0.709	**0.755**
LnL	− 1810.834	− 1750.186	− 1712.809	− 1688.780	− 1618.620	− 1604.470	− 1589.938	− 1552.013	− 1542.832	− 1500.478

Values in bold indicate the smallest value in segments 1-10 for each criterion

Source: by authors

Table 6 Relative segment size

Number	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6	Segment 7	Segment 8	Segment 9	Segment 10
2	0.615	0.385								
3	0.383	0.309	0.308							
4	0.416	0.393	0.150	0.041						
5	0.418	0.322	0.129	0.123	0.008					
6	0.326	0.309	0.127	0.122	0.107	0.009				
7	0.483	0.236	0.118	0.078	0.051	0.027	0.008			
8	0.341	0.265	0.132	0.119	0.068	0.047	0.015	0.013		
9	0.310	0.218	0.215	0.117	0.045	0.036	0.022	0.021	0.015	
10	0.403	0.217	0.118	0.116	0.058	0.026	0.022	0.021	0.010	0.008

Source: by authors

Table 7 IPMA analysis results for MP and FP

Target construct	Performance	Total effect *t* (MP)	Total effect (FP)
OC	60.718	0.215	0.205
BC	71.624	0.222	0.143
IC	56.166	0.154	0.166
RIC	63.155	0.499	0.136
IIC	71.608	0.263	0.531

Source: by authors

Importance–performance Matrix Analysis

Importance–performance matrix analysis (IPMA) played an important role in using latent variable scores to expand the discovery of basic PLS-SEM results (Joseph F. Hair et al., 2016). IPMA drew its conclusions through two dimensions, namely, importance and performance, which had important implications for management practice (Ali, 2020). IPMA could be clearly described through the x and y axes. For a target-dependent variable, the total effect of the PLS path was shown on the x axis (importance dimension), and the mean score of the variable was shown on the y axis (performance dimension). The IPMA results were obtained by targeting construct, market performance, and financial performance, respectively (see Table 7 and Figs. 3, and 4). According to the performance results, BC (71.624) had the highest value, followed by IIC (71.608), RIC (63.155), OC (60.718), and IC (56.166). According to the total effect result, RIC (0.499) was the most important result to

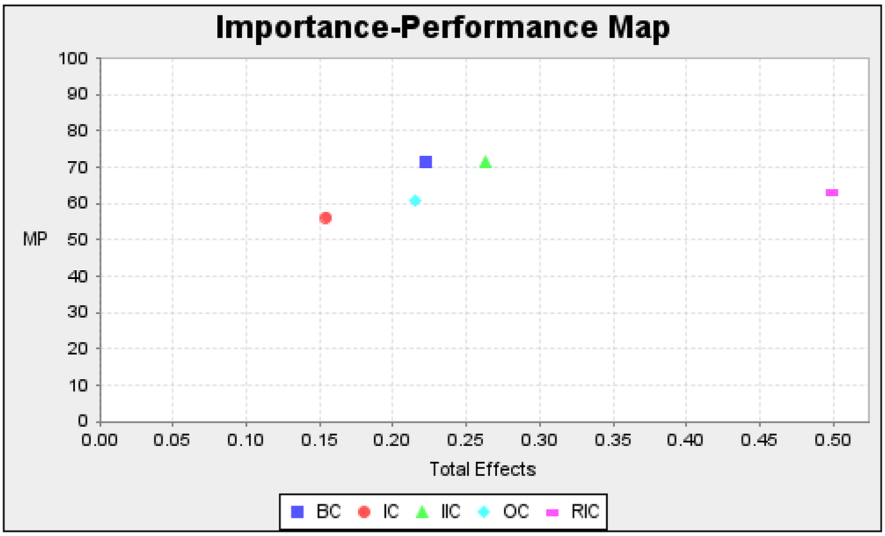

Fig. 3 IPMA results of market performance as target construct (standardized effects)

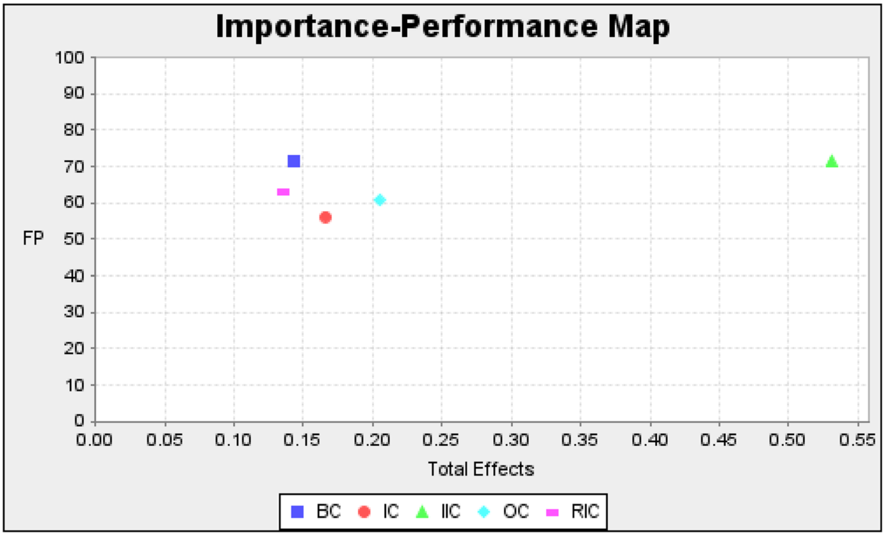

Fig. 4 IPMA results of financial performance as target construct (standardized effects)

explain MP, followed by IIC (0.263), BC (0.222), OC (0.215), and IC (0.154). Similarly, the results showed that IIC was the most important outcome to explain FP (0.531), followed by OC (0.205), IC (0.166), BC (0.143), and RIC (0.136). Therefore, in the PLS path model, RIC and IIC were the most relevant management actions for MP and FP, respectively.

Discussion and Conclusion

Discussion

Drawing on control and innovation literature (Leoni & Parker, 2019), this study sought to contribute to the understanding of governance and innovation processes in platform ecosystems by proposing a research model. This study confirms the influence of outcome control, behavioral control, and informal control on innovation capabilities, including radical innovation capability and incremental innovation capability. The study also identifies the role of incremental innovation capability and radical innovation capability on market performance and financial performance.

The PLS-SEM shows that controls have a positive impact on innovation capabilities. Specifically, the influence of outcome controls and informal controls on incremental innovation capability is more salient than that of radical innovation capability, and the influence of behavior controls on radical innovation capability is more obvious than that of incremental innovation capability, which is in line with previous studies (Shi et al., 2020). This finding implies that the implementation of different types of control by platform owners is conducive to platform bivariate innovation, thus maintaining the consistency of platform ecosystem actions and strategies. Further, the results indicate that innovation capabilities have a positive impact on the performance of firms. The results show that incremental innovation capability has a greater impact on financial performance than market performance, and radical innovation capability is more conducive to improving market performance than financial performance. As stated by Narayan and Hungund (2022), radical innovation capability tends to grow explosively, such as breakthroughs in specific technologies, which increases the rate of expansion and market share due to the network effect of platforms. In contrast, incremental innovation capability maintains steady growth in performance based on existing knowledge.

Moreover, the FIMIX-PLS analysis shows that the results of this study are universal and reliable because there is no unobserved heterogeneity in the supporting survey data (Hair et al., 2016). In addition, IPMA analysis supports the highest performance score of behavioral control. This indicates that behavioral control is of great significance to platform management activities. IPMA analysis also points out that radical innovation capability is highly correlated with the realization of market performance, and incremental innovation capability is highly correlated with the realization of financial performance. This suggests that incremental innovation capability and radical innovation capability are the main areas of improvement that management activities need to address.

Theoretical Implications

The results of this study contribute significantly to the literature by documenting the effects of controls on innovation and performance. First, this research responds to the research on platform governance, which can enhance innovation and performance by designing control mechanisms for ecosystem complementors (Gawer, 2014; Mikalef et al., 2020). Although the existing literature suggests that control is an important component of the orderly activities of platform ecosystems, the role of control on two rather significant innovation capabilities is poorly discussed (Mikalef et al., 2020). By doing so, this finding extends the existing research scope of control and innovation theory.

Second, this study enriches the existing knowledge system by viewing the underexplored effects of different types of innovation capabilities on performance. This understanding is important because the cost of trial and error may be increased without a clear direction for innovation, as the platform ecosystem shortens the competitive cycle. The findings demonstrate the important role of innovation duality on performance (Božič & Dimovski, 2019; Rialti et al., 2019).

Third, the data collected in this study contributes to the literature by evaluating companies in a non-western country, and more research is needed to examine the governance of platform ecosystems (Hossain et al., 2016). This is one of the first studies to record such findings and supports the argument that control and innovation are both important factors in improving performance.

Practical Implications

The conclusions of this examination have significant ramifications for guiding platform firms to utilize control mechanisms reasonably to enhance innovation capabilities and improve organizational performance. First, we recommend behavior controls in which governance is implanted in the control's construction, process, and framework. In practice, since platform owners ordinarily cannot straightforwardly participate in value-creating activities, numerous applications overlook the role of behavior controls, which prompts issues like security and trust on the platform (Adner, 2017; Kapoor, 2018). To keep away from this circumstance, the platform owners ought to reinforce the monitoring of the complementor's conduct and animate essential development abilities. When putting a ton of cash into advancements, platform firms ought to particularly embrace high-cost behavior controls, like checking through the internet of things, to guarantee the systematic activity of the platform.

Second, managers should strike a balance between the connection between incremental innovation capability and radical innovation capability. The empirical results show that incremental innovation capability and radical innovation capability have different effects on achieving market performance and financial performance. Therefore, managers should cultivate the dual innovation capabilities of platform ecosystems when implementing innovation strategies.

Limitations and Future Directions

This study profoundly dissects the mechanism of control on innovation capabilities and organizational performance under the platform ecosystem. Although our research deepens the field of control and innovation, there are still shortcomings. First, this examination uses platform owners as the research object to discuss the impact of control on performance, but complementors are also an important part of the platform ecosystem. It would be meaningful to conduct further research from a complementary perspective. Second, this study only discusses the influence of control, innovation capabilities, and performance under static relationships. In the future, time-series research may be introduced to extend the findings of this study.

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Data Availability The data that support the findings of this study are available from the corresponding author, [Pro Luo], upon reasonable request.

Declarations

Conflict of Interest I would like to declare on behalf of my co-authors that the work described is original research that has not been published previously, and is not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed. No conflict of interest exists in the manuscript submission approved for publication. The authors did not receive support from any organization for the submitted work.

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