Prerequisites for the Innovation Performance of Artificial Intelligence Laboratory: A Fuzzy-Set Qualitative Comparative Analysis

Jincheng Shi and Yingchun Wang

Abstract—**Artificial intelligence (AI) is widely adopted as a general-purpose technology, bringing about disruptive innovative changes. R&D laboratories (labs) from universities, enterprises, and public institutions drive AI innovation. However, research on the factors affecting AI innovation in R&D labs is rarely discussed. To address this gap, we constructed an adjusted technology-organization-environment framework to analyze different configurations that influence AI basic research and engineering breakthroughs. This article uses fuzzy set qualitative comparative analysis for analysis aimed at 43 international typical AI labs. The results indicate that technological, organizational, and environmental conditions jointly impact AI labs' innovation. Specifically, AI basic research depends on strong computing resources and a high-quality innovation ecology, and it is moving from academia to industry. AI Engineering breakthroughs rely on public R&D institutions and leading firms, and high-quality data has a significant impact on applications. The findings highlight the equivalent effect of different configurations in AI innovation. In addition, this study provides implications for the government's AI innovation policies and the technological management of AI labs.**

Index Terms—**Artificial intelligence (AI) laboratory, basic research, engineering breakthrough, innovation performance, qualitative comparative analysis (QCA).**

I. Introduction

As A general-purpose technology, AI innovation activities occur in different industries and organizations [1], [2], [3]. Like other general-purpose technology (electric, ICT, etc.), AI is bringing disruptive and breakthrough innovations, changing the path of technological innovation [4], leading to overall industrial transformation [5] and the emergence of new industries [4]. Various AI laboratories (labs) that support innovation and breakthroughs in AI technology continue to "surface," which are founded by universities, enterprises and national public research and development (R&D) institutes. For example, in 2012, the Artificial Intelligence (AI) Laboratory of Stanford University established the ImageNet computer vision recognition database and launched a challenge project, triggering a new wave of deep learning. Meanwhile, disruptive technologies emerge in firm's R&D lab to achieve and maintain profit monopolies [5]. In 2014, DeepMind launched AlphaGo, allowing humans to see the potential of AI. In 2022, the release of ChatGPT by OpenAI further pushed AI innovation to a new level. These breakthroughs in AI have led us to think about what factors affect the innovation of AI labs, and how to better support such labs in carrying out innovative activities and obtaining innovative results.

Existing studies on R&D labs present those organizational characteristics, policy environments, and industry trends affect lab innovation activities [6], [7], [8]. These studies select labs in traditional technical fields as samples, such as aviation, the automotive, biomedicine, telecommunications, and machinery [9], [10]. There are shortcomings in research on AI as a general-purpose technology innovation. First, regarding technology conditions, AI innovation activities are different from the innovation activities associated with other technologies. The data, computing power, and algorithm requirements are more prominent [11], and they cannot be separated from the support of digital technology infrastructure and data elements [12], [13]. Second, in terms of organization conditions, AI innovation activities are highly knowledge-intensive and capital intensive [14], AI R&D requires a large amount of resource input, and the continuous supply of resources from the government or the market affects AI innovation activities [12]. Third, regarding environment conditions, AI innovation is affected by the digital ecosystem. From the perspective of the innovation chain, AI innovation involves the matching and coordination of the basic layer, framework layer, technology layer, and application layer. High-quality regional AI knowledge clusters and industrial clusters will also generate powerful spillover effects [15].

Therefore, this article tries to answer the following research questions (RQs):

RQ1: What factors affect innovation in AI Labs?
RQ2: How will the matching between these factors affect the innovation performance of AI labs?

Clearly, these questions are very important for AI labs to carry out organizational activities and improve their innovation

Manuscript received 20 September 2023; revised 26 December 2023; accepted 12 January 2024. Date of publication 18 January 2024; date of current version 15 February 2024. This work was supported in part by the National Key R&D Program of China under Grant 2022ZD0116205, in part by Soft Science Research By Shanghai Science and Technology Innovation Action Plan under Grant 23692105600, in part by China Postdoctoral Science Foundation under Grant 2022M721742, and in part by Shanghai AI Lab. Review of this manuscript was arranged by Department Editor G. Marzi. *(Corresponding author: Jincheng Shi.)*

The authors are with the Governance Research Center, Shanghai Artificial Intelligence Laboratory, Shanghai 200232, China (e-mail: shijincheng0819@163.com; wangyingchun@pjlab.org.cn).

Digital Object Identifier 10.1109/TEM.2024.3355235

TABLE I
TYPICAL RESEARCH REGARDING PERFORMANCE, FACTORS IN R&D LAB

R&D lab performance			
Typical references	**Dimensions**	**Measures**	**Types**
Carayol and Matt [18]	Papers and patents	Statistical analysis.	Research performance
Coccia [19]	R&D performance	Publications, patents, etc.	
Coccia [20]	Output (publications) / input (researcher)	DEA model	
Conti and Liu [9]	Breakthrough output	Published in Science, Nature, Cell	
Llanos-Paredes [21]	Patent application	DID model	
Zhang et al. [22]	Radical invention patents	IPC code measurement	
Huang and Shiu [23]	R&D project	DEA model	Application performance
Intarakumnerd and Goto [8]	Number of spin-off companies	/	
Park et al. [24]	Sales, production cost	/	
Wu et al. [25]	Number of new products and patent applications	Questionnaire, likert7 scales	Cooperative performance

Factors influence R&D lab performance		
Typical references	**Dimensions**	**Conditions**
Intarakumnerd and Goto [8]	The mission of the research	Organization
	Competitive grants from the industry	Organization
	Government funding	Organization
	Close ties with the industry	Environment
	The development level of the regional innovation system	Environment
Nambisan et al. [13]	Digital infrastructure (data center, supercomputing)	Technology
Li et al. [26]	Innovation fund	Organization
Wu et al. [25]	Network structure hole	Environment
Fecher et al. [27]	Dynamic interaction of actors	Environment
	Amenities and resources	Technology
Zhang et al. [22]	Frequency of interaction between organization and its direct collaborators	Environment
	Size of the organization (resources available)	Organization
	R&D spending	Organization
	Age of the lab (stage of development)	Organization
Schiuma and Santarsiero [6]	Physical space	Technology
	Tangible infrastructure	Technology
	Intangible infrastructure	Technology

performance, but there is no theoretical research that systematically answers these questions.

To systematically explain AI innovation activities, we construct the adjusted "technology-organization-environment" TOE framework to integrate the influencing factors of AI in conjunction with the innovation context of AI laboratories. This article selects 43 typical AI labs around the world, through fuzzy-set qualitative comparative analysis (fsQCA) [16]. This article explains the impact of the technology foundation, organizational management, and AI ecosystem environment on the innovation performance of AI labs. This article divides the innovation performance of AI labs into basic research performance and engineering breakthrough performance, and it examines the differential performance of AI labs in basic research and engineering breakthroughs. By analyzing the configurations that achieve innovation performance, we obtain results that reveal various types of AI lab innovation paths that occur under different conditions, and we explain the role of different factors in AI lab innovation activities.

First, this study constructs an adjusted TOE framework to provide a systematic explanation of various factors that affect AI innovation [1], [2], [3]. This study focuses on the AI field and takes the configuration perspective to empirically explore the synergistic effect of multiple conditions on promoting innovation performance in AI labs under the TOE framework. Second, this study further demonstrates the raw of basic research on AI. This research finds that AI basic research innovation performance depends on strong computing resources and high-quality innovation ecology and is moving from academia to industry [17]. Third, this study further demonstrates the raw of engineering breakthrough in AI. It relies on public R&D institutions and leading firms, and high-quality data will have a significant impact on applications.

This article is mainly divided into five parts. Section II reviews R&D lab innovation and constructs the TOE analytical framework. Section III introduces the research method. Section IV conducts empirical analysis and obtains results. Section V discusses theoretical implications, and managerial implications. Section VI explains the conclusion, limitations, and future directions.

II. LITERATURE REVIEW AND RESEARCH FRAMEWORK

A. *Innovation Performance of AI Lab*

R&D labs have changed dramatically over the past few decades. Especially, various types of laboratories have emerged in emerging technology fields such as AI [6]. Different types of labs have different performances. Through a systematic literature review (see Table I), the innovation performance of R&D labs is mainly manifested in three aspects. First, research performance mainly reflects the scientific research ability or creativity of the R&D lab. In general, it is measured by the number of various types of papers (such as journal papers and conference papers) and the number of patent applications. Some scholars also classify papers based on their level and identify breakthrough innovations, for example, treating top papers published in Nature, Science, Cell, and various fields as breakthrough achievements [9]. Second, application performance mainly indicates that labs promote product commercialization, identify technology and product development trends [10], number of spin-off firms, and shorten technology usage cycles. Third, cooperative performance refers to the outputs of cooperation between R&D lab and other institutions, and the production of papers, patents, or products according to the needs of cooperation.

Unlike other technologies, as a general-purpose technology, AI has a wide range of impact and a large scope of destruction. Therefore, the measurement of AI Lab innovation performance has its particularity. AI labs make innovative contributions to basic research and engineering applications.

For basic research, most studies have used journal papers to measure basic research performance [8], [9], [18]. However, researchers in the AI field usually publish the latest and most cutting-edge research results at top-level conferences, and each top-level conference selects the best paper of the year. Therefore, the best paper is considered one of the best basic research achievements of the conference. These best papers reflect the breakthrough and disruptive progress of AI during that time.

For applications, some studies utilize patents and products as metrics to assess applied research outcomes [28], these indicators primarily reflect the technological innovation measures and solutions of AI in different fields [29]. It could be challenging to reflect on the overall engineering breakthrough performance of AI lab. Additionally, there is substantial know-how and tacit knowledge present in the engineering process within AI labs that typically do not result in patent or product development [30]. With the development of general AI, many AI labs have launched frontier models (include large language models). The development and training of foundation models require the consideration of various conditions and factors, and such modeling work is complex system engineering. A breakthrough in foundation model engineering reflects the comprehensive ability and overall level of AI labs about industrial applications. Therefore, this article uses AI labs that deploy foundation models as a proxy variable for engineering breakthroughs.

B. *Factors of AI Lab Innovation*

The TOE analysis framework serves as a theoretical foundation for investigating the factors that influence innovation in AI laboratories. Tornatzky and Fleischer introduced this framework in their 1990 book, "The Processes of Technological Innovation." As an organizational-level theory, the TOE analysis framework focuses on the impact of technological, organizational, and environmental factors on technological innovation [31], [32]. Technological factors encompass the characteristics of technology and its relationship with organizations, particularly the effects of technological infrastructure and maturity on organizational innovation. Organizational factors refer to the unique characteristics and resources of an organization, including size, resource quantity, strategy, structure, etc. [33], [34]. Environmental factors primarily concern the industry structure of the organization, regulatory environment of the government, and regional ecological conditions [34].

According to the TOE framework, this article systematically reviewed the factors that affect the innovation performance of R&D labs (see Table I). First, the technology condition refers to the infrastructure configuration of the R&D lab. Infrastructure includes the design of physical space, tangible infrastructure, and intangible infrastructure [35], [36]. Especially with the rise of emerging technologies such as AI and big data, digital infrastructure has had a significant impact on the innovation activities of R&D labs [13], [37]. Second, organization condition refers to the operation and management of R&D labs. For different labs, the goals and visions of the lab determine its future strategic direction [7], and strategic orientation (mission) affect organizational innovation behaviors [8]. The allocation of resources during the development process will affect the development of the lab. In addition, the interdisciplinary background of the lab team [38] the age of personnel, and their research experience can all have an impact on R&D [18]. Third, environment condition refers to the innovation environment in which R&D labs are located. Like universities, enterprises and other organizations, the regional ecosystem, industrial clusters, and innovation networks in which R&D labs are located will also have an impact on lab innovation [39]. For example, if an R&D lab is situated in the epicenter of the innovation network, it is more likely to acquire a plethora of information and make significant strides in its development.

C. *Research Framework*

Based on the above analysis, this article points out that current research has explored the effects of single influencing factors on innovation performance. The development of labs is affected by multiple factors. Different factors may jointly affect lab innovation performance. It is necessary to discuss the combination of such influencing factors in depth. Meanwhile, the resources and conditions required for innovation in different types of technologies are different [40]. According to Table I, the influencing factors related to AI innovation include digital infrastructure (technology), strategic orientation (organization), resource investment (organization), AI innovation ecosystem (environment), etc. This article constructs an adjusted TOE analysis framework in conjunction with the innovation context of AI (see Fig. 1).

Technology condition. The rise of AI and its development in many areas of knowledge in recent years are attributed to key factors: large amounts of data and significantly better computing hardware. This evolution has drawn the attention of large tech-oriented organizations to AI tools [41].

1) *Data foundation:* AI relies on data training algorithms to make predictions and decisions [42]. More data mean higher accuracy and more technical capabilities [43]. With the continuous development of AI technology, the scale of data required has increased significantly. Data elements are rich in resources and large in scale and can provide multisource heterogeneous data for AI training and learning. For example, in 2020, the amount of training data

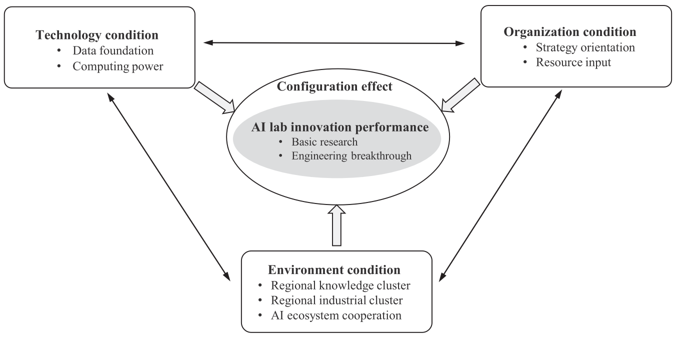

Fig. 1. Research framework (the adjusted TOE model).

for GPT-3 reached 500 billion words, and the latest foundation model will further double the amount of training data.

2) *Computing power:* The computing power realized by using AI chips as carriers is an important measure of the development level of AI. In semiconductors, cutting-edge AI chips are critical for processing big data through machine learning, especially using deep learning [12]. Other studies suggest that the "computing divide" (uneven access to computing power) is a likely primary factor contributing to the concentration of AI research in large technology companies. AI innovation requires a flexible, cost-effective, and scalable computing infrastructure that serves all aspects of the AI lifecycle [44]. Whether or not there are strong computing power resources will affect the development of AI innovation activities.

Organization condition. Like other types of R&D labs, the strategic orientation and resource input of AI labs affect lab innovation activities. In addition to general organizational conditions such as organization size and personnel quantity, the strategic orientation of the AI lab and differentiated resource investment methods can also have impacts on their innovation activities.

3) *Strategic orientation:* Different types of labs have certain differences in the strategic orientation of AI innovation activities. The difference due to goals and visions will affect the development of lab innovation activities [45]. Strategic orientation plays a crucial role in shaping the selection of knowledge resources for searching and evaluating, as well as the types of knowledge invested in for competitive advantage [46]. For example, corporate strategic orientation can be divided into customer orientation, technology orientation, and combined customer/technology orientation [47]. Studies have shown that organizations that focus on both customers and technology tend to perform better than those that prioritize either one over the other [46]. When it comes to AI labs, their strategic orientation can be broadly categorized into four options: market orientation, future orientation (focused on scientific research), a combination of both market and future orientation, and national needs and key tasks. Each option has its unique benefits and considerations, depending on the specific goals and objectives of the laboratory. By aligning their strategic orientation with these factors, AI labs can better navigate the ever-evolving landscape of the industry and stay ahead of the competition.

4) *Resource input:* AI R&D activities need to be supported by a large amount of data and powerful computing power, and knowledge and capital are highly concentrated in the R&D process [48], which requires continuous funding. Laboratory funding can be divided into government investment-dominated and market investment-dominated types, according to the source. Government R&D funds pay more attention to basic research, whereas market-based funds tend to focus more on applied research and product development. Furthermore, the utilization of government R&D funds is typically subject to strict regulations, which limits their flexibility and can lead to efficiency challenges during the R&D process. Nevertheless, government R&D funds offer relative stability compared to market-based funds, providing long-term assurance for laboratory research initiatives [49].

Environment condition: AI innovation is rooted in the ecosystem. Regional knowledge ecosystem, industrial ecosystem, and business ecosystem have positive impacts on AI innovation [50]. Regional clusters knowledge clusters, industrial clusters, and ecosystem cooperation [51] are important factors that affect industrial development and innovation effectiveness.

5) *Regional knowledge clusters:* Regional knowledge clusters formed by universities and scientific research institutes [52] provide a high-quality innovation environment for the development of AI R&D activities. The externality effect of the cluster benefits the innovation subjects. Localized knowledge spillovers within a region can lead to agglomeration, resulting in lower costs of acquiring knowledge within a smaller geographical area [50]. Knowledge spillover allows innovative knowledge to diffuse in the region [53] and laboratories can obtain novel R&D knowledge, reducing their own R&D costs [54].

6) *Regional industrial clusters:* Regional industrial clusters are formed by enterprises and venture capital institutions [55]. For example, Montreal is considered to be one of the cities with the densest AI in the world. Through a case study, Doloreux and Turkina [15] found that the emergence of Montreal's AI industry is rooted in a strong information and communication technology (ICT) industry knowledge base and advantageous geographical decisions. The dense network of ICT participants has laid an important foundation for the survival and prosperity of AI participants.

7) *AI ecosystem cooperation:* The innovation ecosystem is a stable structure formed by multilateral partners who interact to realize the value proposition [56]. The relationship between the focal organization and its upstream and downstream partners in the ecosystem affects its competitive advantage [57]. Therefore, when the partners in the ecosystem collaborate, the focal organization can create value that no single organization can create alone [58]. Therefore, the innovation of the focal organization in the AI innovation ecosystem is also influenced by cooperation

with ecological partners. Having more partners and deeper cooperative relationships in AI ecosystem are beneficial for technological innovation. Collaborative research with a wide range of partners can enable innovative enterprises to obtain the necessary information from various sources, thereby generating more synergies and supplementing knowledge, thereby improving innovation performance. Meanwhile, cooperation can enable people to acquire more intangible and implicit knowledge and tricks. For example, after international leaders such as Google and Facebook set up AI labs in Montreal, the local AI industry developed rapidly [15]. The cooperation between a lab and enterprises, universities, scientific research institutes and venture capital institutions is conducive to reducing the cost of technical exchange, acquiring external knowledge, and promoting innovation.

Fig. 1 presents the adjusted TOE framework. The technology condition includes computing power and data foundation. The organization's condition includes strategic orientation and resource inputs. The environment condition includes regional knowledge clusters, regional industrial clusters, and AI ecosystem operations. AI lab innovation performance encompasses both basic research performance and engineering breakthrough performance. By analyzing these various components, we can better understand how they interact and influence one another to drive AI innovation.

III. Methodology

A. Sample and Data

The qualitative comparative analysis (QCA) method was proposed by Ragin. Due to the advantages that traditional statistical analysis methods do not have and the concurrent nature of multiple factors, the academic community has shown a significant upward trend in the use of this method. Research using this method involves various disciplines [59], [60]. This study examines the various influencing factors of AI lab innovation from the perspective of configuration analysis, including the synergistic effects of the AI technology conditions, organization conditions, and environment conditions on AI lab innovation. QCA based on set theory overcomes the traditional binary relation statistical method of independent variables and dependent variables and presents the complex mechanism underlying multiple variables and integrates the advantages of case studies to achieve multiple configurations based on case induction reasoning.

This article mainly conducts theoretical sampling based on three aspects. First, the types of AI labs include those created by enterprises, universities, and public R&D institutes. These different types of labs play active roles in AI innovation activities. Therefore, from the perspective of the breadth of the case, the sample should include AI labs created by different entities. Second, this study takes an international comparative perspective and needs to consider the country distribution of AI labs. At present, global research on AI is mainly concentrated in the United States, China, and Europe. Therefore, in terms of case selection, this article considers the key regions mentioned above and selects typical regions such as Southeast Asia and North America, comprehensively covering labs from different

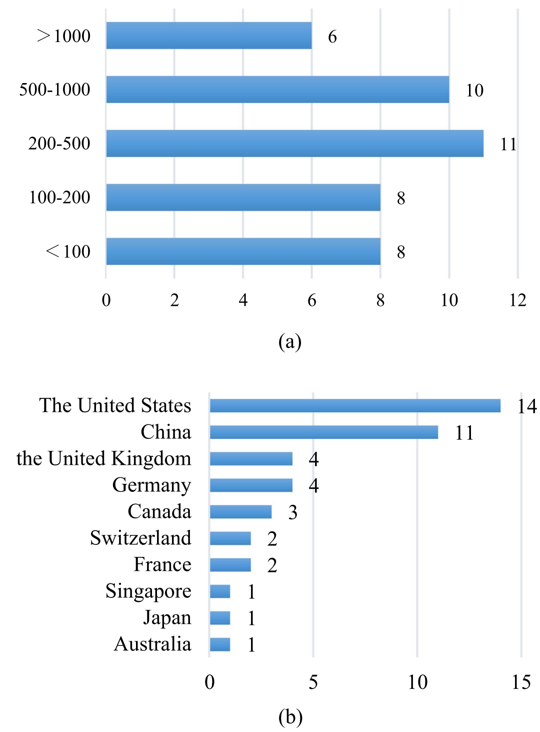

Fig. 2. Case descriptions. (a) Number of laboratory personnel. (b) Laboratory country distribution.

countries and regions. Third, based on the requirements of QCA, we need to reflect more heterogeneity in as few cases as possible so that the possibilities of configuration combinations are sufficiently diverse and have a high case coverage rate. Therefore, we should consider the heterogeneity of different AI labs as much as possible in case selection. Based on the analytical framework of the study, there are differences in the technology conditions, organization conditions, and environment conditions of the selected cases.

Based on the criteria above, we selected 43 typical AI labs as cases (see Fig. 2). This study divided the number of laboratory personnel into 5 levels, and according to Table II, the distribution of laboratories with different personnel sizes is relatively uniform. It should be noted that traditional statistical regression analysis emphasizes data normalization. The laboratory innovation discussed in this paper is influenced by national innovation ability, R&D resources, etc. In order to enhance the comparability of samples, most of the data measurements in this article adopt categorical variables, which not only avoids the complexity and inaccuracy of normalization processing but also helps identify multiple configurations and give full play to the advantages of fsQCA method. In subsequent research, we conducted a configuration combination analysis based on the level of innovation performance in AI labs, exploring the combination of factors that affect the innovation performance of such labs.

B. Measures of Variables

Outcome variable: Innovation performance is divided into two aspects: basic research performance and engineering breakthrough performance.

TABLE II
MEASUREMENT AND CALIBRATION OF CASUAL CONDITION OPERATIONS

Conditions		Measurement	Calibration		
			Unaffiliated	**Intermediate**	**Affiliated**
Innovation performance	Basic research performance	Number of best papers at top conferences in the AI field	0	1	2
	Engineering breakthrough performance	Deployment of foundation model in the AI field	0	2	3
Technology condition	Computing power	Two types: self-built or relying on parent computing platforms; relying on external computing platforms	0	/	1
	Data foundation	Four categories: massive amounts of data; large amount of data about an industry; segmented domain data; need to collaborate to obtain relevant data from external sources	1, 0.67, 0.33, 0		
Organization condition	Strategic orientation	Four categories: market orientation; market and future orientation; core task orientation; future orientation	1, 0.67, 0.33, 0		
	Resource input	Two types: government input mainly; market input mainly	0	/	1
Environment condition	Regional knowledge cluster	The output of academic institutions based on the basic research index in the 2020 Global Artificial Intelligence Most Innovative Cities List	59	70	80
	Regional industrial cluster	The output of enterprises based on the applied research index in the 2020 Global Artificial Intelligence Most Innovative Cities List	59	70	80
	Ecosystem cooperation	The degree of cooperation between AI labs and ecosystem partners	1， 0.67， 0.33， 0		

1) Basic Research Performance: Basic research performance can be calculated by calculating the score of the best paper in the conference. The top conferences in the AI field defined in this article are determined according to the CCF Class A conference standards, including seven important conferences.[1] This article summarizes the lab to which the best paper belongs, with a statistical period from 2020 to 2022. In general, the authorship order in a paper is determined by the level of contribution each individual made to the research. The scoring rules are arranged in descending order of author units.

The rules are as follows.

1) The first unit receives 1 point, the second unit receives 0.5 points, the third unit receives 0.25 points, and the fourth unit receives 0.1 points.
2) The communication unit is considered the first unit and receives 1 point.
3) If an author annotates multiple units at the same time, the units will be ranked in order of priority.
4) This article points out that authors have equal contributions and represent units with the same scores, regardless of order. If the authors of the first, second, and third units have equal contributions, they shall be considered the first unit.
5) The author's unit in this article is determined based on the discipline to which the author belongs and the location of his or her research training.

For example, if the author belongs to the Department of Computer Science at Stanford University but his or her research group or research training is located in the Stanford University Artificial Intelligence Laboratory, the unit will be counted as the Stanford University Artificial Intelligence Laboratory.

2) Engineering Breakthrough Performance: The time window observed in this article is from 2020 to 2023, and the main achievements of various AI labs are observed. This article compares and analyses the deployment of foundation model R&D in different labs based on two dimensions: foundation model iteration (fast iteration, slow iteration) and foundation model layout (multipoint layout, single-point layout). The iteration speed of foundation models refers to the continuous training of AI labs to optimize foundation models; foundation model layout refers to the layout of AI labs on foundation models. In the former, a single-point layout around areas such as language, speech, images, and videos is formed, while in the latter, a multipoint layout is formed and simultaneously promoted. Based on these two dimensions, current engineering breakthroughs in foundation models in AI labs can be divided into three typical stages (see Fig. 3).

The rules are as follows.

1) The initial stage is for a single-point layout on a foundation model that has not yet undergone iteration and is assigned a value of 1.
2) The development stage is divided into two types. The first type involves a multipoint layout in the field of foundation models, which have a slower iteration speed and are assigned a value of 3. The second type focuses on a single-point layout that quickly achieves iteration, with a value of 3.
3) Regarding the breakthrough stage, an AI lab forms a multi-point layout and iterates quickly, with a value of 5. Between the development stage and breakthrough stage,

[1] The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Neural Information Processing Systems (NeuroIPS), IEEE International Conference on Computer Vision (ICCV), International Conference on Machine Learning (ICML), AAAI Conference on Artificial Intelligence (AAAI), Annual Meeting of the Association for Computational Linguistics (ACL), and International Joint Conference on Artificial Intelligence (IJCAI). Among them, ICCV is held every two years.

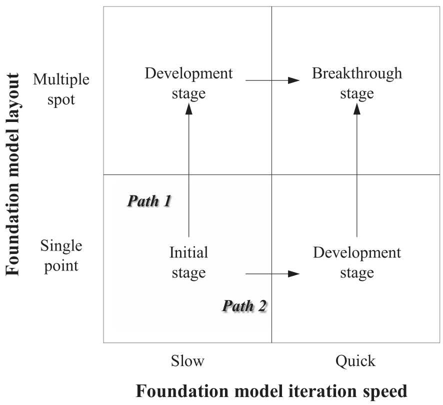

Fig. 3. Deployment and assignment of the foundation model AI lab.

a value of 4 is assigned. Between the initial stage and development stage, a value of 2 is assigned. In addition, for labs that have not deployed large-scale model engineering, a value of 0 is assigned.

Condition variables. The conditions in this article are mainly divided into the technology condition, organization condition, and environment condition of AI labs.

1) *Computing power:* This indicator is used to measure the computing power of AI labs. At present, there are different types of computing power construction in AI labs. The first type is self-built or relies on parent computing power platforms. The second type relies on external computing platforms. The assignment rules in this article are as follows: For the first type, we assign a value of 1, and for the second type, we assign a value of 0. The data was sourced from information regarding the construction of computing infrastructure that was made publicly available on the laboratory's official website or the parent company's official website.
2) *Data foundation:* This indicator is used to measure the database of AI labs. This article divides the data foundation into four categories: The first category has its own massive data, including data from various industries and fields. The second type has a large amount of industry data, focusing on a certain industry and possessing rich data in that industry, such as a large amount of image and video data in the e-commerce industry. The third category has segmented domain data, such as medical scenarios, transportation scenarios, and education scenarios. In the fourth type, AI labs do not have data and require cooperation to obtain relevant data from external sources. The richness of these four types of data decreases in sequence. The assignment rules of this article are as follows: The first type is assigned a value of 1, the second type is assigned a value of 0.67, the third type is assigned a value of 0.33, and the fourth type is assigned a value of 0. The data was obtained from two sources: perusing publicly available dataset information on the laboratory's website and integrating it with third-party research reports and news media articles for data validation.
3) *Strategic orientation:* Innovation performance varies among labs with different strategic orientations. Based on the mission of AI labs, this article divides the strategic orientation of AI labs into four categories. The first type of strategic goal is oriented towards the market. The second type of strategic goal is oriented towards the market and towards the future (scientific research). The third type of strategic goal is oriented towards national needs and key tasks. The fourth type of strategic goal is oriented towards the future (scientific research). This study compared the keywords in the vision and goals of the laboratory. The market orientation includes keywords such as enterprise development, technology and industry integration, products, and market leadership. The future orientation involves keywords such as basic research, disruptive innovation, and focusing on the forefront. The national needs and key task orientation involve keywords such as key core technologies, projects, and maintaining national status. Market orientation and future orientation are two completely different types of strategic orientation. Based on the degree of differentiation in strategic orientation, the first type is assigned a value of 1, the second type is assigned a value of 0.67, the third type is assigned a value of 0.33, and the fourth type is assigned a value of 0.
4) *Resource input:* Resource input refers to the source channels of AI lab resources (mainly funds). There are differences in the funding sources of different AI labs, which can be generally divided into two categories: government input and market input, including enterprises, venture capital, charitable organization donations, etc. The assignment rules of this article are as follows: Government input is assigned a value of 1, and market input is assigned a value of 0. The data are sourced from publicly available information on the laboratory's official website and annual reports.
5) *Regional knowledge cluster:* This indicator refers to the agglomeration effect of regional AI basic research, and knowledge cluster actors typically include universities, research institutes, etc. If a regional knowledge cluster has a large output of achievements, it will generate spillover effects, which are conducive to the innovative development of AI labs. This article takes the output of academic institutions as the research object of basic research innovation, and the research results are measured by papers. The data are sourced from the 2020 Global AI Most Innovative Cities List.
6) *Regional industrial cluster:* This indicator refers to the agglomeration effect of regional AI applied research, and industry cluster actors usually include upstream and downstream enterprises in the AI industrial chain. If the regional industrial cluster is good and has a large amount of applied research results, it is conducive to the innovative development of AI labs. This article takes the output of enterprise institutions as the research object of application innovation, and the research results are measured by papers. The data are sourced from the 2020 Global AI Most Innovative Cities List.
7) *Ecosystem cooperation:* This indicator refers to the degree of cooperation between AI labs and AI ecosystem partners. This article summarizes the ecosystem cooperation of AI labs and finds that there are four different degrees of

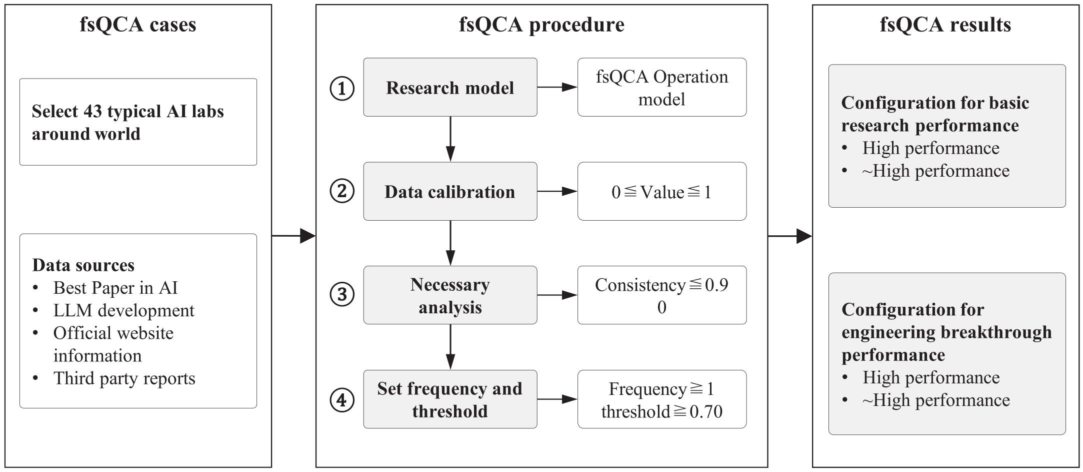

Fig. 4. Implementation steps.

cooperation: In the first type, AI labs obtain venture capital or funding support, form close strategic cooperation (stock support), and form strategic alliances, which are very close in degree. In the second type, AI labs jointly establish research institutes with partners in the AI lab to carry out joint research work. In the third type, AI labs conduct external talent cultivation and internship exchanges in AI labs, attracting personnel to conduct research in the labs. In the fourth type, AI labs actively release projects to the public, participate in meetings and discussions, etc. In response to these types, the assignment rules of this article are as follows: The first type is assigned a value of 1, the second type is assigned a value of 0.67, the third type is assigned a value of 0.33, and the fourth type is assigned a value of 0. The data are sourced from the laboratory's official website, annual reports, and media reports. This study sorted out the cooperation information from each laboratory and assigned values based on the degree of cooperation. For example, when a laboratory establishes a strategic alliance with industry enterprises and receives financial support, it is assigned a value of 1.

B. Models and Data Analysis Procedure

The implementation steps of this article are as follows (see Fig. 4):

According to Table I, unlike existing DEA, DID, and statistical regression analyses [61], this study is based on the principle of Boolean algebra for fsQCA operation (Quine McCluskey). The fsQCA method allows us to analyze the interactions between different variables and the effects of configurations, which is also the advantage of the method used in this article.

The research models are as

$$\mathrm{BRP} = f\,(\mathrm{cp}, \mathrm{df}, \mathrm{so}, \mathrm{ri}, \mathrm{kc}, \mathrm{ic}, \mathrm{ec}) \tag{1}$$

$$\mathrm{EBP} = f\,(\mathrm{cp}, \mathrm{df}, \mathrm{so}, \mathrm{ri}, \mathrm{kc}, \mathrm{ic}, \mathrm{ec})\,. \tag{2}$$

BRP is the basic research performance, EBP is the engineering breakthrough performance, cp is the computing power, df is the data foundation, so is the strategic orientation, ri is the resource input, kc is the regional knowledge cluster, ic is the regional industrial cluster, ec is the ecosystem cooperation.

This study used fsQCA3.0 as an analytical tool and followed the following steps [62].

First, data calibration. Before starting fsQCA, it is necessary to transform the values of the variables and adjust the original metric to a fuzzy score ranging from 0.0 to 1.0. An example of the Calibrate command is as follows, BRP^1 is the calibrated value.

$$\mathrm{BRP}^1 = \mathrm{Calibrate}\,(\mathrm{BRP}, \mathrm{affiliated}, \mathrm{intermediate}, \mathrm{unaffiliated}). \tag{3}$$

When there is a lack of theoretical support, the thresholds for each metric should be based on substantive knowledge and the original score distribution across cases. Based on current practice, we conducted an investigation of 43 samples using a direct calibration method to set unaffiliated points, affiliated points, and intermediate points (see Table II). Descriptive analysis of data is shown in Table III.

Second, necessary analysis. The fsQCA based on subjective assignment relaxed the requirements for initial accuracy but added consistency score and coverage score indicators to measure the reliability of the conclusion. As shown in Appendix Table IX and X, conditions do not constitute sufficient and necessary conditions for the realization of outcome variables. Except for computing power, the necessity of all individual antecedent conditions affecting the outcome variable does not exceed 0.9, which does not constitute or approximate a necessary condition. It shows no single antecedent variable constitutes a sufficient condition for innovation performance, further conditional combination analysis is needed.

Third, set sample frequency and consistency threshold. The sample frequency is determined based on the sample size, and small samples are generally 1. The consistency threshold is generally not less than 0.70. To enhance the explanatory power of the study, a consistency threshold will be set based on existing research experience and natural breakpoints.

Fourth, configuration analysis. Software operations generally export three types of solutions, namely complex solution, parsimonious solution, and intermediate solution. Generally, we

TABLE III
DESCRIPTIVE STATISTICS

Conditions	Mean (calibrated)	SD (calibrated)	Skew (calibrated)	Kurt (calibrated)
Basic research performance	0.41	0.39	0.47	-1.48
Engineering breakthrough performance	0.45	0.39	0.45	-1.63
Computing power	0.91	0.29	-2.90	6.75
Data foundation	0.54	0.36	0.08	-1.33
Strategic orientation	0.48	0.33	-0.23	-1.05
Resource input	0.58	0.50	-0.34	-1.98
Regional knowledge cluster	0.45	0.43	0.32	-1.85
Regional industrial cluster	0.53	0.35	0.06	-1.51
Ecosystem cooperation	0.71	0.27	-0.54	-0.33

Note: Data analysis after fsQCA calibration.

TABLE IV
CONFIGURATION OF HIGH BASIC RESEARCH PERFORMANCE IN AI LABS[2]

Conditions	Configurations for high basic research performance				
	1		2		3
	1a	1b	2a	2b	
Computing power	•	•	•	•	●
Data foundation		•	•		⨂
Strategic orientation	⊗		●	●	●
Resource input	•	•		⊗	•
Regional knowledge cluster	●	●	●	●	⊗
Regional industrial cluster	●	●	●	●	●
Ecosystem cooperation	●	●	●	●	●
Raw coverage	0.271	0.174	0.360	0.311	0.133
Unique coverage	0.106	0	0	0.022	0.074
Consistency	0.864	0.847	0.792	0.797	0.774
Overall solution coverage	0.665				
Overall solution consistency	0.813				
Frequency cut-off	1.000				
Consistency cut-off	0.749				

choose the parsimonious solution. If the antecedent condition occurs simultaneously in both the simplified path and the intermediate path, it is the core condition; If this condition only appears in the middle path, it is referred to as an edge condition. Consistency measures the degree to which each solution and the entire solution are subsets of the result set. Coverage measures the extent to which each solution and the entire solution cover (or explain) the results. These measurements are calculated by examining the original fuzzy data set corresponding to one or more schemes.

[2]● represents the existence of core causal conditions; ⨂ represents the absence of core causal conditions; • represents the existence of auxiliary causal conditions; ⊗ represents the absence of auxiliary causal conditions; and a blank cell indicates that the condition in the configuration can or cannot exist.

IV. RESULTS

A. *Configurations of Basic Research Performance*

For high basic research performance, this study sets the frequency threshold as 1. According to the truth table, there is an obvious natural breakpoint between 0.67 and 0.74; thus, 0.70 is selected as the consistency threshold. The overall consistency of the middle path is 0.81, and the coverage rate is 0.67, which better explains the real case. Based on the core conditions, we divide basic research performance into three configurations (see Table IV).

Based on Table IV, this study found three typical paths to achieve high basic research performance.

The first type of configuration is a free exploration type (include 1a, 1b in Table IV). AI labs affiliated with universities usually rely mainly on government investment to build powerful computing resources. They are located in regional knowledge and industrial clusters with high spill overs and carry out close ecosystem cooperation, which can achieve basic research innovation. For universities, basic research is one of their core missions. Thus, their AI labs need to carry out breakthrough research in the AI field. The resources of labs affiliated with such universities mostly rely on government investment, and the parent universities generally have leading supercomputing, high-performance computing platforms, etc. These favorable resource conditions lay the foundation for universities to carry out basic research on AI. At the same time, most of these labs are in highly overflowing AI cluster environments, with strong regional innovation ecosystems formed by upstream and downstream enterprises and research institutes in the AI industrial chain. These labs obtain AI technology development trends and richly heterogeneous knowledge through close ecosystem cooperation. Specifically, AI labs affiliated with universities are guided by the pursuit of scientific research, forming a free exploration mode in basic research, thereby promoting the continuous development of basic theories of AI.

For example, labs, such as Stanford University's AI Laboratory, MIT CSAIL, and the Paul G. Allen School of Computer Science & Engineering have made fundamental theoretical breakthroughs in AI, playing a leading theoretical role globally.

The second type of configuration is the market-driven type (include 2a, 2b in Table IV). AI labs affiliated with enterprises are market oriented, and by building powerful computing resources, being in regional knowledge and industrial clusters with high spill overs, and conducting close ecosystem cooperation, basic research innovation can be achieved. For leading enterprises, breakthroughs in basic research can bring them technological advantages and potential market benefits. Therefore, we see that most of the leading enterprises in the world are gradually carrying out basic research. The resources of labs affiliated with such enterprises mostly rely on the investment of the parent enterprise. Notably, these leaders usually have the key technology foundation to carry out AI innovation. They possess powerful cloud computing platforms or supercomputing, which provide computing power support for conducting a large amount of cutting-edge research. At the same time, leading enterprises have accumulated a large amount of industry or field data in the process of business development, and these data become the "fuel" for AI innovation. At the same time, most of these leading enterprises are located in areas with highly developed AI industries. A strong regional innovation ecosystem provides a source of driving force for the sustainable innovation of enterprises. Specifically, AI labs affiliated with enterprises are market oriented, forming a market-driven mode in basic research. On the one hand, such labs serve enterprises' own business; on the other hand, they achieve basic theoretical guidance. For example, Google Research focuses on the frontier of AI and makes pioneering achievements in the fields of transformer architecture, machine learning, responsible AI, natural language processing, etc. Microsoft Research continues to explore fundamental issues in fields such as deep learning, reinforcement learning, dynamic system learning, etc.

The third configuration is a platform expansion type (include 3 in Table IV). AI labs affiliated with public R&D institutes are market oriented, and for them, the government is the main source of funding. They build a strong computing platform and collaborate to obtain relevant data, and they are in a highly overflowing regional industrial cluster and conduct close ecosystem cooperation, which can achieve basic research innovation. For public R&D institutes, their core mission is to follow national strategies, complete core tasks, and carry out basic research work under the guidance of their task orientation. AI labs affiliated with such public R&D institutes are usually established with government support. The government provides funding to conduct R&D. At the same time, the area where such labs are located is also unique, and they are usually located in areas with developed AI industries. On the one hand, when setting up this type of lab, the government will consider the platform empowerment role of public R&D institutes to promote the sustainable development of regional industrial operations. On the other hand, the AI industry with regional concentration will also provide abundant resources for the development of labs. Specifically, AI labs affiliated with public R&D institutes are market oriented (task oriented) and promote basic research by integrating the innovative resources of regional industries, forming a platform expansion model in basic research. For example, as a public R&D institute supported by the Canadian government's AI strategic budget, the Vector Institute for AI conducts research with more than 30 enterprises from various fields, including Google, Nvidia, Thomson Reuters, and KPMG.

TABLE V
CONFIGURATION OF ~HIGH BASIC RESEARCH PERFORMANCE IN AI LABS

Conditions	Configurations for ~high basic research performance		
	4	5	6
Computing power	●	⊗	●
Data foundation	⊗	⊗	●
Strategic orientation		⊗	●
Resource input	●	●	⊗
Regional knowledge cluster	⊗	⊗	⊗
Regional industrial cluster	⊗	●	⊗
Ecosystem cooperation	●	●	●
Raw coverage	0.191	0.046	0.123
Unique coverage	0.191	0.046	0.123
Consistency	0.816	0.873	0.934
Overall solution coverage	0.361		
Overall solution consistency	0.860		
Frequency cut-off	2.000		
Consistency cut-off	0.850		

For ~high basic research performance, this study sets the frequency threshold as 2 and chooses 0.80 as the consistency threshold. The overall consistency of the middle path is 0.86, and the coverage rate is 0.36, which well explains the real-world cases. The core condition of ~high basic research performance is the regional knowledge cluster, and there are three configurations (see Table V).

We find that regional knowledge clusters have a significant impact on basic research on AI (include 4, 5, and 6 in Table V). Even if some AI labs have strong computing power and a good data foundation, it is still difficult for them to achieve high performance. From the perspective of basic research activities, more diverse and heterogeneous knowledge is beneficial for knowledge creation. In general, basic research in AI labs benefits from spill over regional knowledge clusters. A group of research-oriented universities and top research institutes has gathered in the region, forming a strong knowledge base. Through in-depth communication, discussion, and learning, this knowledge has spill over and diffusion effects, providing rich "nourishment" for AI labs. For example, the San Francisco Bay Area, Seattle, Beijing, and Shanghai have leading research universities and top scientific research institutes, forming a strong knowledge cluster within the space.

B. *Configurations of Engineering Breakthrough Performance*

For high engineering breakthrough performance, this study sets the frequency threshold as 1. According to the truth table,

TABLE VI
CONFIGURATION OF HIGH ENGINEERING BREAKTHROUGH PERFORMANCE IN AI LABS

Conditions	Configurations for high engineering breakthrough performance			
	1		2	3
	1a	1b		
Computing power	●	●	●	●
Data foundation	⬤	⬤		⬤
Strategic orientation	⬤	⬤	⊗	⬤
Resource input	⊗	⊗	●	⊗
Regional knowledge cluster	⊗	⊗	⬤	●
Regional industrial cluster	⊗		●	●
Ecosystem cooperation		⊗	⬤	●
Raw coverage	0.182	0.099	0.218	0.288
Unique coverage	0.091	0.023	0.218	0.254
Consistency	0.913	0.919	0.763	0.859
Overall solution coverage	0.677			
Overall solution consistency	0.837			
Frequency cut-off	1.000			
Consistency cut-off	0.780			

there is an obvious natural breakpoint between 0.69 and 0.78; thus, 0.70 is selected as the consistency threshold. The overall consistency of the intermediate path is 0.84, with a coverage rate of 0.68, which better explains real-world cases. There are three configurations in total (see Table VI).

Based on the configurations in Table VI, this research finds that there are three typical paths for engineering breakthroughs in AI.

The first type of configuration is technology driven (include 1a, 1b in Table VI). AI labs affiliated with enterprises are market oriented, and for them, the market is the main source of funding. They build powerful computing platforms and possess a massive database, making it possible to achieve engineering breakthroughs. For enterprises, achieving breakthroughs in AI engineering is a key link in the commercialization process. Thus, enterprises have an inherent motivation to achieve engineering breakthroughs, and therefore, they are willing to invest high amounts of money in engineering breakthroughs in pursuit of sustained competitive advantages in the market and the competitiveness of their technology/products. Meanwhile, for leading enterprises, their AI labs have the technology foundation for engineering breakthroughs. Strong computing power and massive data provide the technical conditions for conducting AI R&D training and engineering breakthroughs. Specifically, AI labs affiliated with enterprises form a technology-driven model in engineering breakthroughs, with a strong technology foundation and financial investment ensuring the stability of the AI R&D process. For example, relying on the powerful Alibaba cloud computing platform and various types of language data on the internet, the Alibaba Dharma Academy launched the "Tongyi Qianwen" foundation model in 2023, empowering industry enterprises to explore more insights, explore new business models, expand their business, and create more cutting-edge products and services for society.

The second type of configuration is ecologically driven (include 2 in Table VI). AI labs affiliated with universities or public R&D institutes are oriented towards scientific research and mainly rely on government investment to build a powerful computing power platform. They are in highly overflowing regional knowledge clusters and industrial clusters and carry out close ecosystem cooperation to achieve engineering breakthroughs. This path has more constraints on AI labs. On the one hand, these labs are oriented towards scientific research, with the government as the core funding entity, supporting the construction of supercomputing centers and high-performance computing platforms. On the other hand, the regions where such labs are located have highly developed knowledge clusters and industrial clusters, forming an active regional innovation ecosystem for universities, enterprises, research institutes, etc. Through close ecosystem cooperation, AI labs establish strategic alliances, collaborate on technological breakthroughs, and obtain rich data to support their R&D training work. Specifically, AI labs affiliated with universities or public R&D institutes form an ecologically driven model in engineering breakthroughs, with strong knowledge and industrial cluster resources providing a rich resource supply for AI R&D. For example, the Department of Computer Science and Technology at Tsinghua University in Beijing has benefited from the high-quality regional innovation ecosystem, leading to engineering breakthroughs in AI. From a regional perspective, Beijing has the highest number of highly influential AI scholars in China, with a total scale of over 40 000 core industry professionals and approximately 1500 related enterprises, accounting for 28% of the country's total. It ranks first in China and has produced more than 30 AI unicorn enterprises, becoming the largest gathering place for academic and industrial talent in AI in China.

The third type of configuration is dual technology and ecologically driven (include 3 in Table VI). AI labs affiliated with enterprises are market oriented, build a powerful computing power platform, have a massive database, are in a highly overflowing regional knowledge cluster and industrial cluster, and carry out close ecosystem cooperation. This configuration can enable engineering breakthroughs. The EB3 configuration is like the EB1 configuration. In addition to having the same technical capabilities, this type of lab is in a well-established regional ecosystem. Regional knowledge clusters and industrial clusters are highly overflowing, and AI labs are engaged in close ecosystem cooperation. Specifically, AI labs affiliated with enterprises form a technology and ecologically driven model in engineering breakthroughs, with a strong technology foundation and high-quality regional ecosystem providing internal and external strength for AI R&D. For example, OpenAI, Meta AI, and NVIDIA Research, three top AI labs, are in the San Francisco Bay Area. The regional innovation ecological index is among the highest in the world. According to the 2020 list of the most innovative cities in global AI, the Bay Area is in the first class in terms of the regional knowledge cluster and industrial cluster. In

TABLE VII
CONFIGURATION OF ~HIGH ENGINEERING BREAKTHROUGH PERFORMANCE IN AI LABS

Conditions	Configurations for ~high engineering breakthrough performance	
	4	5
Computing power	●	⊗
Data foundation	⊗	⊗
Strategic orientation		⊗
Resource input	●	●
Regional knowledge cluster	⊗	⊗
Regional industrial cluster	⊗	●
Ecosystem cooperation	●	●
Raw coverage	0.238	0.057
Unique coverage	0.238	0.057
Consistency	0.944	1.000
Overall solution coverage	0.295	
Overall solution consistency	0.954	
Frequency cut-off	2.000	
Consistency cut-off	0.903	

addition, these three labs have outstanding technical capabilities. Behind OpenAI is Microsoft Azure, Meta has a globally leading supercomputer, and NVIDIA is a hardware manufacturer of AI chips. The three have successively launched a series of foundation models, such as GPT, LLaMA, and Megatron Turing.

For ~high engineering breakthrough performance, this study sets a frequency threshold of 2 and selects 0.80 as the consistency threshold. The overall consistency of the intermediate path is 0.95, with a coverage rate of 0.29, which better explains real-world cases. There are two configurations in Table VII.

According to Table VII, this research finds that the data foundation and regional knowledge cluster have a significant impact on AI engineering breakthroughs (include 4, 5 in Table VII). Even if some AI labs receive government investment, it is still difficult for them to achieve high performance. From the perspective of AI R&D, their engineering breakthroughs rely on massive data support. Currently, AI system engineering represented by foundation models urgently requires a large amount of data for training. The scale of foundation model parameters has reached billions, and whether there is a large amount of data affects AI training. At the same time, an active regional knowledge cluster has a positive impact on breakthroughs in AI engineering. The reason is that the spillover effect of regional knowledge reduces the input cost of basic AI research, which can make AI labs focus on engineering to achieve breakthroughs.

C. Robustness Analysis

This study conducted robustness analysis based on the research steps in the fsQCA guidance manual. In general, robustness is tested by adjusting the consistency threshold and frequency threshold. The raw consistency threshold determines the number of rows in the truth table (that is, the number of configurations) entering the minimization analysis process, thus affecting the final analysis results. If the consistency threshold is increased, the new configuration will eventually be a subset of the previous configuration [59]. We increased the consistency threshold from 0.70 to 0.80 and performed separate calculations (Appendix Table XI). There are two configurations of high basic research performance that constitute a subset of the configurations in Table IV. There are four configurations with high engineering breakthrough performance that are consistent with the configurations in Table VI. The robustness analysis shows that the nature of the configuration results has not changed significantly. Therefore, the research conclusions obtained by fsQCA based on the 0.70 consistency threshold are stable and reliable.

V. DISCUSSION

We have obtained Table VIII based on the research results from the previous section.

A. Theoretical Implications

First, this study constructs an adjusted TOE framework to provide a systematic explanation of various factors that affect AI innovation. This article empirically discusses the synergistic effect of multiple conditions in the TOE framework to promote the innovation performance of AI labs, and it explains the equivalent effect of the combination of multiple conditions on achieving innovation in AI labs. Previous studies have explored the effect of single influencing factors on the innovation performance of R&D labs [6], [37], [38]. The development of labs is influenced by multiple factors, and different factors may jointly affect the innovation performance of labs. Although these studies have obtained effective results [9], [10], they have ignored the impact of the characteristics of the technology itself on lab innovation. This study focuses on the AI field and takes the configuration perspective to empirically explore the synergistic effect of multiple conditions on promoting innovation performance in AI labs under the TOE framework.

Second, this study further demonstrates the raw of basic research on AI. This research finds that AI basic research innovation performance depends on strong computing resources and high-quality innovation ecology and is moving from academia to industry. This finding is somewhat different from the traditional belief that universities have a dominant advantage in basic research [63]. The underlying reason behind this result is that leading firms or public R&D institutions have a large amount of data and strong computing power and are at the forefront of the market and technology, giving them a first-mover advantage in conducting scientific research in the AI field. This result is also consistent with the findings of existing research, and leading enterprises are also important subjects of AI's basic research [12], [17].

Third, this study further demonstrates the raw of engineering breakthroughs in AI. It relies on public R&D institutions and leading firms, and high-quality data will have a significant impact on applications. Through empirical research, this article

TABLE VIII
MAIN FINDINGS, CONTRIBUTIONS, IMPLICATIONS

<table>
<tr><th></th><th>AI basic research</th><th>AI engineering breakthrough</th></tr>
<tr><td>Configurations</td><td>✧ Free exploration type (include 1a, 1b in Table IV).
✧ Market-driven type (include 2a, 2b in Table IV).
✧ Platform expansion type (include 3 in Table IV).</td><td>✧ Technology driven (include 1a, 1b in Table VI).
✧ Ecologically driven (include 2 in Table VI).
✧ Dual technology and ecologically driven (include 3 in Table VI).</td></tr>
<tr><td>Findings</td><td>✧ Basic research in AI not only occurs in university labs, but also in the firms and public R&D institution.
✧ Basic research in AI is influenced by regional knowledge clusters, AI labs located in rich knowledge clusters are more likely to achieve knowledge innovation.</td><td>✧ Engineering breakthrough occurs in leading firms and public R&D institutions. The former relies on strong digital infrastructure, the latter emphasizes ecosystem cooperation.
✧ Weak data foundation and weak regional knowledge clusters hinder AI labs from achieving engineering breakthroughs.</td></tr>
<tr><td rowspan="2">Contributions</td><td colspan="2">✧ AI innovation equivalent effect: based on the adjusted TOE framework, this article provides a synergistic explanation of various factors, proposes different paths to achieve AI innovation.</td></tr>
<tr><td>✧ The rules of AI basic research depend on strong computing resources and high-quality innovation ecology and is moving from academia to industry.</td><td>✧ The rules of AI engineering breakthroughs: rely on public R&D institutions and leading firms, and high-quality data will have a significant impact on applications.</td></tr>
<tr><td>Implications</td><td>✧ For government: provides more resources to AI labs in basic research activities, and strengthens the combination of industry, academia and research.
✧ For AI Labs: try to deepen ecological cooperation and strengthen industry-academia-research cooperation in the region as much as possible.</td><td>✧ For government: integrate more resources and achieve success by deploying public R&D labs in regions with developed regional ecosystems.
✧ For AI Labs: labs in underdeveloped regions need to obtain more data and be embedded in knowledge clusters, form a strong innovation ecosystem.</td></tr>
</table>

finds that breakthroughs in AI engineering require strong systematic capabilities, fully integrating the advantages of laboratories in digital facilities, resource supply, ecological cooperation, and other aspects. Public R&D institutions and leading firms have the strength to transform cutting-edge achievements into large-scale applications. Meanwhile, the study indicates that under the breakthrough of computing power, AI engineering breakthroughs will pay more attention to the accumulation of data.

B. *Managerial Implications*

This article has practical implications for the government's layout and management of AI labs.

For government, on the one hand, it needs to provide more resources to AI labs in basic research activities and strengthens the combination of industry, academia, and research. Basic research of AI technologies is spreading from universities to other institutions, with industry organizations becoming important players. Regional basic research interactive activities have significant knowledge spillover effects, which can drive related institutions to carry out innovation. On the other hand, this article indicates that it is an effective path to integrate more resources and achieve success by deploying public R&D labs in regions with developed regional ecosystems. The regional industrial cluster formed by the aggregation of upstream and downstream enterprises and venture capital institutions in the AI industrial chain reduces the cost of AI R&D training and product development, providing a rich supply of resources. The regional knowledge cluster formed by universities and research institutes provides a rich knowledge foundation for basic research work on AI and supports the exploration of scientific frontiers in AI labs.

For AI labs, on the one hand, deepening ecological cooperation and strengthening industry-academia-research cooperation in the region are effective ways to improve basic research. The basic research activities of AI are closely related to computing power (GPU), data, and training frameworks (TensorFlow, PyTorch), which are crucial for basic research activities. By forming complementary cooperative relationships, it will be beneficial to strengthen the basic research of AI. On the other hand, leading firms' and R&D institutions' labs are the main bodies of engineering breakthroughs, with technology and ecology being the key to breakthroughs. Therefore, labs in underdeveloped regions need to obtain more data and be embedded in knowledge clusters, form a strong innovation ecosystem.

V. DISCUSSION

This article selects 43 AI labs worldwide for fsQCA. The results indicate that the innovation activities of AI labs are jointly influenced by the technology condition, organization condition, and the environment condition, forming unique configurations for AI labs to achieve high basic research and engineering breakthrough performance. The main contribution of this study is the construction of a TOE framework for AI innovation. In addition, there are still some shortcomings in this article.

First, fsQCA method neglects the issue of causal mechanisms. To make up for this deficiency, the results focus on explaining AI innovation through the TOE framework and deriving possible causal relationships from practical cases. In addition, it may have the problem of residual conditional combination logic. In theory, if there are k conditional variables, there needs 2^k cases to cover all combinations. However, as the number of conditional variables increases, it is often difficult to collect enough cases, and some cases may not even appear in reality. Therefore, we conducted theoretical analysis on various configuration combinations in our research to remove some configurations that did not conform to reality. Future research can also obtain more cases to cover different configurations.

Second, this article spans the spatial scope and selects AI labs from different regions to analyse them based on

TABLE IX
NECESSARY ANALYSIS FOR BASIC RESEARCH PERFORMANCE

Conditions	**High basic research performance**		**~High basic research performance**	
	Consistency	**Coverage**	**Consistency**	**Coverage**
Computing power	0.963	0.439	0.867	0.561
~Computing power	0.037	0.163	0.133	0.838
Data foundation	0.711	0.543	0.566	0.613
~Data foundation	0.493	0.445	0.578	0.740
Strategic orientation	0.547	0.470	0.567	0.691
~Strategic orientation	0.641	0.511	0.565	0.639
Resource input	0.534	0.380	0.615	0.620
~Resource input	0.466	0.460	0.385	0.540
Regional knowledge cluster	0.750	0.683	0.347	0.448
~Regional knowledge cluster	0.393	0.298	0.754	0.810
Regional industrial cluster	0.856	0.662	0.446	0.490
~Regional industrial cluster	0.341	0.303	0.692	0.872
Ecosystem cooperation	0.894	0.523	0.714	0.593
~Ecosystem cooperation	0.305	0.429	0.426	0.850

TABLE X
NECESSARY ANALYSIS FOR ENGINEERING BREAKTHROUGH PERFORMANCE

Conditions	**High engineering breakthrough performance**		**~High engineering breakthrough performance**	
	Consistency	**Coverage**	**Consistency**	**Coverage**
Computing power	0.990	0.495	0.838	0.505
~Computing power	0.010	0.050	0.162	0.950
Data foundation	0.842	0.705	0.448	0.452
~Data foundation	0.345	0.342	0.708	0.844
Strategic orientation	0.624	0.588	0.487	0.553
~Strategic orientation	0.526	0.460	0.637	0.671
Resource input	0.374	0.292	0.754	0.708
~Resource input	0.626	0.678	0.246	0.322
Regional knowledge cluster	0.654	0.653	0.371	0.446
~Regional knowledge cluster	0.446	0.371	0.712	0.712
Regional industrial cluster	0.735	0.624	0.544	0.556
~Regional industrial cluster	0.477	0.465	0.632	0.742
Ecosystem cooperation	0.837	0.538	0.715	0.553
~Ecosystem cooperation	0.304	0.470	0.402	0.748

TABLE XI
ROBUSTNESS ANALYSIS RESULTS

Conditions	**High basic research performance**		**High engineering breakthrough performance**			
	1a	**1b**	**1**	**2**	**2**	**4**
Computing power	•	•	•	•	•	•
Data foundation		•	●	●	●	●
Strategic orientation	⊗		●	●	⨂	●
Resource input	●	●	⨂	⨂	•	⨂
Regional knowledge cluster	●	●	⊗	⊗	●	•
Regional industrial cluster	●	●	⊗		•	•
Ecosystem cooperation	●	●		⊗	•	•
Raw coverage	0.271	0.174	0.182	0.099	0.140	0.288
Unique coverage	0.106	0.010	0.091	0.023	0.140	0.254
Consistency	0.864	0.847	0.913	0.919	0.804	0.859
Overall solution coverage	0.280		0.599			
Overall solution consistency	0.857		0.858			
Frequency cut-off	1.000		1.000			
Consistency cut-off	0.818		0.804			

cross-sectional data. Although interesting research conclusions have been obtained, there is still room to strengthen the comparative analysis from the temporal dimension. Due to the fast iteration speed of AI technology innovation, future research can compare the configuration combination of innovation performance and the influencing factors of AI labs from a vertical evolutionary perspective.

Third, this article regards AI as a general-purpose technology. Although we conduct QCA analysis at the macro level, AI technology is complex and heterogeneous at the micro level. Future research could explore the influencing factors of innovation in different types of AI technology.

Appendix

See Tables IX–XI.

Acknowledgment

The authors wish to express their appreciation to the reviewers for their exceptionally valuable and constructive comments and suggestions, which have greatly enhanced the quality of this manuscript. The authors also would like to extend their thanks to the Co-Editor in Chief and Area Editor for their support.

References

[1] N. Haefner, J. Wincent, V. Parida, and O. Gassmann, "Artificial intelligence and innovation management: A review, framework, and research agenda," *Technological Forecasting Social Change*, vol. 162, Jan. 2021, Art. no. 120392, doi: 10.1016/j.techfore.2020.120392.

[2] S. G. Bouschery, V. Blazevic, and F. T. Piller, "Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models," *J. Product Innov. Manage.*, vol. 40, no. 2, pp. 139–153, Jan. 2023, doi: 10.1111/jpim.12656.

[3] A. Brem, F. Giones, and M. Werle, "The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation," *J. Product Innov. Manage.*, vol. 40, no. 2, pp. 770–776, Feb. 2023, doi: 10.1109/TEM.2021.3109983.

[4] M. Coccia, "Asymmetry of the technological cycle of disruptive innovations," *Technol. Anal. Strategic Manage.*, vol. 32, no. 12, pp. 1462–1477, Jul. 2020, doi: 10.1080/09537325.2020.1785415.

[5] M. Coccia, "Sources of technological innovation: Radical and incremental innovation problem-driven to support competitive advantage of firms," *Technol. Anal. Strategic Manage.*, vol. 29, no. 9, pp. 1048–1061, 2017, doi: 10.1080/09537325.2016.1268682.

[6] G. Schiuma and F. Santarsiero, "Innovation labs as organisational catalysts for innovation capacity development: A systematic literature review," *Technovation*, vol. 123, May 2023, Art. no. 102690, doi: 10.1016/j.technovation.2023.102690.

[7] C. Moller, "Process innovation laboratory: A new approach to business process innovation based on enterprise information systems," *Enterprise Inf. Syst.*, vol. 1, no. 1, pp. 113–128, Feb. 2007, doi: 10.1080/17517570601092143.

[8] P. Intarakumnerd and A. Goto, "Role of public research institutes in national innovation systems in industrialized countries: The cases of Fraunhofer, NIST, CSIRO, AIST, and ITRI," *Res. Policy*, vol. 47, no. 7, pp. 1309–1320, Sep. 2018, doi: 10.1016/j.respol.2018.04.011.

[9] A. Conti and C. C. Liu, "Bringing the lab back in: Personnel composition and scientific output at the MIT Department of Biology," *Res. Policy*, vol. 44, no. 9, pp. 1633–1644, Nov. 2015, doi: 10.1016/j.respol.2015.01.001.

[10] R. Rohrbeck, N. Thom, and H. Arnold, "IT tools for foresight: The integrated insight and response system of deutsche Telekom innovation laboratories," *Technological Forecasting Social Change*, vol. 97, pp. 115–126, Aug. 2015, doi: 10.1016/j.techfore.2013.09.015.

[11] A. Arenal, C. Armuna, C. Feijoo, S. Ramos, Z. Xu, and A. Moreno, "Innovation ecosystems theory revisited: The case of artificial intelligence in China," *Telecommun. Policy*, vol. 44, no. 6, Jul. 2020, Art. no. 101960, doi: 10.1016/j.telpol.2020.101960.

[12] B. Lundvall and C. Rikap, "China's catching-up in artificial intelligence seen as a co-evolution of corporate and national innovation systems," *Res. Policy*, vol. 51, no. 1, Jan. 2022, Art. no. 104395, doi: 10.1016/j.respol.2021.104395.

[13] S. Nambisan, M. Wright, and M. Feldman, "The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes," *Res. Policy*, vol. 48, no. 8, Oct. 2019, Art. no. 103773, doi: 10.1016/j.respol.2019.03.018.

[14] J. Robertson, J. Fossaceca, and K. Bennett, "A cloud-based computing framework for artificial intelligence innovation in support of multidomain operations," *IEEE Trans. Eng. Manage.*, vol. 69, no. 6, pp. 3913–3922, Dec. 2022, doi: 10.1109/TEM.2021.3088382.

[15] D. Doloreux and E. Turkina, "New path creation in the artificial intelligence industry: Regional preconditions, new actors and their collective actions, and policies," *Regional Stud.*, vol. 55, no. 10/11, pp. 1751–1763, Jun. 2021, doi: 10.1080/00343404.2021.1919610.

[16] T. Greckhamer, S. Furnari, P. C. Fiss, and R. V. Aguilera, "Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research," *Strategic Org.*, vol. 16, no. 4, pp. 482–495, Jul. 2018, doi: 10.1177/1476127018786487.

[17] S. J. Jee and S. Y. Sohn, "Firms ' influence on the evolution of published knowledge when a science-related technology emerges: The case of artificial intelligence," *J. Evol. Econ.*, vol. 33, no. 1, pp. 209–247, Dec. 2023, doi: 10.1007/s00191-022-00804-4.

[18] N. Carayol and M. Matt, "Does research organization influence academic production? Laboratory level evidence from a large European university," *Res. Policy*, vol. 33, no. 8, pp. 1081–1102, Oct. 2004, doi: 10.1016/j.respol.2004.03.004.

[19] M. Coccia, "New models for measuring the R&D performance and identifying the productivity of public research institutes," *R&D Manage.*, vol. 34, no. 3, pp. 267–280, May 2004, doi: 10.1111/j.1467-9310.2004.00338.x.

[20] M. Coccia, "Measuring scientific performance of public research units for strategic change," *J. Informetrics*, vol. 2, no. 3, pp. 183–194, Jul. 2008, doi: 10.1016/j.joi.2008.04.001.

[21] P. Llanos-Paredes, "The effect of applied research institutes on invention: Evidence from the Fraunhofer centres in Europe," *Res. Eval.*, vol. 32, no. 3, pp. 566–576, Jul. 2023, doi: 10.1093/reseval/rvad028.

[22] N. Zhang, D. You, L. Tang, and K. Wen, "Knowledge path dependence, external connection, and radical inventions: Evidence from Chinese Academy of Sciences," *Res. Policy*, vol. 52, no. 4, May 2023, Art. no. 104738, doi: 10.1016/j.respol.2023.104738.

[23] C. Hung and P. Shiu, "Evaluating project performance by removing external effects: Implications to the efficiency of research and development resource allocation," *Res. Eval.*, vol. 23, no. 4, pp. 366–380, Oct. 2014, doi: 10.1093/reseval/rvu022.

[24] M. Y. Park, H. S. Choi, and J. C. Yoon, "Determinants of technology innovation performance," in *21st ACIS Int. Winter Conf. Softw. Eng., Artif. Intell., Netw. Parallel/Distrib. Comput.*, 2021, pp. 119–121, doi: 10.1109/SNPDWinter52325.2021.00034.

[25] H. Wu, X. Gu, Y. Zhao, and W. Liu, "Research on the relationship between structural hole location, knowledge management and cooperative innovation performance in artificial intelligence," *Knowl. Manage. Res. Pract.*, vol. 26, no. 5, pp. 1–10, Sep. 2020, doi: 10.1080/14778238.2020.1813642.

[26] J. Li, Z. Liu, and J. Zhou, "How to become the chosen one in the artificial intelligence market: The evidence from China," *Int. J. Technol. Manage.*, vol. 84, no. 1/2, pp. 8–24, Dec. 2020, doi: 10.1504/IJTM.2020.112122.

[27] F. Fecher, J. Winding, K. Hutter, and J. Fueller, "Innovation labs from a participants' perspective," *J. Bus. Res.*, vol. 110, pp. 567–576, Mar. 2020, doi: 10.1016/j.jbusres.2018.05.039.

[28] A. Giczy, N. A. Pairolero, and A. A. Toole, "Identifying artificial intelligence (AI) invention: A novel AI patent dataset," *J. Technol. Transfer*, vol. 47, no. 2, pp. 476–505, Apr. 2022, doi: 10.1007/s10961-021-09900-2.

[29] V. Verendel, "Tracking artificial intelligence in climate inventions with patent data," *Nature Climate Change*, vol. 13, no. 1, pp. 40–47, Jan. 2023, doi: 10.1038/s41558-022-01536-w.

[30] P. B. Maurseth and R. Svensson, "The importance of tacit knowledge: Dynamic inventor activity in the commercialization phase," *Res. Policy*, vol. 49, no. 7, Sep. 2020, Art. no. 104012, doi: 10.1016/j.respol.2020.104012.

[31] A. Marrucci, R. Rialti, and M. Balzano, "Exploring paths underlying Industry 4.0 implementation in manufacturing SMEs: A fuzzy-set qualitative comparative analysis," *Manage. Decis.*, to be published, doi: 10.1108/MD-05-2022-0644.

[32] N. Ameye, J. Bughin, and N. van Zeebroeck, “How uncertainty shapes herding in the corporate use of artificial intelligence technology,” *Technovation*, vol. 127, Sep. 2023, Art. no. 102846, doi: 10.1016/j.technovation.2023.102846.

[33] H. Lin, “Understanding the determinants of electronic supply chain management system adoption: Using the technology-organization-environment framework,” *Technological Forecasting Social Change*, vol. 86, pp. 80–92, Jul. 2014, doi: 10.1016/j.techfore.2013.09.001.

[34] S. Kinkel, M. Baumgartner, and E. Cherubini, “Prerequisites for the adoption of AI technologies in manufacturing-evidence from a worldwide sample of manufacturing companies,” *Technovation*, vol. 110, Feb. 2022, Art. no. 102375, doi: 10.1016/j.technovation.2021.102375.

[35] M. Lewis and J. Moultrie, “The organizational innovation laboratory,” *Creativity Innov. Manage.*, vol. 14, no. 1, pp. 73–83, Feb. 2005, doi: 10.1111/j.1467-8691.2005.00327.x.

[36] S. Schmidt, V. Brinks, and S. Brinkhoff, “Innovation and creativity labs in Berlin: Organizing temporary spatial configurations for innovations,” *Zeitschrift Wirtschaftsgeographie*, vol. 58, no. 4, pp. 232–247, Oct. 2014.

[37] O. Henfridsson and B. Bygstad, “The generative mechanisms of digital infrastructure evolution,” *MIS Quart.*, vol. 37, no. 3, pp. 907–931, Sep. 2013, doi: 10.25300/MISQ/2013/37.3.11.

[38] A. Lungeanu, Y. Huang, and N. S. Contractor, “Understanding the assembly of interdisciplinary teams and its impact on performance,” *J. Informetrics*, vol. 8, no. 1, pp. 59–70, Jan. 2014, doi: 10.1016/j.joi.2013.10.006.

[39] L. Rothschild and A. Darr, “Technological incubators and the social construction of innovation networks: An Israeli case study,” *Technovation*, vol. 25, no. 1, pp. 59–67, Jan. 2005, doi: 10.1016/S0166-4972(03)00064-6.

[40] D. Siegel, M. L. A. M. Bogers, P. D. Jennings, and L. Xue, “Technology transfer from national/federal labs and public research institutes: Managerial and policy implications,” *Res. Policy*, vol. 52, no. 1, Jan. 2023, Art. no. 104646, doi: 10.1016/j.respol.2022.104646.

[41] A. F. S. Borges, F. J. B. Laurindo, M. M. Spinola, R. F. Goncalves, and C. A. Mattos, “The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions,” *Int. J. Inf. Manage.*, vol. 57, Apr. 2021, Art. no. 102225, doi: 10.1016/j.ijinfomgt.2020.102225.

[42] M. Haenlein and A. Kaplan, “A brief history of artificial intelligence: On the past, present, and future of artificial intelligence,” *California Manage. Rev.*, vol. 61, no. 4, pp. 5–14, Jul. 2019, doi: 10.1177/0008125619864925.

[43] Z. Yu, Z. Liang, and L. Xue, “A data-driven global innovation system approach and the rise of China’s artificial intelligence industry,” *Regional Stud.*, vol. 56, no. 4, pp. 619–629, 2022, doi: 10.1080/00343404.2021.1954610.

[44] S. Gupta, S. Modgil, R. Meissonier, and Y. K. Dwivedi, “Artificial intelligence and information system resilience to cope with supply chain disruption,” *IEEE Trans. Eng. Manage.*, early access, Oct. 26, 2021, doi: 10.1109/TEM.2021.3116770.

[45] F. Osorio, L. Dupont, M. Camargo, P. Palominos, J. I. Pe A, and M. Alfaro, “Design and management of innovation laboratories: Toward a performance assessment tool,” *Creativity Innov. Manage.*, vol. 28, no. 1, pp. 82–100, Jan. 2019, doi: 10.1111/caim.12301.

[46] P. Adams, I. M. B. Freitas, and R. Fontana, “Strategic orientation, innovation performance and the moderating influence of marketing management,” *J. Bus. Res.*, vol. 97, pp. 129–140, Apr. 2019, doi: 10.1016/j.jbusres.2018.12.071.

[47] G. Di Stefano, A. Gambardella, and G. Verona, “Technology push and demand pull perspectives in innovation studies: Current findings and future research directions,” *Res. Policy*, vol. 41, no. 8, pp. 1283–1295, Oct. 2012, doi: 10.1016/j.respol.2012.03.021.

[48] P. Tubaro and A. A. Casilli, “Micro-work, artificial intelligence and the automotive industry,” *J. Ind. Bus. Econ.*, vol. 46, no. 3, pp. 333–345, Jun. 2019, doi: 10.1007/s40812-019-00121-1.

[49] E. Vanino, S. Roper, and B. Becker, “Knowledge to money: Assessing the business performance effects of publicly -funded R&D grants,” *Res. Policy*, vol. 48, no. 7, pp. 1714–1737, Sep. 2019, doi: 10.1016/j.respol.2019.04.001.

[50] L. Scaringella and A. Radziwon, “Innovation, entrepreneurial, knowledge, and business ecosystems: Old wine in new bottles?,” *Technological Forecasting Social Change*, vol. 136, pp. 59–87, Nov. 2018, doi: 10.1016/j.techfore.2017.09.023.

[51] G. Tappeiner, C. Hauser, and J. Walde, “Regional knowledge spillovers: Fact or artifact?,” *Res. Policy*, vol. 37, no. 5, pp. 861–874, Jun. 2008, doi: 10.1016/j.respol.2007.07.013.

[52] M. R. D. Peruta, M. D. Giudice, R. Lombardi, and P. Soto-Acosta, “Open innovation, product development, and inter-company relationships within regional knowledge clusters,” *J. Knowl. Economy*, vol. 9, no. 2, pp. 680–693, Jun. 2018, doi: 10.1007/s13132-016-0356-x.

[53] H. Choi and H. Zo, “Network closure versus structural hole: The role of knowledge spillover networks in national innovation performance,” *IEEE Trans. Eng. Manage.*, vol. 69, no. 4, pp. 1011–1021, Aug. 2022, doi: 10.1109/TEM.2020.2972347.

[54] Y. Xu, X. Li, C. Tao, and X. Zhou, “Connected knowledge spillovers, technological cluster innovation and efficient industrial structure,” *J. Innov. Knowl.*, vol. 7, no. 3, Jul.–Sep. 2022, Art. no. 100195, doi: 10.1016/j.jik.2022.100195.

[55] A. Weterings and R. Ponds, “Do regional and non-regional knowledge flows differ? An empirical study on clustered firms in the dutch life sciences and computing services industry,” *Ind. Innov.*, vol. 16, no. 1, pp. 11–31, Mar. 2009, doi: 10.1080/13662710902728035.

[56] R. Adner, “Ecosystem as structure: An actionable construct for strategy,” *J. Manage.*, vol. 43, no. 1, pp. 39–58, Jan. 2017, doi: 10.1177/0149206316678451.

[57] R. Adner and R. Kapoor, “Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations,” *Strategic Manage. J.*, vol. 31, no. 3, pp. 306–333, Nov. 2010, doi: 10.1002/smj.821.

[58] R. Adner, “Match your innovation strategy to your innovation ecosystem,” *Harvard Bus. Rev.*, vol. 84, no. 4, pp. 98–107, Apr. 2006.

[59] A. Ordanini, A. Parasuraman, and G. Rubera, “When the recipe is more important than the ingredients: A qualitative comparative analysis (QCA) of service innovation configurations,” *J. Service Res.*, vol. 17, no. 2, pp. 134–149, May 2014, doi: 10.1177/1094670513513337.

[60] F. Wei, N. Feng, R. D. Evans, R. Zhao, and S. Yang, “How do innovation types and collaborative modes drive firm performance? An fsQCA analysis based on evidence from software ecosystems,” *IEEE Trans. Eng. Manage.*, vol. 69, no. 6, pp. 3648–3659, Dec. 2022, doi: 10.1109/TEM.2021.3102321.

[61] R. J. W. Tijssen, “Co-authored research publications and strategic analysis of public-private collaboration,” *Res. Eval.*, vol. 21, no. 3, pp. 204–215, Sep. 2012, doi: 10.1093/reseval/rvs013.

[62] M. Balzano and G. Marzi, “Exploring the pathways of learning from project failure and success in new product development teams,” *Technovation*, vol. 128, Dec. 2023, Art. no. 102878, doi: 10.1016/j.technovation.2023.102878.

[63] P. J. Bentley, M. Gulbrandsen, and S. Kyvik, “The relationship between basic and applied research in universities,” *Higher Educ.*, vol. 70, no. 4, pp. 689–709, Mar. 2015, doi: 10.1007/s10734-015-9861-2.

Jincheng Shi was born in Shucheng County, China, in 1995. He received the M.S. degree in public management from the China University of Geosciences, Wuhan, Hubei, China, in 2017, and the Ph.D. degree in management from Zhejiang University, Zhejiang, China, in 2022.

Since 2022, he has been an Assistant Research Fellow with Governance Research Center, Shanghai Artificial Intelligence Laboratory. He has authored more than ten articles. His research interests include technology innovation management and artificial intelligence governance.

Yingchun Wang received the Ph.D. degree in philosophy of science and technology from Fudan University, Shanghai, China, in 2010.

He is currently working as a Research Fellow with the Governance Research Center, Shanghai Artificial Intelligence Laboratory, Shanghai, China. He hosted and participated in dozens of national and provincial research projects. His research interests include artificial intelligence innovation and governance strategy, foundation model security, and value alignment.