A Meta-Analysis-Based Study on the Influencing Factors of Open Innovation

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Abstract: Open innovation serves as a crucial pathway for enhancing corporate performance. How to elevate corporate open innovation capabilities has garnered widespread attention. Although existing research has explored the influencing factors of open innovation from multiple perspectives, no consensus has been reached. We conducted an empirical study using meta-analysis on 52,558 independent samples from 74 literature sources. Key findings include: (1) The technological dimension (digital capability and technical capability), organizational dimension (absorptive capacity, knowledge management capability, and executive leadership), and environmental dimension (intellectual property protection and institutional environment) all exert significant positive effects on open innovation; (2) Cultural differences play a significant moderating role in the effects of absorptive capacity, executive leadership, and intellectual property protection on open innovation. The findings underscore the critical importance of these three dimensions in shaping open innovation outcomes, offering significant implications for corporate open innovation practices.

Keywords: Open Innovation; Influencing Factors; TOE Framework; Meta-Analysis

1. Introduction

Amid industrial restructuring and the rise of the digital economy, the business environment enterprises face is undergoing profound transformation. Against this backdrop, organizational boundaries are increasingly blurred, resources and information flow freely across borders, and value chains are being digitally realigned and optimized. Closed innovation relying solely on internal resources has become unsustainable, prompting many enterprises to seek new innovation approaches to maintain competitive advantage. Open innovation offers enterprises a novel approach to overcoming innovation challenges, playing a vital role in enhancing innovation outcomes and strengthening core competitiveness [1]. Consequently, advancing open innovation within enterprises and improving its effectiveness have become focal points in academic research. Xu et al. [2] argue that digital transformation presents significant opportunities for open innovation. Furthermore, as open innovation involves knowledge exploration and utilization, it requires human capital capable of selecting, acquiring, transforming, and applying knowledge to achieve innovation objectives. Consequently, open innovation necessitates leaders who can effectively manage human capital [3]. These factors drive corporate open innovation performance from different perspectives.

Reviewing prior research, although scholars worldwide have explored the drivers of open innovation from multiple angles, no consensus has been reached. Furthermore, existing studies have not examined which variables moderate the influence of these factors on corporate open innovation. Consequently, two research questions emerge: (a) What factors influence corporate open innovation? (b) If these factors influence open innovation, do moderating variables exist that affect their relationship? To address these gaps, we employ meta-analysis to conduct a secondary analysis of existing research data. By synthesizing and re-examining findings from prior literature, we derive more generalizable and objective conclusions. Furthermore, we identify moderating variables from contextual factors and utilize subgroup analysis to explore their moderating effects, yielding systematic insights.

Based on the Technology-Organization-Environment (TOE) theoretical framework, we identify influencing factors at three levels: technology, organization, and environment.

Subsequently, we employ meta-analysis to examine the combined effects of these factors on corporate open innovation. Next, we utilize moderation analysis to explore potential moderating mechanisms, comprehensively elucidating the underlying situational mechanisms. Finally, based on the meta-analysis findings, we propose management strategies to enhance corporate open innovation, offering practical insights for improving innovation performance.

2. Theory and Hypotheses

2.1 Technological Dimension

The rapid development of the digital economy and the application of digital technologies have reshaped corporate resources and capabilities, opening diversified new pathways for business development. When enterprises successfully acquire and establish specialized knowledge and capability systems related to these digital technologies, they can more effectively drive open innovation. On one hand, digital technologies significantly advance the digitization of technical resources. Dispersed innovation resources can be efficiently integrated and widely showcased through digital platforms. On the other hand, applying digital technologies enhances enterprises' capabilities in searching, mining, and analyzing information. Through digital platforms, enterprises establish closer technical cooperative relationships with other innovation actors. This enables the sharing and complementarity of technical resources, thereby boosting innovation capabilities [4]. Thus, digital capabilities may positively influence enterprise open innovation.

Technical capability plays a pivotal role in open innovation [5], as it fundamentally represents the accumulation of an enterprise's knowledge resources [6]. Existing research indicates that the strength of technical capability influences an enterprise's openness to innovation [7]. In open innovation activities, enterprises must expand organizational boundaries to seek, absorb, and effectively utilize external knowledge resources. Only with robust technological capabilities can external resources be integrated with internal knowledge reserves to generate new knowledge and technologies [5]. Conversely, insufficient technological capabilities leave enterprises overwhelmed by vast, highly heterogeneous knowledge repositories, hindering open innovation progress. Open innovation emphasizes external collaboration; relying solely on internal capabilities may yield suboptimal results. Technologically strong enterprises typically possess diverse knowledge, information, and other resources. Guided by principles of mutual assistance and shared benefits, other organizations often seek partnerships with such enterprises [5]. In summary, we propose the following hypothesis:

H1: There exists a significant positive relationship between digital capabilities and corporate open innovation.

H2: There is a significant positive relationship between technological capability and corporate open innovation.

2.2 Organizational Dimension

Open innovation is not merely a model of utilizing external resources for innovation. Enterprises must identify, validate, and select appropriate resources to integrate with internal knowledge, thereby forming novel innovation systems and frameworks. Absorptive capacity plays a crucial role in monitoring, evaluating, assimilating, and utilizing external resources. It effectively integrates internal and external resources, assists enterprises in identifying and acquiring valuable resources, and enhances resource utilization efficiency through approaches better aligned with organizational needs, making it a key driver of open innovation. In essence, absorptive capacity efficiently channels externally provided resources into an enterprise's open innovation activities.

From a resource-based view perspective, the extent to which enterprises leverage external knowledge and resources is a critical factor in achieving innovation performance mechanisms. Open innovation represents a boundary-crossing collaboration model that emphasizes synergistic innovation and knowledge co-creation through the management and integration of core enterprise knowledge, thereby driving organizational development. From a process perspective of knowledge management, relying solely on knowledge acquisition is insufficient to drive corporate innovation. Effective stimulation of an enterprise's innovative vitality requires the organic integration of knowledge transfer and consolidation [8]. Therefore, the ability to integrate new and existing resources both within and outside the enterprise is a key factor in achieving open innovation performance.

Enterprises with robust knowledge management capabilities can leverage existing knowledge to generate new knowledge, thereby enhancing open innovation performance.

Open innovation is not merely a choice of innovation method; it often involves transforming business models and even corporate strategy, a reality particularly evident in SMEs. Decision-makers must therefore systematically examine the enterprise's internal and external environments, identify opportunities, and make choices amid complex and uncertain circumstances. As decision-makers, leaders play a crucial role in open innovation. When selecting and implementing open innovation, numerous factors must be considered and balanced, including industrial structure upgrades, technological iteration and renewal, intricate network relationships, and resource, time, and institutional constraints. The relationships among these factors are complex and ambiguous. Leaders possessing innovation, insight, and a willingness to take risks can make swift decisions when facing challenges [9]. In summary, we propose the following hypothesis:

H3: There exists a significant positive relationship between absorptive capacity and corporate open innovation.

H4: Knowledge management capabilities have a significant positive relationship with corporate open innovation.

H5: There is a significant positive relationship between leader empowerment and corporate open innovation.

2.3 Environmental Dimension

Open innovation carries the risk of core intellectual property leakage, making effective IP protection a critical factor influencing firms' choice of innovation paradigms. On one hand, strengthened IP enforcement by local governments can curb patent infringement by enterprises. Based on resource dependence theory and cost minimization theory, manufacturing firms struggle to allocate innovation risk costs solely through internal resources. By exchanging innovation resources and sharing innovation benefits, firms can effectively reduce innovation risk costs. During the long-term search for external resources, commercial trust mechanisms and the linkage effects of collaborative R&D are enhanced, thereby driving enterprises toward open innovation [10]. On the other hand, the development of intellectual property demonstration cities enables enterprises to effectively mitigate moral hazards, further strengthening their potential willingness to collaborate and fostering a cooperative atmosphere with other innovation entities. Cooperative win-win approaches such as contractual partnerships and joint ventures enhance regional commercial credibility, increase enterprises' willingness to transition to open innovation paradigms, and achieve technological progress through collaborative innovation.

All corporate activities are embedded within their institutional environment, and open innovation exhibits contextual dependency, meaning it may be influenced by institutional factors [11]. First, government policy support provides crucial external organizational backing for corporate innovation and entrepreneurship. For instance, governments may issue specific policies and regulations to support the development of corporate open innovation network platforms. Governments may also implement corresponding subsidy policies (such as tax incentives and innovation grants) to elevate corporate open innovation capabilities. Additionally, under the influence of societal values that champion, encourage, and support innovation, corporate members become more receptive to and aligned with the principles of innovation and entrepreneurship. Consequently, enterprises can regularly host innovation exchange forums and engage in industry-academia-research collaborations to facilitate the sharing of knowledge, resources, and information among companies, achieving mutual benefits and collective advancement. In summary, we propose the following hypothesis:

H6: Intellectual property protection and corporate open innovation exhibit a significant positive relationship.

H7: There is a significant positive relationship between the institutional environment and corporate open innovation.

2.4 The Moderating Role of Cultural Differences

An open atmosphere often fosters open innovation more effectively. Foreign cultures differ significantly from Chinese culture. Foreign enterprises, influenced by overseas cultural exposure, tend to possess an open-minded perspective that helps break

organizational mental models and create a conducive environment for open innovation, playing a crucial role in its implementation. Overseas companies exhibit international thinking, greater receptivity to novel ideas, and strong learning capabilities. Western cultures frequently adopt broad, comprehensive perspectives, which also foster positive innovation environments conducive to open innovation. Eastern cultures, however, are deeply influenced by Confucianism. Chinese enterprises typically aspire to moderation, exhibit stronger risk-averse tendencies, and make more conservative investment decisions. Consequently, this innovation culture rooted in Eastern Confucianism appears to exert less pronounced influence on open innovation adoption compared to overseas enterprises. This paper treats cultural differences as a moderating variable and proposes the following hypothesis:
H8: Cultural differences exert a moderating effect on firms' adoption of open innovation.

3. Method/Research Design

3.1 Method Selection

Meta-analysis is a systematic evaluation and quantitative synthesis of findings from multiple independent studies. This method aims to integrate research outcomes and synthesize existing evidence [12]. Meta-analysis not only examines correlations between variables but also investigates the moderating effects of measurement factors on these relationships. We employ meta-analysis to investigate factors influencing corporate open innovation. Previous empirical studies on open innovation determinants have yielded inconsistent conclusions, exhibiting variations in effect size, statistical significance, and even directionality. Meta-analysis enables more scientifically grounded conclusions drawn from a broader sample space. Therefore, we reanalyze existing research findings through meta-analysis to provide scientific decision-making support for enhancing corporate innovation efficiency.

3.2 Sample

To maximize coverage of relevant studies, we collected literature using "open innovation" and its related terms alongside Chinese and English expressions for "influencing factors." Relevant terms included "open innovation," "openness," "influencing factors," "influence," "impact," and "affect". Databases searched included Web of Science, Google Scholar, Elsevier Science Direct, Springer, Emerald, SAGE, Wiley Online Library, and China National Knowledge Infrastructure (CNKI). To prevent omissions, we also collected references from retrieved articles, cross-referencing them with the collected literature to identify gaps. As of December 2025, a total of 5,532 relevant articles were collected, comprising 3,294 English-language publications and 2,229 Chinese-language publications.
Considering the requirements of meta-analysis and the alignment of literature content with our research objectives, we established three screening criteria: (1) The literature must explore the impact on corporate open innovation. Therefore, we excluded studies where the outcome variable pertained to other dimensions of innovation. (2) The studies must be empirical. Included literature must report sample size, correlation coefficients or regression coefficients that can be converted into correlation coefficients, path coefficients, etc. (3) Samples must be mutually independent. Where multiple studies utilized the same sample, we selected the one with the higher impact factor for analysis.
Following these steps, a total of 207 studies were entered into the database of open innovation influence factors, including 141 Chinese-language studies and 66 English-language studies.

3.3 Data Encoding

Following the coding recommendations of Lipsey and Wilson [13], two experts in the relevant field independently coded the literature in the database. The coding encompassed two categories: basic literature information and effect size statistics. Basic information included article title, first author, publication year, journal, and research variables. Effect size statistics comprised sample size, correlation coefficients, and other effect measures convertible to correlation coefficients (e.g., regression coefficients, path coefficients). Second, due to the examination of moderator variables, cultural differences were coded. Domestic firms were coded as 0, while foreign firms were coded as 1. Finally, the coding results from both experts were cross-checked, with discrepancies resolved through mutual agreement.

3.4 Effect Value Conversion

Common meta-analysis software includes CMA, Revman, and Stata. We selected CMA3.0 (Comprehensive Meta Analysis 3.0), specifically designed for meta-analysis. Before importing coded data into the software, we converted non-correlation coefficient effect sizes. We employed the specialized meta-analysis software CMA 3.0, using the correlation coefficient r as the effect size. To mitigate attrition bias arising from scale reliability limitations [14], we processed data using CMA3.0. Each correlation coefficient was converted to a Z-score via Fisher's Z transformation formula. The weighted average of Fisher's Z values was calculated based on sample size, then converted back to correlation coefficients to yield the final effect sizes. Literature exclusion followed. At this stage, we obtained 86 effect sizes from 74 studies, involving 52,558 independent samples.

Table 1. Main Effect Analysis Results

Variable	N	95%CI			Z	Q	Heterogeneity Test			Model
		Effect Estimates	LL	UL			df	p	I^2 (%)	
Digital capability	13	0.297	0.163	0.420	4.239***	739.848	12	0.000	98.378	Random
Technical capability	16	0.404	0.275	0.518	5.762***	779.752	15	0.000	98.076	Random
Absorptive capacity	8	0.477	0.332	0.599	5.850***	79.451	7	0.000	91.190	Random
Knowledge management capability	24	0.416	0.321	0.502	7.881***	622.928	23	0.000	96.308	Random
Executive leadership	10	0.346	0.219	0.460	5.143***	176.308	9	0.000	94.895	Random
Intellectual property protection	5	0.396	0.138	0.604	2.933**	135.600	4	0.000	97.050	Random
Institutional environment	10	0.256	0.160	0.347	5.115***	163.991	9	0.000	94.512	Random

4. Results

4.1 Heterogeneity Testing

Heterogeneity testing analyzes the degree of variation among multiple independent samples. According to statistical principles, only homogeneous data can be pooled. If heterogeneity exists, a random-effects model must be selected for adjustment. Common heterogeneity tests include the Q-value test and the I^2 test. The choice of model depends on the Q-value and the number of effect sizes K: When $Q > K-1$, the random-effects model should be used. The I^2 value also determines model selection: if $I^2 \geq 50\%$, indicating heterogeneity, use the random-effects model; if $I^2 \leq 50\%$, use the fixed-effects model. We combined these two approaches. The results of the heterogeneity test are shown in Table 1. The Q-values (indicating the degree of heterogeneity among effect sizes across studies) all exceeded the critical value of 51, and the p-value was <0.001. This indicates the presence of heterogeneity in the studies, suggesting the existence of potential moderating variables. Additionally, the I^2 (indicating the proportion of total variation attributable to differences in effect sizes across studies) were all greater than 75%. This result indicates that the observed differences primarily stem from variations in effect sizes across studies, further confirming the presence of heterogeneity. In summary, we selected the random-effects model.

4.2 Bias Test

Given that some literature may inevitably be omitted during the literature collection process, a publication bias test must be conducted on the database. Funnel plots are commonly used for this purpose, but relying solely on visual interpretation may introduce bias influenced by subjective judgment. Therefore, quantitative analysis was conducted using CMA 3.0 software to calculate the failure safety factor and its critical value N×5+10 (where N represents the number of studies). The failure safety factor indicates the number of negative studies required to reverse the meta-analysis conclusion. With higher values indicating greater reliability of the meta-analysis conclusions (Liu Zhiying et al., 2017). Calculations revealed that the failure safety factor for the literature on digital capabilities' impact on corporate open innovation was 2386, far exceeding the critical value of 75 (effect size × 5 + 10). The failure safety factors for the other influencing factors also surpassed the critical value. Thus, the meta-analysis results based on the selected empirical literature can be deemed reliable.

4.3 Main Effect Tests

Based on the heterogeneity test results, we selected the random-effects model for the experiment. The overall effect test results are shown in Table 1. The analysis indicates that all influencing factors exhibit statistically significant positive correlations with open innovation ($p<0.05$). The effect values of the seven influencing factors, ranked from highest to lowest, are: Absorptive capacity, Knowledge management capability, Technical capability, Intellectual property protection, Executive leadership, Digital capability, and Institutional environment. Therefore, research hypotheses H1-H7 are all strongly supported by empirical evidence.

4.4 Moderating Effect Analysis

We employed subgroup analysis to calculate the effect values between the next influencing factor under the moderating variable and open innovation. The results are presented in Table 2. As shown in Table 2, the moderating effect of cultural differences is specific, significantly moderating the influence of absorptive capacity, managerial leadership, and intellectual property protection on open innovation. However, cultural differences did not exert a moderating effect on the remaining four influencing factors. Therefore, we can conclude that Hypothesis H8 is partially supported. The moderating effect of cultural differences exists but does not apply to all factors.

Table 2. Moderator Effect Analysis Results

Variable	N	95%CI			Z	Q	Heterogeneity Test			Model	
		Effect Estimates	LL	UL			df	p	I^2 (%)		
Cultural Differences	DC→OI	China	12	0.316	0.169	0.449	4.094	0.000			
		foreign	1	0.068	0.028	0.108	3.337	0.000			
									9.869	1	0.002
	TC→OI	China	12	0.378	0.222	0.516	4.522	0.000			
		foreign	4	0.479	0.344	0.595	6.276	0.000			
									1.041	1	0.308
	AC→OI	China	4	0.297	0.223	0.368	7.520	0.000			
		foreign	4	0.628	0.532	0.709	9.894	0.000			
									25.817	1	0.000
	KC→OI	China	19	0.454	0.338	0.556	6.795	0.000			
		foreign	5	0.261	0.142	0.373	4.204	0.000			
									5.498	1	0.019
	EL→OI	China	3	0.118	0.086	0.149	7.226	0.000			
		foreign	7	0.448	0.357	0.530	8.713	0.000			
									39.750	1	0.000
	IP→OI	China	1	0.096	0.049	0.142	4.005	0.000			
		foreign	4	0.468	0.198	0.672	3.245	0.001			
									6.755	1	0.009
	IE→OI	China	7	0.199	0.153	0.245	8.254	0.000			
		foreign	2	0.120	0.015	0.222	2.245	0.025			
									1.909	1	0.167

5. Conclusions

Through literature collection and coding, we obtained 74 studies on factors influencing open innovation. We conducted meta-analysis on the effect sizes in these studies, including effect size transformation, calculation of composite effect sizes, heterogeneity testing, outlier testing, and publication bias testing. Subsequently, we discussed the data analysis results, including main effect testing and moderation effect testing. The main research conclusions are as follows:

(1) Digital capability, technological capability, absorptive capacity, knowledge management capability, executive leadership, intellectual property protection, and institutional environment all positively promote corporate open innovation. This indicates that technology, organization, and environment are all key factors in fostering open innovation. Enterprises applying digital technologies can enhance their search, mining, and analytical capabilities, integrating external resources with internal knowledge reserves to generate new knowledge and technologies. Throughout this process, firms require robust absorption capacity and knowledge management capabilities to reconfigure and utilize external resources, transforming them into internal knowledge assets. Leaders must identify opportunities and make decisive choices amid complex and uncertain conditions. Additionally, various institutional measures implemented by governments—such as innovation subsidies, tax incentives, and intellectual property protection policies—serve as powerful drivers for corporate

open innovation.

(2) Compared to the Chinese cultural context, enterprises in foreign cultural settings demonstrate more pronounced promotion of open innovation through absorption functions, executive leadership, and intellectual property protection. On one hand, foreign-based enterprises exhibit greater risk-taking spirit and higher propensity for external collaboration. Their thinking is also relatively more open. On the other hand, Eastern cultures are deeply influenced by Confucianism. Chinese enterprises typically favor moderation, exhibit stronger risk-averse tendencies, and make more conservative innovation decisions.

The limitations of this study are primarily reflected in: (1) During literature collection, this study prioritized quality over quantity by applying stringent criteria to ensure data reliability. Consequently, some relevant literature was excluded from the meta-analysis. Future research should expand the literature database and employ larger, more evenly distributed samples to reduce sampling errors and enhance scientific rigor. (2) This study examined only one potential moderator variable, with insufficient depth in its exploration. Subgroup analysis revealed significant variations across different research samples, such as the number of dimensions, cultural differences, and measurement methods. Future research should therefore further supplement and refine the identification of potential moderator variables to continuously enhance the precision of research conclusions.

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References

[1] Ebersberger B, Bloch C, Herstad S J, et al. Open innovation practices and their effect on innovation performance. International Journal of Innovation and Technology Management, 2012, 9(06): 1250040.

[2] Xu C, Chen X, Chen J. Effect of digital transformation on open innovation. Technology Analysis & Strategic Management, 2025, 37(13): 4113-4126.

[3] Naqshbandi M M, Tabche I. The interplay of leadership, absorptive capacity, and organizational learning culture in open innovation: Testing a moderated mediation model. Technological forecasting and social change, 2018, 133: 156-167.

[4] Chen X. Q, Chen L. M. Digital Transformation, Customer Collaboration, and Open Innovation Performance. Productivity Research, 2024, (07): 112-117.

[5] Shi Z. L, He J. S. Research on Enterprise Open Innovation Based on the Synergy of Technological Capabilities and Network Capabilities. Journal of Intelligence, 2011, 30(1): 99-103+98.

[6] Sanni M. Drivers of eco-innovation in the manufacturing sector of Nigeria. Technological Forecasting and Social Change, 2018, 131: 303-314.

[7] Ma W. J, Gao L. M. Research on Open Innovation Models Based on Different Motivations: The Case of Shenyang Machine Tool. Journal of Management Science, 2014, 11(2): 163-170.

[8] Wang X. Y, Ma W. R. The Impact of Knowledge Management on the Performance of Manufacturing Enterprises. Science of Science Research, 2018, 36(12): 2223-2232.

[9] Alameddine A. The mediating impact of knowledge-based HRM practices on the relationship between transformational leadership and open innovation. VINE Journal of Information and Knowledge Management Systems, 2025: 1-25.

[10]Chen Y. C, Sun P. B, Wang H. M. Can Intellectual Property Protection Policies Promote Open Innovation in Enterprises? An Empirical Study Using the National Intellectual Property Demonstration City Policy as a Quasi-Experiment. Research in Economics and Management, 2023, 44(04): 90-107.

[11]Li Y. J. A Study on the Mechanism of Enterprise Open Innovation from an Institutional Perspective. South China University of Technology, 2017.

[12]Wei H. G, Li H. Competency Model for Insurance Salespeople: A Qualitative Meta-Analysis. Management Review, 2015, 27(7): 146-155.

[13]Mark W. Lipsey, Wilson D B. Practical meta-analysis. Thousand Oaks, CA: Sage Publications, 2001.

[14]Hunter J E, Schmidt F L. Methods of meta-analysis: Correcting error and bias in research findings. Sage, 2004.

