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# Innovation Ecosystems and Sustainable High Innovation Performance: Evidence from the Guangdong–Hong Kong–Macao Greater Bay Area

**Fan Wu *, Mingyang Li and Huanshui Huang**

School of Public Policy and Management, Guangxi University, Nanning 530004, China; limingyang2081@163.com (M.L.); creativehuang@163.com (H.H.)
* Correspondence: gxwufan@163.com

**Abstract:** The innovation ecosystem has a significant impact on regional innovation development. Based on the "actor-resource-environment" analytical framework, this study takes nine cities in mainland China within the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) from 2012 to 2022 as case studies. By applying a comprehensive evaluation model and kernel density estimation, the study analyzes the development level and dynamic evolution of the innovation ecosystem in the GBA. Furthermore, using a mixed-method approach of dynamic QCA and NCA, the study explores the pathways to achieving high innovation performance in the GBA. The key findings are as follows: (1) The comprehensive score of the GBA innovation ecosystem shows a rising trend, with a pattern of multi-polarization, "top-tier effect", and the persistence of strong performance within the region. (2) Technological innovation actors and the digital economy environment have become necessary conditions for achieving sustained high innovation performance in the GBA. Inter-group results highlight the significant temporal effects of technological innovation actors, R&D personnel input, and a public service environment, which exhibit S-shaped, W-shaped, and U-shaped patterns, respectively. Intra-group results reveal notable regional differences in the necessity level of seven conditional variables across GBA cities. (3) There are two types of innovation ecosystems driving high innovation performance in the GBA: actor-driven and resource–environment synergy-driven ecosystems. While no significant cross-time or cross-case effects exist between these two types, inter-group consistency changes indicate that the innovation ecosystem in the GBA has become more mature and stable since the establishment of the GBA in 2017.

**Keywords:** Guangdong–Hong Kong–Macao Greater Bay Area (GBA); innovation ecosystem; innovation performance; dynamic qualitative comparative analysis (QCA); necessary condition analysis (NCA)

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## 1. Introduction

Innovation is the core driving force behind social progress and economic growth [1]. It not only promotes technological advancements, but also profoundly transforms lifestyles and business models, becoming a major driver of global economic competitiveness. In the context of globalization, innovation enhances productivity, fosters the emergence of new industries, and creates employment opportunities, making it a central element of national strategies and regional policies. Examples include China's innovation-driven strategy [2] and the European Union's "Horizon Europe" program [3]. Moreover, innovation plays a critical role in supporting the global transition towards sustainability. The world is currently facing significant challenges such as climate change [4] and energy shortages [5], which urgently require technological advancements and policy coordination driven by innovation. In fact, innovation is not merely the result of isolated technological breakthroughs; it involves multi-level and multi-dimensional collaboration, ultimately driving profound societal transformation.

In the development of regional innovation, the establishment of an innovation ecosystem plays a pioneering and overarching role, serving as the foundation for enhancing scientific and technological innovation capacity [6]. Through the interactive collaboration of multiple stakeholders, the innovation ecosystem forms a dynamic network that supports knowledge flow, technology diffusion, resource integration, and innovation entrepreneurship [7], further strengthening the innovation capacity and competitive advantage of both regions and nations. Therefore, determining how to effectively construct and optimize innovation ecosystems has become a focal issue of global scholarly attention [8]. Scholars have sought to conduct in-depth studies of innovation ecosystems in different regions, such as the San Francisco Bay Area [9], the Tokyo Bay Area [10], and the New York Bay Area [11], in order to provide theoretical support and practical guidance for the high-quality development of regional economies [12].

The current research on innovation ecosystems is relatively extensive. In terms of content, scholars have engaged in in-depth discussions on the structure and components of innovation ecosystems [13], cooperation and symbiosis [14], ecosystem health [15], and value co-creation [16]. From a methodological perspective, most existing studies rely on traditional regression approaches, such as static panel models, spatial Durbin models, and difference-in-differences models. These approaches, based on "reductionism", explore the "marginal net effects" of individual innovation ecosystem elements on regional innovation performance [17,18]. However, traditional regression methods face limitations in fully analyzing the complexities of such ecosystems. Although some scholars have recognized that innovation ecosystems are complex and dynamic systems, and have begun to explore their configurational effects on regional innovation performance using the fsQCA method, the current research is often limited by technical constraints and reliant on cross-sectional data, which fails to incorporate the temporal dimension [12,19]. Therefore, new methodological approaches are urgently needed to better capture and explain the complexity and dynamism of innovation ecosystems. In light of this, this study will use the GBA as a case study and apply the dynamic QCA method. By incorporating the time dimension and the interaction between elements of the innovation ecosystem, this research aims to further explore the impact of innovation ecosystems on achieving sustainable high innovation performance.

This study's contributions are threefold: First, grounded in innovation ecosystem theory, it constructs an "Actors-Resources-Environment" analytical framework, offering a systematic perspective to comprehensively explore the core elements of the GBA's innovation ecosystem and their interactions, thereby providing a new theoretical tool for understanding the internal mechanisms of regional innovation.

Second, from a configurational perspective, the study identifies three types of innovation ecosystems that achieve sustainable high innovation performance in the GBA, illustrating how different combinations of elements collectively enhance regional innovation capacity. This enriches empirical research on innovation ecosystems and offers valuable insights for innovation practices in other regions.

Third, by utilizing the dynamic QCA method, the study investigates the evolution of the GBA's innovation ecosystem from aggregate, between-group, and within-group perspectives across time and case dimensions. This effectively addresses the limitations of the fsQCA method and provides a more detailed analytical tool for capturing the dynamics of innovation ecosystems, thereby deepening the understanding of complex system evolution.

The structure of this study is as follows: The second section constructs the analytical framework of the research based on innovation ecosystem theory; the third section introduces the overview of the study region and the data sources; the fourth section explains the research design, methods, and data construction process; the fifth section conducts an empirical analysis based on the data from the GBA; and the sixth section summarizes the research findings and provides insights into future research directions.

## 2. Literature Review and Construction of the Analytical Framework

### *2.1. The "Rational Critique", from Innovation Systems to Innovation Ecosystems*

Since Joseph Schumpeter, the "father of innovation theory", first systematically introduced the concept of "innovation" in his work The Theory of Economic Development [1], innovation theory has undergone multiple evolutions—from the early linear models of innovation to the widely applied innovation system theory, and now to the increasingly prominent concept of the innovation ecosystem [20]. This shift represents not only a deepening of theoretical understanding but also a "rational critique" of traditional innovation system theory.

Innovation system theory emerged in the 1980s as a significant milestone in the study of innovation. Lundvall was the first to introduce the concept of the "innovation system", emphasizing that innovation is not an isolated act of technological advancement but a complex process embedded within broader socio-economic networks [21]. Building on this idea, Christopher Freeman further developed the theory in his concept of the National Innovation System, highlighting how public sectors at the national level can drive technological innovation and economic growth through policies, resources, and institutional arrangements. These theories provided a systematic framework for understanding innovation activities at both national and regional levels, offering a solid theoretical foundation for the formulation of innovation policies worldwide [22].

However, as innovation practices have evolved, the limitations of traditional innovation system theory have become apparent. While this theory emphasizes collaboration and interaction among multiple stakeholders, it often leans towards analyzing static system structures and linear processes, neglecting the non-linear and dynamically evolving nature of the innovation process [23]. Innovation is not merely about cooperation among different actors; it is a complex ecosystem influenced by various external factors, including environmental conditions, resource flows, and policy changes. This critique of innovation system theory has driven the development of the innovation ecosystem concept.

The concept of the innovation ecosystem further expands the scope of research on innovation systems, emphasizing the complex interactions among diverse stakeholders and the ecological characteristics of innovation activities [23]. In an innovation ecosystem, various stakeholders—such as enterprises, research institutions, governments, financial institutions, markets, and consumers—actively participate, sharing and exchanging resources, information, and knowledge. This interaction creates a complex network characterized by self-organization and adaptability. This theory goes beyond the static structure of traditional innovation systems, offering a more dynamic and comprehensive analytical framework, as illustrated in Figure 1.

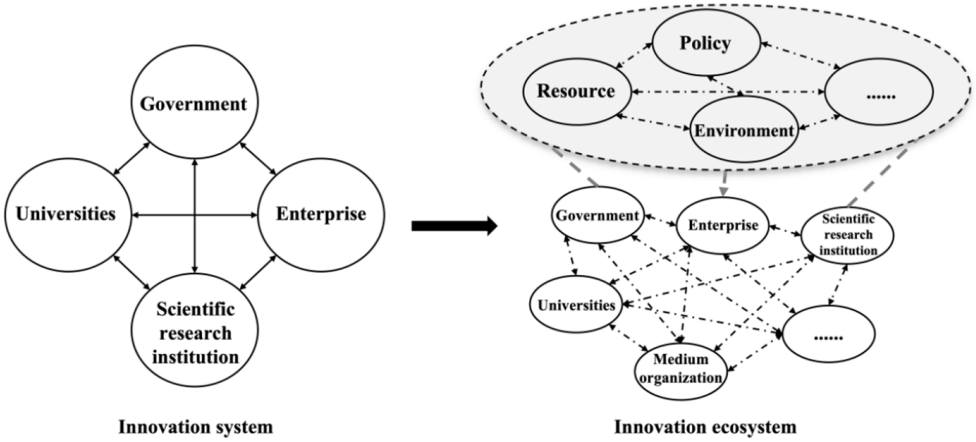



**Figure 1.** From innovation system to innovation ecosystem. Source: Compiled by the authors.

### *2.2. The Constituent Elements of Innovation Ecosystems*

The innovation ecosystem perspective posits that innovation actors, innovation resources, and the innovation environment are the fundamental elements that constitute an innovation ecosystem, with close interactions among them [24]. Innovation actors, based on shared goals, collaboratively integrate the innovation resources within the ecosystem and, within an environment conducive to innovation, jointly build an innovation network aimed at win–win outcomes, thereby achieving co-creation, mutual benefit, and shared value [25,26]. Following this perspective, this study constructs an analytical framework for the innovation ecosystem in the GBA from the three levels of innovation actors, innovation resources, and the innovation environment.

#### 2.2.1. Innovation Actors

Innovation actors are the active participants within the innovation ecosystem, playing a crucial role in driving and supporting innovation [17]. These actors primarily include two types: the first is technological innovation actors, centered around enterprises, which play a significant role in technological development and product innovation [27]. Enterprises can build innovation networks through vertical integration of upstream and downstream actors, significantly enhancing innovation performance [28]; the second type is knowledge innovation actors, represented by universities and research institutions [27], which focus on fundamental research and theoretical innovation, providing the knowledge base for technological innovation [26,29]. Universities, as open knowledge production systems, are crucial in the processes of knowledge creation, dissemination, and application [30]. These two types of actors are interdependent within the innovation ecosystem, collectively promoting the flourishing of innovation activities [31].

#### 2.2.2. Innovation Resources

Innovation resources are critical elements that support innovation activities and serve as the foundation for the innovation practices of various actors within the innovation ecosystem [32]. Innovation resources primarily consist of two major components: the input of research personnel and the input of research funding [33]. Research personnel, as the core executors of innovation activities, have knowledge and skills that directly influence the effectiveness and efficiency of innovation, and they significantly impact regional innovation performance. Research funding provides the necessary material support for innovation activities, ensuring that all stages, from basic research to technological development, can proceed smoothly. Additionally, research funding is a crucial indicator for measuring the innovation ecosystem and is a key factor in driving the transformation of innovative outcomes [34]. Through the rational allocation of innovation resources, innovation actors can better realize their potential, thereby promoting the overall enhancement of regional innovation performance [35].

#### 2.2.3. Innovation Environment

The innovation environment is a crucial external condition that ensures the smooth progress of innovation activities. It not only provides the necessary material conditions for innovation but also fosters a social atmosphere conducive to innovation, stimulating the creativity and enthusiasm of innovation actors [36]. A favorable innovation environment can effectively integrate innovation resources and promote collaboration among various innovation actors, thereby driving the continuous development of innovation activities within the region [37]. The public service environment offers innovation actors a stable space for operation and development, with well-developed public service facilities providing a solid social support system for innovation activities [38]. The work undertaken by innovation actors often requires intense intellectual labor, and a good natural environment can provide a space for relaxation and energy recovery, helping to maintain a high level of work performance and innovation capability [39]. Existing research indicates

that the natural environment can help researchers alleviate stress, and improve focus and creativity [40].

With the advent of the information age, the importance of the digital economy has become increasingly prominent, making it an indispensable part of the innovation environment. The digital economy environment provides advanced technological infrastructure and information networks, creating an efficient and flexible platform for innovation activities [31], enhancing the efficiency and quality of innovation [41], and creating more opportunities and possibilities for innovation [42].

The linear impact of individual elements within the innovation ecosystem on innovation performance offers valuable insights for this study. However, since the innovation ecosystem is a complex and dynamic whole, a single linear perspective is insufficient to fully explain the intricate and multi-dimensional causal relationships between the innovation ecosystem and regional innovation performance. Additionally, the innovation ecosystem in the GBA may exhibit various combination patterns of one-dimensional drive, two-dimensional linkage, and three-dimensional interaction (Table 1), reflecting different modes of linkage and synergy among innovation actors, innovation resources, and the innovation environment. Optimizing the innovation ecosystem to enhance regional innovation performance is a complex system management challenge that requires the introduction of new methodologies for analysis [43]. Dynamic QCA analysis, based on a holistic perspective, emphasizes the synergy among multiple elements and the interactions between subsystems, effectively capturing and analyzing the complex relationships and dynamic evolution that emerge within the system [44]. This method is particularly suitable for revealing the dynamic synergistic effects among multiple subsystems within the overarching innovation ecosystem and their mechanisms of influence on innovation performance.

**Table 1.** Analysis of potential innovation ecosystem combination models in the GBA.

| Drive Path | Type | Innovation Actors | Innovation Resources | Innovation Environment |
|---|---|---|---|---|
| One-Dimensional Drive | Actor-Driven | 1 | 0 | 0 |
| | Resource-Driven | 0 | 1 | 0 |
| | Environment-Driven | 0 | 0 | 1 |
| Two-Dimensional Linkage | Actor–Resource Linkage | 1 | 1 | 0 |
| | Actor–Environment Linkage | 1 | 0 | 1 |
| | Resource–Environment Linkage | 0 | 1 | 1 |
| Three-Dimensional Interaction | Actor–Resource–Environment Interaction | 1 | 1 | 1 |

Source: Compiled by the authors. Note: 1 indicates that the condition has an impact, 0 indicates that the condition does not have an impact.

In light of this, the present study, grounded in innovation ecosystem theory, constructs an analytical framework that includes innovation actors, innovation resources, and the innovation environment (Figure 2). Using innovation ecosystem data from nine mainland cities in the GBA from 2012 to 2022, the study applies the dynamic QCA method to uncover the causal relationships behind the complex phenomenon of regional innovation performance in terms of both temporal and case dimensions. This study delves into the dynamic synergistic effects among various elements and their mechanisms of influence on innovation performance.

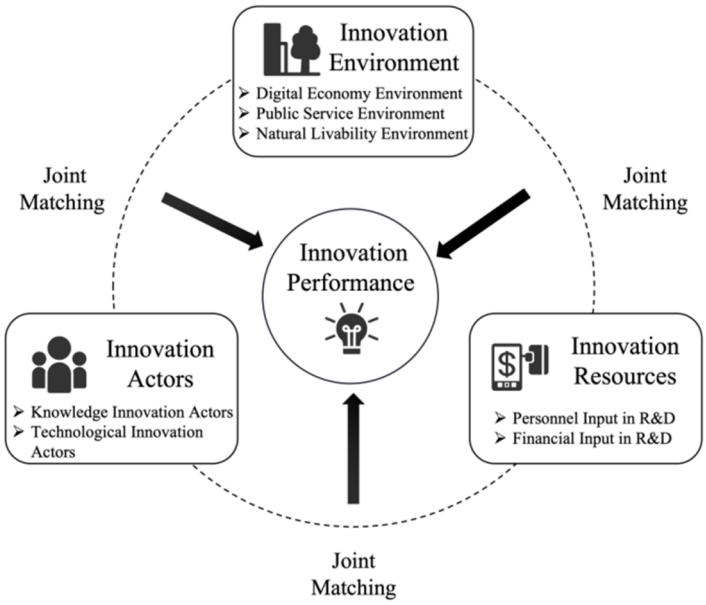



**Figure 2.** Composition of the innovation ecosystem in the GBA. Source: Compiled by the authors.

## 3. Study Area and Data Sources

### *3.1. Overview of the Study Area*

GBA is located along the southern coast of China (111°21′–114°53′ E, 21°28′–24°29′ N) in the Pearl River Delta, adjacent to the South China Sea. It consists of nine cities in Guangdong Province—Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing—as well as the two Special Administrative Regions of Hong Kong and Macao. The GBA covers a total area of approximately 56,000 square kilometers, with a population exceeding 86 million, as shown in Figure 3.

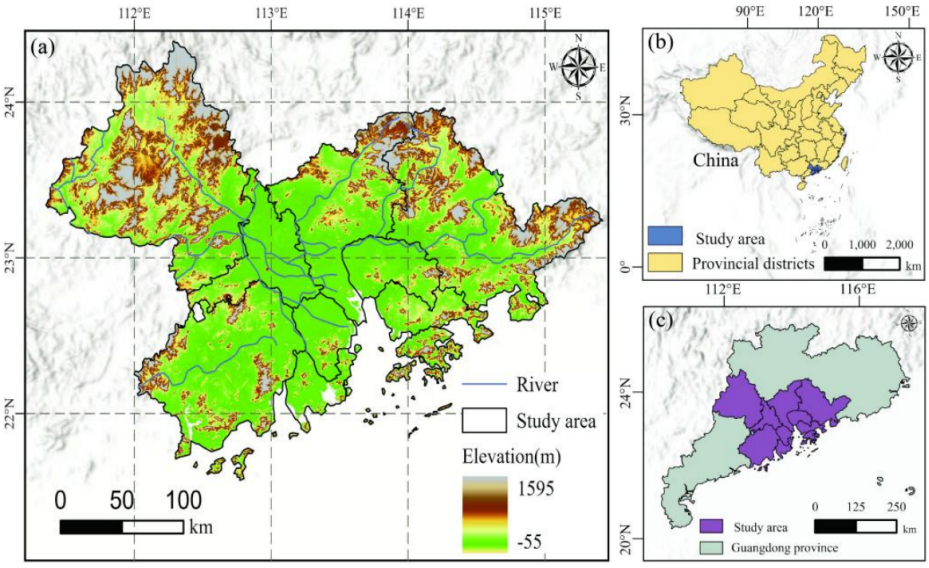



**Figure 3.** Research area map. Source: Compiled by the authors. Note: (**a**) represents the map of the GBA, (**b**) shows the location of Guangdong Province in China, and (**c**) indicates the location of the GBA within Guangdong Province.

As the frontier of China's reform and opening-up, and a major engine for national innovation-driven development, the GBA has emerged as a prominent player on the global innovation landscape [45]. Concentrating world-class technological resources and innovative talent, it has become a key region driving China's rising economic and technological

prowess [41]. The GBA serves as a demonstration zone for deep cooperation between Mainland China, Hong Kong, and Macao, and as a model for high-quality urban agglomeration development [46]. According to statistics, in 2021, Guangdong Province ranked first in China in overall regional innovation capability for the fifth consecutive year. The province's R&D expenditure exceeded RMB 380 billion, accounting for 3.14% of its gross regional product. Indicators such as the number of valid invention patents and Patent Cooperation Treaty applications ranked first nationwide. Additionally, foreign talent in Guangdong accounted for about one-fifth of the national total, and the province had over 1.1 million R&D personnel. The "Shenzhen-Hong Kong-Guangzhou" technology cluster was ranked second globally.

### *3.2. Data Sources*

Given the significant administrative and economic system differences between the nine mainland cities of the GBA, Hong Kong, and Macao, as well as the distinct economic focuses of these regions—Hong Kong prioritizing finance and services, and Macao focusing on entertainment and tourism—this study concentrates on analyzing the innovation ecosystem within the mainland cities of the GBA. Specifically, the selected cities include Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing, totaling nine cities.

The data used in this study span from 2012 to 2022. To ensure the accuracy and scientific rigor of the research, the data were primarily sourced from the "Guangdong Statistical Yearbook", "Guangdong Science and Technology Statistical Yearbook", "GBA Statistical Yearbook", and "China City Statistical Yearbook", as well as the respective statistical yearbooks and statistical bulletins of the cities involved. For any missing data, interpolation methods were applied to complete the dataset.

## 4. Research Design

### *4.1. Research Methods*

#### 4.1.1. Comprehensive Evaluation Model

By using Stata17 software to calculate the weights and composite scores of various secondary indicators, this study reflects the basic status of the innovation ecosystems in different cities within the GBA. Based on existing research, this study employs the entropy method for calculating the weights. Step 1 involves processing the original data of each secondary indicator through normalization (both positive and negative). This step simultaneously addresses the issues of data directionality and dimensionality.

$$X_{ij} = \frac{X_{ij} - min\{X_j\}}{max\{X_j\} - min\{X_j\}} (i = 1, 2, 3 \ldots n; j = 1, 2, 3 \ldots m), \text{Positive Indicator} \quad (1)$$

$$X_{ij} = \frac{max\{X_j\} - X_{ij}}{max\{X_j\} - min\{X_j\}} (i = 1, 2, 3 \ldots n; j = 1, 2, 3 \ldots m), \text{Negative Indicator} \quad (2)$$

Step 2: Calculation of indicator weights. First, calculate the proportion of the indicator value $P_{ij}$:

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X'_{ij}} (i = 1, 2, 3 \ldots n; j = 1, 2, 3 \ldots m) \quad (3)$$

Step 3: Calculate the information entropy $e_j$ of the indicators:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} (P_{ij} \times \ln P_{ij}) \ (i = 1, 2, 3 \ldots n; j = 1, 2, 3 \ldots m) \quad (4)$$

Step 4: Calculate the weight of the evaluation indicators $W_j$:

$$W_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

The coefficient of variation is:

$$d_j = 1 - e_j \ (j = 1, 2, 3 \ldots m) \tag{5}$$

Step 5: Calculate the comprehensive score $S_{ij}$ for each primary indicator of the innovation ecosystem.

$$S_{ij} = W_j \times X_{ij} (i = 1, 2, 3 \ldots n; j = 1, 2, 3 \ldots m) \tag{6}$$

In Formulas (1) through (6), $i$ refers to the tertiary innovation ecosystem indicators, and j refers to the nine cities in the GBA. The comprehensive score is the decisive measure derived using the entropy method to evaluate the results. It is calculated by multiplying the secondary indicators under each primary indicator by their respective weights and summing them up. In this study, the comprehensive score for each primary indicator ranges within [0, 1], with a higher score indicating better performance in that indicator for the given case.

#### 4.1.2. Kernel Density Estimation Function

This study utilizes kernel density estimation plots generated using MATLAB R2024b software to explore the distribution, trends, extensibility, and polarization tendencies in the development of innovation ecosystems within the GBA. Compared to traditional parametric estimation methods, the kernel density estimation method is better suited to handling data of varying scales and forms, effectively capturing the complex differences in the development levels of regional innovation ecosystems [47]. The calculation formula for kernel density estimation is as follows:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right) \tag{7}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{x^2}{2}\right) \tag{8}$$

where $N$ is the total number of research samples, $Xi$ represents the innovation ecosystem development level of each city, $x$ is the mean development level of the innovation ecosystem, $h$ is the bandwidth, and $K(\cdot)$ is the kernel function. In this study, the Gaussian kernel function is employed to analyze the dynamic evolution of the innovation ecosystem development level in the GBA.

#### 4.1.3. Dynamic QCA and NCA Methods

The QCA method is grounded in set theory and uses a configurational approach and holistic perspective to explain the complex logic underlying phenomena. This method posits that the impact of conditional variables on outcome variables results from the interaction and combined effects of these conditional variables [48,49]. Traditional QCA methods are often limited by the temporal dimension, typically analyzing problems based on cross-sectional data. However, analyzing a single time point may fail to reveal the full picture of a problem. In the context of the GBA, the innovation ecosystem's contribution to enhancing innovation performance varies over different time points, and traditional QCA methods struggle to explain the interaction between causality and time.

To overcome the temporal limitations of traditional QCA, scholars such as García-Castro and Ariño have proposed relevant theories and methods. They introduced the concepts of "between" to discuss differences among cases in the spatial dimension, "within" to address differences among cases in the temporal dimension, and "pooled" to analyze the

overall level of cases over a period of time [50]. Additionally, by introducing a consistency adjustment distance, they could assess the fluctuation and variation in consistency across time and space [51]. The formulas for calculating consistency and coverage among groups, within groups and in summary are shown in Table 2.

**Table 2.** Formulas for calculating between-group, within-group, and pooled consistency and coverage in the dynamic QCA method.

| Calculation Content | Formula |
| --- | --- |
| Pooled Consistency | $\frac{\sum_{i=1}^{N}\sum_{t=1}^{T} min(X_{it},Y_{it})}{\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}}$ |
| Pooled Coverage | $\frac{\sum_{i=1}^{N}\sum_{t=1}^{T} min(X_{it},Y_{it})}{\sum_{i=1}^{N}\sum_{t=1}^{T} Y_{it}}$ |
| Between Consistency | $\frac{\sum_{i=1}^{N} min(X_{it},Y_{it})}{\sum_{i=1}^{N} X_{it}}$ |
| Between Coverage | $\frac{\sum_{i=1}^{N} min(X_{it},Y_{it})}{\sum_{i=1}^{N} Y_{it}}$ |
| Within Consistency | $\frac{\sum_{i=1}^{T} min(X_{it},Y_{it})}{\sum_{i=1}^{T} X_{it}}$ |
| Within Coverage | $\frac{\sum_{i=1}^{T} min(X_{it},Y_{it})}{\sum_{i=1}^{T} Y_{it}}$ |

Source: Compiled by the authors. Note: $N$ is the number of samples; $T$ is the total number of time periods; $X_{it}$ represents the membership score of the condition variable for individual $i$ in time period $t$; $Y_{it}$ represents the membership score of the outcome variable for individual $i$ in time period $t$.

However, QCA methods can only qualitatively identify necessary conditions, meaning they can only determine whether a condition is necessary but cannot explain the degree to which a condition is necessary for an outcome. The NCA method effectively addresses this limitation by not only identifying necessary conditions quantitatively but also demonstrating the level of necessity through the bottleneck level. Research by Vis et al. has shown that the combination of QCA and NCA methods can generate greater value [52]. Therefore, this study combines the dynamic QCA method with the NCA method to explore the kinds of innovation ecosystem that lead to high innovation performance in the GBA. The specific implementation tools for this analysis are the R packages "QCA", "SetMethods", and "NCA".

### *4.2. Indicator System Construction*

Among the innovation actors, both knowledge innovation actors and technological innovation actors are included [27]. Higher-education institutions, as core knowledge innovation actors, play a crucial role in the processes of knowledge creation, dissemination, and application [30]. Additionally, in the context of China, educational expenditure reflects the government's support for knowledge innovation activities and indicates the influence of policies in promoting knowledge innovation [53]. The level of investment in education can, to some extent, indicate the strength of key entities involved in knowledge innovation. Therefore, four tertiary indicators are selected to comprehensively measure knowledge innovation actors: the number of regular higher-education institutions, the number of students enrolled in higher-education institutions, full-time teachers in higher-education institutions, and educational expenditure in general public budget.

Industrial enterprises hold a significant position in China's economy and play a leading role in innovation activities [54]. Therefore, industrial enterprises are selected as representatives of technological innovation actors. Additionally, based on data availability and concentration, the number of industrial enterprises above a designated size is chosen to reflect the scale of technological innovation actors. The number of foreign-invested industrial enterprises above a designated size is selected to represent the degree of internationalization and technology transfer capabilities of these actors, while the total profits of industrial enterprises above a designated size are used to reflect their economic benefits and sustainable innovation capacity.

In terms of innovation resources, both human and financial inputs are considered [33]. "Talent is the primary resource", and the quantity and quality of researchers are viewed as "reserve resources" for innovation capacity [12], directly affecting innovation performance. Therefore, the number of R&D personnel in industrial enterprises above a designated size is used to represent the quantity of researchers, while the proportion of R&D personnel and the ratio of master's and doctoral degree holders among R&D personnel in scientific institutions are used to reflect the quality of researchers. Financial investment in research is a fundamental resource for innovation activities, measured through science and technology expenditures in the general public budget and internal R&D expenses, to indicate the level of financial support and sustainability of innovation activities.

In the innovation environment category, the system includes the digital economy environment, public service environment, and natural livability environment. The digital economy environment is assessed using the Digital Inclusive Finance Index, telecom business revenue, and the number of mobile phone users at year-end [55], reflecting the level of digital infrastructure development and the penetration of the digital economy. The public service environment is assessed using the collection size of public libraries, the number of museums, the number of hospital beds, and local general public budget expenditures, reflecting the supply level of public service resources and their support for innovation activities. The natural livability environment is measured by the area of park green spaces and the greening coverage rate of built-up areas, indicating the quality of the urban ecological environment.

The outcome variable for the dynamic QCA analysis is regional innovation performance, which is measured by the number of patent applications and the number of patents granted [56,57]. The specific indicator system is detailed in Table 3.

**Table 3.** Measurement indicator system for the innovation ecosystem in the GBA.

| Primary Indicator | | Secondary Indicator | Tertiary Indicator | Indicator Direction | Data Source |
|---|---|---|---|---|---|
| Conditional Variables | Innovation Actors | Knowledge Innovation Actors | Number of Regular Higher Education Institutions | + | China City Statistical Yearbook |
| | | | Number of Students Enrolled in Higher-Education Institutions | + | China City Statistical Yearbook |
| | | | Number of Full-time Teachers in Higher-Education Institutions | + | China City Statistical Yearbook |
| | | | Educational Expenditure in General Public Budget | + | Guangdong Statistical Yearbook |
| | | Technological Innovation Actors | Number of Industrial Enterprises Above Designated Size | + | Guangdong Statistical Yearbook |
| | | | Number of Foreign-Invested Industrial Enterprises Above Designated Size | + | China City Statistical Yearbook |
| | | | Total Profits of Industrial Enterprises Above Designated Size | + | China City Statistical Yearbook |

**Table 3.** *Cont.*

| Primary Indicator | | Secondary Indicator | Tertiary Indicator | Indicator Direction | Data Source |
|---|---|---|---|---|---|
| Conditional Variables | Innovation Resources | Personnel Input | Number of R&D Personnel in Industrial Enterprises Above | + | Guangdong Science and Technology Statistical Yearbook |
| | | | Proportion of R&D Personnel | + | Guangdong Statistical Yearbook |
| | | | Ratio of Master's and Doctoral Degree Holders Among R&D Personnel in Scientific Institutions | + | Guangdong Science and Technology Statistical Yearbook |
| | | Financial Input | Scientific and Technological Expenditure in General Public Budget | + | Guangdong Statistical Yearbook |
| | | | Internal R&D Expenditure | + | Guangdong Science and Technology Statistical Yearbook |
| | Innovation Environment | Digital Economy Environment | Digital Inclusive Finance Index | + | Peking University Digital Financial Inclusion Index |
| | | | Telecom Business Revenue | + | China City Statistical Yearbook |
| | | | Number of Mobile Phone Users at Year-end | + | China City Statistical Yearbook |
| | | Public Service Environment | Collection Size of Public Libraries | + | China City Statistical Yearbook |
| | | | Number of Museums | + | China City Statistical Yearbook |
| | | | Number of Hospital Beds | + | Guangdong Statistical Yearbook |
| | | | Local General Public Budget Expenditure | + | Guangdong Statistical Yearbook |
| | | Natural Livability Environment | Area of Park Green Spaces | + | China City Statistical Yearbook |
| | | | Greening Coverage Rate of Built-up Areas | + | China City Statistical Yearbook |
| Outcome Variables | Innovation Performance | Number of Patents | Number of Patent Applications | + | China National Patent Database |
| | | | Number of Patents Granted | + | China National Patent Database |

Source: Compiled by the authors.

### *4.3. Data Construction and Calibration*

Before conducting the dynamic QCA analysis, it is necessary to calibrate the data, converting the variable dimensions into set membership scores ranging from 0 to 1. Following the approach outlined by Professor Ragin C.C., the founder of QCA, and taking into account the characteristics of the data in this study, direct calibration is employed [49]. The 95th, 50th, and 5th percentiles are selected as calibration anchors: the 95th percentile corresponds to the point of "full membership", with a score of 1; the 50th percentile represents the "crossover point", with a score of 0.5; and the 5th percentile corresponds to the point of "full non-membership", with a score of 0. Each variable's calibration anchors are shown in Table 4. To prevent cases with a membership score of 0.5 from being excluded from the analysis, the score of 0.5 is replaced by 0.501 for the analysis [58].

**Table 4.** Calibration anchors for innovation ecosystem data in the GBA.

| Variable Type | Variable Name | Full Membership (95%) | Crossover Point (50%) | Full Non-Membership (5%) |
|---|---|---|---|---|
| Outcome Variable | Y Innovation Performance | 180,401.90 | 26,865.00 | 4830.70 |
| Conditional Variables | X1 Knowledge Innovation Actors | 0.82 | 0.05 | 0.01 |
| | X2 Technological Innovation Actors | 0.74 | 0.21 | 0.02 |
| | X3 Personnel Input in R&D | 0.62 | 0.18 | 0.07 |
| | X4 Financial Input in R&D | 0.64 | 0.05 | 0.02 |
| | X5 Digital Economy Environment | 0.80 | 0.22 | 0.07 |
| | X6 Public Service Environment | 0.69 | 0.10 | 0.03 |
| | X7 Natural Livability Environment | 0.44 | 0.07 | 0.02 |

Source: Compiled by the authors.

## 5. Empirical Analysis

### *5.1. Evaluation of the Innovation Ecosystem in the GBA*

Figure 4 illustrates the comprehensive scores of the innovation ecosystem in the GBA. As shown in the figure, the comprehensive scores of the innovation ecosystem across cities within the GBA have generally exhibited a continuous upward trend from 2012 to 2022. Notably, after the establishment of the GBA in 2017, the score growth significantly accelerated, reflecting the remarkable effectiveness of regional coordinated development and innovation-driven strategies. Based on the stratification of the comprehensive scores, the innovation ecosystem in the GBA can be divided into three tiers, as shown in Table 5.

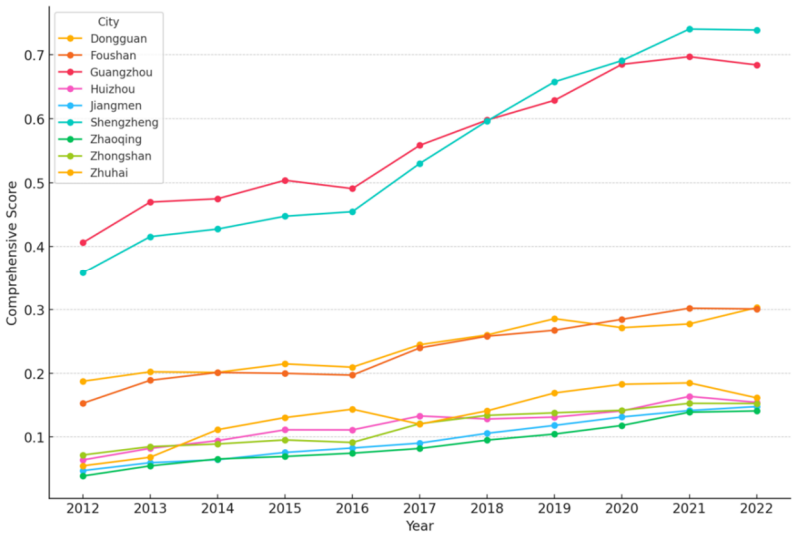



**Figure 4.** Comprehensive scores of the innovation ecosystem in the GBA. Source: Compiled by the authors.

**Table 5.** Classification of the innovation ecosystem levels in the GBA.

| Type | Cities |
|---|---|
| First tier | Shenzhen, Guangzhou |
| Second tier | Dongguan, Foushan |
| Third tier | Zhuhai, Zhongshan, Jiangmen, Huizhou, Zhaoqing |

Source: Compiled by the authors.

Shenzhen and Guangzhou, as the core cities of the GBA, are in a leading position. Shenzhen has seen rapid growth in its scores, showcasing its outstanding achievements in technological innovation, industrial upgrading, and global talent attraction. Guangzhou, benefiting from its abundant research resources and policy support, has also maintained steady growth.

Dongguan and Foshan follow closely behind, forming the second tier of cities. Dongguan's score significantly increased after 2017, reflecting its rapid development in intelligent manufacturing and high-tech industries. Foshan, on the other hand, has steadily advanced its innovation transformation based on its traditional manufacturing base, with its scores increasing year by year.

In contrast, Zhuhai, Zhongshan, Jiangmen, Huizhou, and Zhaoqing belong to the third tier, with relatively lower comprehensive scores and slower growth rates. Among these cities, Zhuhai slightly leads the other third-tier cities in innovation ecosystem scores, thanks to the policy advantages of being a Special Economic Zone and the development of the Hengqin New Area. Although the scores of Zhongshan, Jiangmen, Huizhou, and Zhaoqing are relatively low, these cities have shown potential for improvement by continuously introducing emerging industries and optimizing the allocation of innovation resources, driven by the overall development of the GBA.

As cooperation among cities within the GBA deepens and further policy implementation takes place, the innovation ecosystem of the entire region is expected to achieve more balanced and coordinated rapid development.

The dynamic evolution characteristics of the innovation ecosystem development in the GBA are illustrated through the kernel density estimation curves, as shown in Figure 5. From the perspective of distribution position, the overall kernel density curve has shifted to the right, indicating that the overall state of the GBA's innovation ecosystem has been continuously optimized from 2012 to 2022, with the innovation ecosystem gradually maturing. In terms of the number of peaks, the kernel density curve mainly exhibits three peaks during the study period, suggesting a multi-polarization in the comprehensive score of the GBA's innovation ecosystem. This also reveals significant differences in innovation development across different regions within the GBA. Regarding distribution extensibility, the kernel density curve shows a right-tailed trend, which has become increasingly pronounced, indicating that the gap between regions with high innovation ecosystem development levels and those with average levels is widening. The leading regions in terms of innovation are exerting an increasingly stronger pulling effect on the overall GBA innovation ecosystem, contributing to a "head effect" within the GBA's innovation development. Moreover, the overall extensibility of the curve has broadened year by year during the study period, reflecting that the absolute differences are expanding annually. As high-level innovation regions accelerate their development, the disparities between regions may further widen, leading to a "strong-get-stronger" scenario.

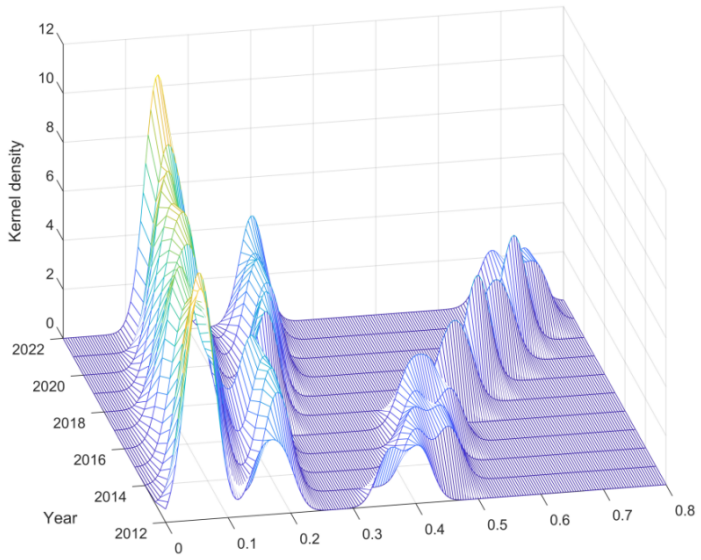



**Figure 5.** Kernel density estimation curve of the comprehensive scores of the innovation ecosystem in the GBA. Source: Compiled by the authors.

After analyzing the overall development level and dynamic evolution characteristics of the GBA's innovation ecosystem using the comprehensive evaluation model and kernel density estimation, the overall trends and key differences in regional innovation development have been preliminarily identified. However, merely analyzing distribution and trends is insufficient to fully uncover the underlying mechanisms and driving factors of the GBA's innovation ecosystem. To gain a deeper understanding of the factors that play a decisive role in the development of different regions, and how these factors interact to collectively drive the GBA toward high innovation performance, this study employs dynamic QCA and NCA methods to further reveal the key elements and pathways for achieving high innovation performance in the GBA's innovation ecosystem.

### *5.2. Necessary Condition Analysis*

Before conducting configurational analysis, it is essential to perform a necessity test on each conditional variable. This test helps determine whether a condition is necessary for the outcome variable. According to Schneider, a condition can be considered necessary for the outcome variable if the overall consistency level exceeds 0.9 and the overall coverage exceeds 0.5 [59]. In the dynamic QCA analysis, the necessity of a single condition across cases is assessed for variations across time and regional dimensions by using consistency-adjusted distances. Based on prior research, if the between-group consistency-adjusted distance exceeds 0.1, it indicates significant temporal variation in the necessity of that condition. Similarly, if the within-group consistency-adjusted distance exceeds 0.1, it indicates significant regional variation in the necessity of that condition [51].

#### 5.2.1. Analysis of the Summary Results of Necessary Conditions

As shown in Table 6, the consistency of the technological innovation actors (X2) and the digital economy environment (X5) exceeds 0.9, and their coverage is greater than 0.5. This indicates that, overall, technological innovation actors (X2) and the digital economy environment (X5) constitute necessary conditions for achieving high innovation performance in the GBA.

**Table 6.** Results of the necessary condition analysis.

| Conditional Variables | Consistency | Coverage | Between-Group Consistency-Adjusted Distance | Within-Group Consistency-Adjusted Distance |
|---|---|---|---|---|
| X1 Knowledge Innovation Actors | 0.63 | 0.79 | 0.09 | 0.56 |
| X2 Technological Innovation Actors | 0.90 | 0.81 | 0.11 | 0.27 |
| X3 Personnel Input in R&D | 0.73 | 0.76 | 0.11 | 0.47 |
| X4 Financial Input in R&D | 0.77 | 0.84 | 0.09 | 0.36 |
| X5 Digital Economy Environment | 0.92 | 0.82 | 0.09 | 0.11 |
| X6 Public Service Environment | 0.84 | 0.82 | 0.11 | 0.39 |
| X7 Natural Livability Environment | 0.87 | 0.80 | 0.07 | 0.20 |

Source: Compiled by the authors.

#### 5.2.2. Analysis of Between-Group Results for Necessary Conditions

As shown in Table 6, the between-group consistency-adjusted distances for technological innovation actors (X2), personnel input in research and development (X3), and the public service environment (X6) all exceed 0.1. This indicates that the necessity of these three elements of the innovation ecosystem underwent significant changes during the study period and warrants further analysis. Scatter plots were drawn based on the between-group consistency of technological innovation actors (X2), personnel input in R&D (X3), and the public service environment (X6).

Figure 6 reveals three distinct patterns of necessity variation for the three conditions, characterized as S-shaped, W-shaped, and U-shaped:

- Technological innovation actors (X2): The necessity of this condition for achieving high innovation performance in the GBA shows an S-shaped dynamic growth pattern. From 2012 to 2013, the level of necessity grew relatively slowly. Between 2014 and 2016, with increased policy support, rising demand for industrial upgrading and transformation, and the gradual maturation of the innovation ecosystem, the necessity level rose rapidly. Since 2017, with the formal establishment of the GBA, the role of technological innovation actors has stabilized, becoming a necessary condition for achieving high innovation performance in the region.
- Personnel input in R&D (X3): The necessity level of this condition exhibits a W-shaped fluctuation pattern, varying significantly within the range of 0.6 to 0.9. During the study period, this condition did not constitute a necessary condition, which indirectly reflects that the high innovation performance in the GBA relies on diversified innovation inputs. The instability in the impact of personnel input in R&D on innovation performance may be due to fluctuations in the efficiency of research resource utilization, the diversity of innovation models, and changes in the external environment.
- Public service environment (X6): The necessity of this condition for achieving high innovation performance in the GBA presents a U-shaped variation. From 2012 to 2018, the necessity of this condition gradually declined; however, from 2019 to 2022, it showed an upward trend, constituting a necessary condition for the years 2012–2015 and 2022. This suggests that, during the early stages of innovation development in the GBA, the public service environment played a significant role in enhancing innovation performance. However, as infrastructure and the innovation ecosystem improved, its relative importance decreased. Nevertheless, with the emergence of new challenges and adjustments in regional policies after 2019, the importance of the public service environment increased again, with the quality and efficiency of public services once more becoming key factors in enhancing regional innovation performance.

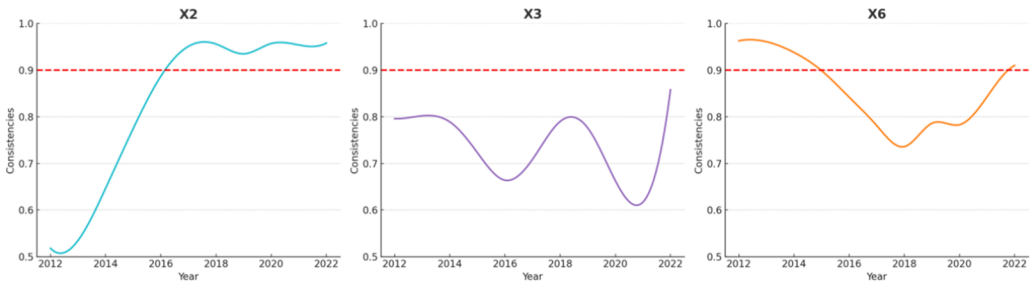



**Figure 6.** Variation of between-group consistency for necessary conditions. Source: Compiled by the authors.

5.2.3. Analysis of Within-Group Results for Necessary Conditions

As indicated in Table 6, the within-group consistency-adjusted distances for all seven conditional variables exceed 0.1, suggesting significant regional differences in the level of necessity for these variables across the cities within the GBA. The within-group consistency data are illustrated in Figure 7.

Specifically:

- Knowledge innovation actors (X1) is a necessary condition for achieving high innovation performance in Guangzhou, Zhaoqing, and Zhuhai;
- Technological innovation actors (X2) is a necessary condition for achieving high innovation performance in Dongguan, Foshan, Guangzhou, Shenzhen, and Zhongshan;
- Personnel input in R&D (X3) is a necessary condition for achieving high innovation performance in Foshan, Jiangmen, Shenzhen, and Zhaoqing;
- Financial input in R&D (X4) is a necessary condition for achieving high innovation performance in Guangzhou, Shenzhen, Zhaoqing, and Zhuhai;

- Digital economy environment (X5) is a necessary condition for achieving high innovation performance in Dongguan, Guangzhou, Huizhou, Jiangmen, Shenzhen, Zhaoqing, and Zhuhai;
- Public service environment (X6) is a necessary condition for achieving high innovation performance in Foshan, Guangzhou, Huizhou, Jiangmen, Shenzhen, and Zhaoqing;
- Natural livability environment (X7) is a necessary condition for achieving high innovation performance in Dongguan, Guangzhou, Huizhou, Jiangmen, Shenzhen, Zhaoqing, and Zhuhai.

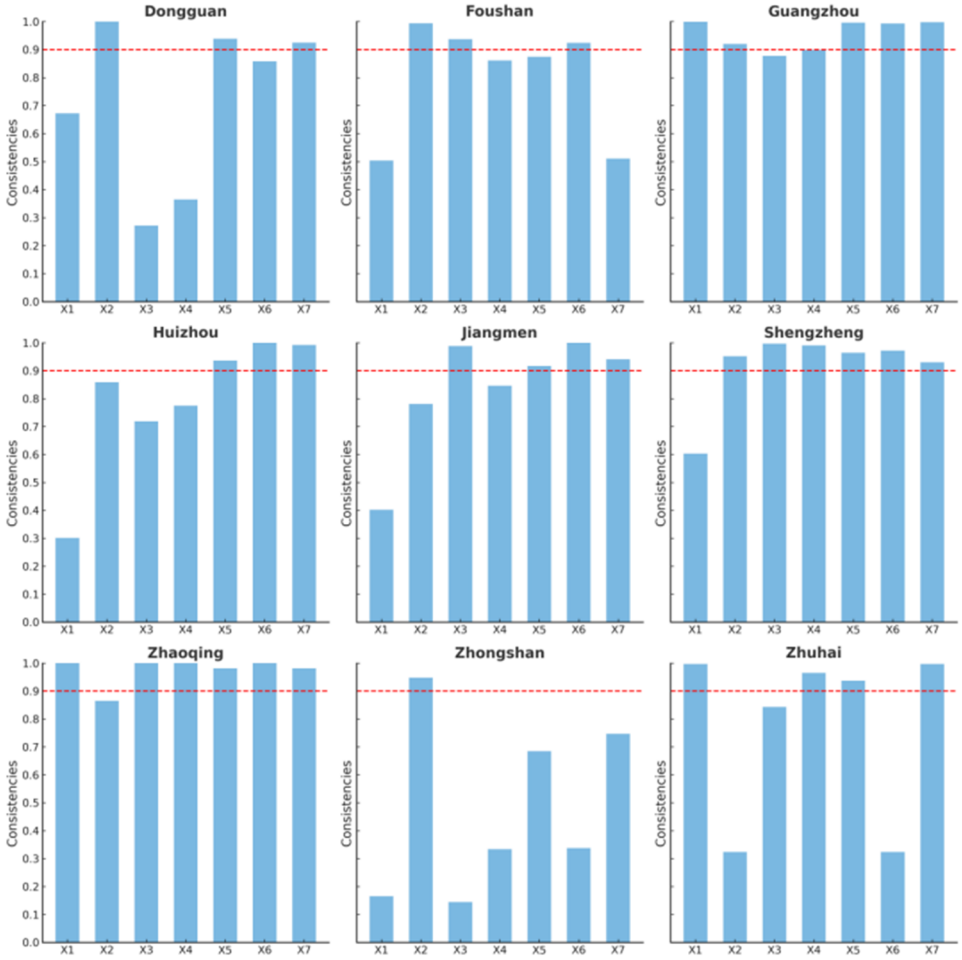



**Figure 7.** Within-group consistency data for necessary condition analysis. Source: Compiled by the authors.

These regional differences reflect the diversity in resources, industrial structures, and stages of economic development within the GBA cities. This further suggests that each city in the GBA should formulate differentiated innovation strategies based on its own resource endowments and development stage. At the same time, there should be strengthened regional cooperation to achieve complementary and shared resource advantages, thereby enhancing the overall innovation capacity and competitiveness of the entire region.

#### 5.2.4. NCA Bottleneck Level Analysis

NCA evaluates the necessity level of variable conditions through bottleneck level analysis [52]. Figure 8 presents the results of the bottleneck level analysis using the ceiling regression (CR) method. The digital economy environment (X5) is identified as the first bottleneck factor constraining the improvement of innovation performance in the GBA, with a bottleneck level of 4.2%. This is followed by knowledge innovation actors (X1) and

technological innovation actors (X2), whose bottleneck levels gradually increase as the innovation performance level rises.

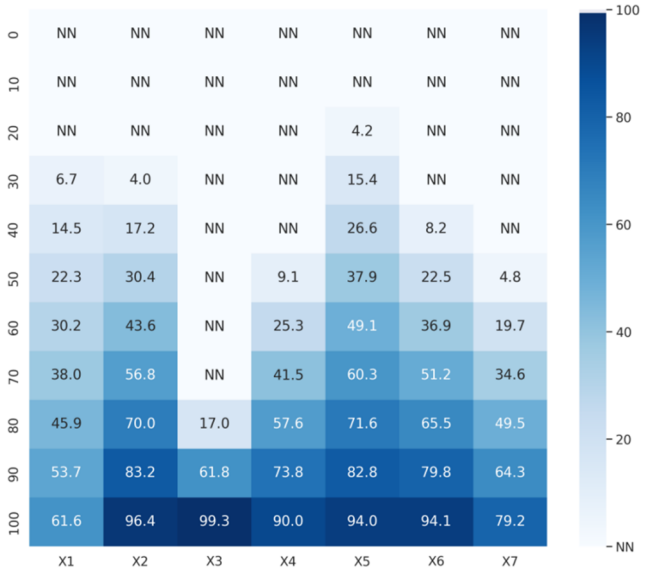



**Figure 8.** Results of NCA bottleneck level analysis. Source: Compiled by the authors. Note: NN means not necessary.

To achieve 90% of the regional innovation performance in the GBA, the following minimum levels are required: 53.7% for knowledge innovation actors (X1), 83.2% for technological innovation actors (X2), 61.8% for personnel input in R&D (X3), 73.8% for financial input in R&D (X4), 82.8% for the digital economy environment (X5), 79.8% for the public service environment (X6), and 64.3% for the natural livability environment (X7). This indicates that no single condition can fully support the comprehensive improvement in regional innovation performance; a simultaneous effort across multiple areas is necessary.

Furthermore, when the goal is to reach 100% of regional innovation performance, the bottleneck levels of several factors exceed 90%, indicating that achieving top-tier innovation performance in the GBA will present greater challenges and more complex constraints. Therefore, it is essential to deeply optimize and enhance areas such as technological innovation actors, innovation resource inputs, the digital economy, and public services to break through these bottlenecks and ensure a comprehensive enhancement of regional innovation capabilities. This also reflects the complexity and systemic nature of improving regional innovation performance, emphasizing the importance of coordinated development across various innovation elements.

### *5.3. Configurational Analysis*

Configurational analysis attempts to examine the sufficiency of multiple causal conditions forming specific configurations that lead to a particular outcome. Based on existing research, the following settings were used when running the analysis in R: a consistency threshold of 0.7, a case frequency of 2, and a PRI threshold of 0.8, resulting in the final inclusion of 99 cases [58]. During the counterfactual analysis, no directional assumptions were made for the seven conditional variables; both presence and absence were considered [51]. Following the study by Du, conditions that appear in both the intermediate and parsimonious solutions are treated as core conditions, while those appearing only in the intermediate solution are considered peripheral conditions [60]. This process led to the identification of three innovation ecosystem models that contribute to high innovation performance in the GBA.

5.3.1. Summary of Configurational Results and Case Analysis

As shown in Table 7, the consistency levels of the three configurations are 0.95, 0.99, and 0.96, all of which exceed 0.95, indicating that these three configurations have strong explanatory power. Additionally, the between-group and within-group consistency-adjusted distances for these configurations are all less than 0.1, suggesting that there are no significant temporal or regional differences among the configurations. This means that all three configurations can sufficiently explain how the innovation ecosystem in the GBA drives high innovation performance across both time and case dimensions. The overall consistency is 0.98, indicating that 98% of the cities that fit these three configurations have achieved high innovation performance. The overall coverage is 0.72, indicating that these configurations collectively explain approximately 72% of the cases of high innovation performance in the GBA.

**Table 7.** Results of configurational analysis.

| Conditional Variables | | H1 | H2 | H3 |
|---|---|---|---|---|
| Innovation Actors | X1 Knowledge Innovation Actors | ★ | ★ | |
| | X2 Technological Innovation Actors | ★ | ★ | • |
| | X3 Personnel Input in R&D | | **U** | • |
| Innovation Resources | X4 Financial Input in R&D | | **U** | ★ |
| | X5 Digital Economy Environment | • | | ★ |
| Innovation Environment | X6 Public Service Environment | • | • | • |
| | X7 Natural Livability Environment | • | • | **U** |
| Consistency | | 0.95 | 0.99 | 0.96 |
| Coverage | | 0.54 | 0.31 | 0.30 |
| Unique Coverage | | 0.20 | 0.01 | 0.09 |
| Between-Group Consistency-Adjusted Distance | | 0.08 | 0.03 | 0.07 |
| Within-Group Consistency-Adjusted Distance | | 0.07 | 0.07 | 0.06 |
| Overall Consistency | | | 0.72 | |
| Overall Coverage | | | 0.98 | |

Source: Compiled by the authors. Note: ★ indicates that the core condition exists, • indicates that the edge condition exists, **U** indicates that the core condition is missing, **U** indicates that the edge condition is missing, and blank indicates that the condition can either occur or not occur.

Based on the consistency of the core conditions, the three innovation ecosystem configurations in the GBA can be further categorized into two types: innovation actor-driven and resource–environment linkage-driven. The innovation actor-driven ecosystem includes configurations H1 and H2, while the resource–environment linkage-driven ecosystem corresponds to configuration H3.

Configuration H1: In this configuration, the core conditions are knowledge innovation actors and technological innovation actors, while the peripheral conditions include the digital economy environment, public service environment, and natural livability environment. The conditions of personnel input in R&D and financial input in R&D are considered non-essential. This indicates that within the GBA, driven by innovation actors, there is a synergistic interaction with the innovation environment, leading to high innovation performance regardless of the level of innovation resources. This configuration reflects that, under specific conditions, the quality and activity of innovation actors are more critical than resource input. Furthermore, these actors engage in positive interactions with the digital economy environment, public service environment, and natural livability environment, collectively driving regional innovation development. Representative cases of this configuration are Shenzhen and Guangzhou.

Shenzhen: Driven by globally renowned technology companies such as Huawei, Tencent, and DJI, Shenzhen has developed into an innovation ecosystem centered on technological innovation actors. According to the Guangdong Statistical Yearbook, in 2022, the number of national high-tech enterprises in Shenzhen reached 23,000. These technological innovation actors, through sustained R&D investment and market-driven innovation practices, have propelled the city's technological advancement and industrial upgrading, becoming the primary engine of Shenzhen's high innovation performance. Meanwhile, Shenzhen's digital economy environment, public service infrastructure, and natural livability have provided critical support, effectively fostering the growth and development of these innovation actors and enhancing the city's overall innovation capacity. According to the China Internet Development Report, the added value of Shenzhen's core digital economy industries surpassed 900 billion yuan in 2021, accounting for 30.5% of the city's GDP, and ranking first in both scale and quality among major cities in China. Additionally, Shenzhen's air quality ranked eighth in China.

Guangzhou: With top universities such as Sun Yat-sen University and South China University of Technology, Guangzhou's knowledge innovation actors play a crucial role in fundamental research and technological innovation. According to the China City Statistical Yearbook, as of 2021, Guangzhou had 83 higher-education institutions, ranking third in China. The number of enrolled university students reached 1.5583 million, the highest in the country. Moreover, technology-oriented companies in Guangzhou, like Guangzhou Automobile Group and Midea Group, have successfully industrialized and commercialized their technologies through industry–academia collaboration. The digital economy environment and livable environment have also created favorable conditions for attracting and retaining high-end talent. The interaction between these innovation actors and the environment has sustained high levels of innovation output.

Configuration H2: In this configuration, knowledge innovation actors and technological innovation actors are core conditions, while the public service environment and natural livability environment are peripheral conditions. The conditions of personnel input in R&D and financial input in R&D are absent, and the digital economy environment is considered non-essential. This suggests that even with limited innovation resources, high innovation performance can be achieved in the GBA through the interaction between innovation actors and the public service and livable environments. The representative case of this configuration is Dongguan.

In Dongguan's innovation ecosystem, knowledge and technological innovation actors play a central role, driving the city's industrial transformation and upgrading. High-tech companies rooted in manufacturing, such as Huawei's terminal headquarters, OPPO, and VIVO, have become the core drivers of Dongguan's innovation ecosystem through continuous technological innovation and product upgrades. According to the Guangdong Statistical Yearbook, in 2022, the number of large-scale industrial enterprises in Dongguan reached 13,800, ranking first in Guangdong Province. In recent years, Dongguan has also strengthened its cooperation with renowned universities and research institutions, attracting significant innovation resources and enhancing the city's knowledge innovation capacity. Despite relatively limited resources in R&D personnel and financial input, Dongguan's robust public service environment and livable environment have provided crucial support for the development of innovation actors. By simplifying administrative procedures, optimizing the business environment, offering efficient public services, and providing a high-quality living environment, Dongguan has successfully attracted a large influx of highly qualified talent, further strengthening the competitiveness of its innovation actors, and driving continuous innovation and upgrading in local industries.

Configuration H3: This configuration is characterized by core conditions of financial input in R&D and the digital economy environment, with the absence of the natural livability environment as a core condition. Peripheral conditions include technological innovation actors, personnel input in R&D, and the public service environment, while knowledge innovation actors are considered non-essential. This suggests that under the

core drivers of financial investment in R&D and the digital economy environment, even without a superior livable environment, high innovation performance can still be achieved in the Greater Bay Area. The representative case of this configuration is Foshan.

As an industrial and manufacturing hub in the GBA, Foshan's government and enterprises have driven industrial upgrading and technological innovation in high-end manufacturing and intelligent manufacturing through substantial financial investment. According to the Guangdong Provincial Science and Technology Expenditure Bulletin, Foshan's R&D expenditure in 2022 amounted to 35.953 billion yuan, ranking fourth in Guangdong Province. Moreover, Foshan has made significant progress in building a digital economy environment. According to the 2022 China Digital City Competitiveness Research Report, Foshan's digital infrastructure development was listed among China's top 100 cities. Digital transformation has been widely applied in manufacturing, from supply chain management to production process optimization, ensuring that companies maintain a competitive edge in the global market. Through the development of industrial internet, Internet of Things, and big data technologies, Foshan has further enhanced the city's innovation capacity and secured a significant position in the global market.

#### 5.3.2. Analysis of Between-Group and Within-Group Results for Configurations

The analysis of Table 7 reveals that the between-group consistency-adjusted distances for the three configurations are 0.08, 0.03, and 0.07, respectively—all of which are less than 0.1. This indicates that the consistency levels of these configurations exhibit minimal variation over time, showing no significant cross-temporal effects. These configurations maintain strong explanatory power throughout the entire period from 2012 to 2022.

Further analysis using the between-group consistency variation graphs (Figure 9) shows that configuration H2 experienced a sharp decline in between-group consistency in 2013. The random fluctuation observed in configuration H3 can be considered a "benign deviation" [51,61]. Additionally, throughout the study period, the between-group consistency for all three configurations remains above 0.8, indicating strong explanatory power. The overall trend for between-group consistency shows a gradual increase, with the explanatory power strengthening each year, and by 2017, the consistency of all three configurations reaches a peak of 1.

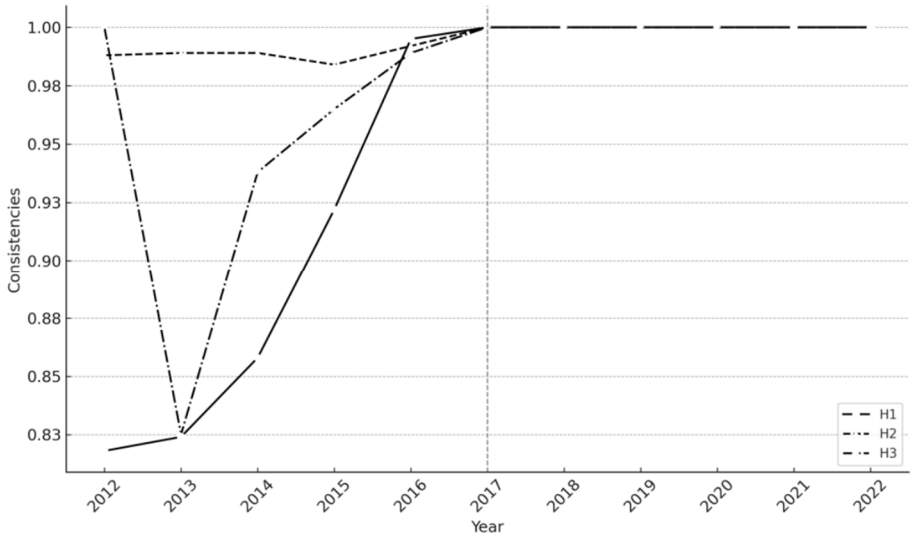



**Figure 9.** Between-group consistency variation for each configuration. Source: Compiled by the authors.

Based on the analysis of between-group consistency, the development of the innovation ecosystem in the GBA can be divided into two distinct phases:

Phase 1 (2012–2016): This phase represents the developmental and construction period of the GBA's innovation ecosystem. During this time, the innovation ecosystem in the

region exhibited a trend of fluctuating growth. This trend reflects the process of building the innovation ecosystem, where, despite experiencing some adjustments and fluctuations, the overall structure and function of the ecosystem were continuously optimized and improved.

Phase 2 (2017–2022): This phase marks the formal establishment of the GBA. Driven by policy, the innovation ecosystem of the GBA rapidly matured and stabilized during this period, displaying stronger synergies and higher levels of consistency. This phase is characterized by the comprehensive enhancement of regional innovation capacity and the systematic development of the innovation ecosystem.

The analysis of Table 7 reveals that the within-group consistency-adjusted distances for all three configurations are also less than 0.1, indicating that the consistency levels of these configurations exhibit minimal variation across the spatial dimension, with no significant cross-case effects. The within-group consistency variation graph (Figure 10, left) shows that the within-group consistency for all three innovation ecosystems in the GBA is greater than 0.84. This suggests that these three innovation ecosystems have strong explanatory power across the nine cities in the GBA.

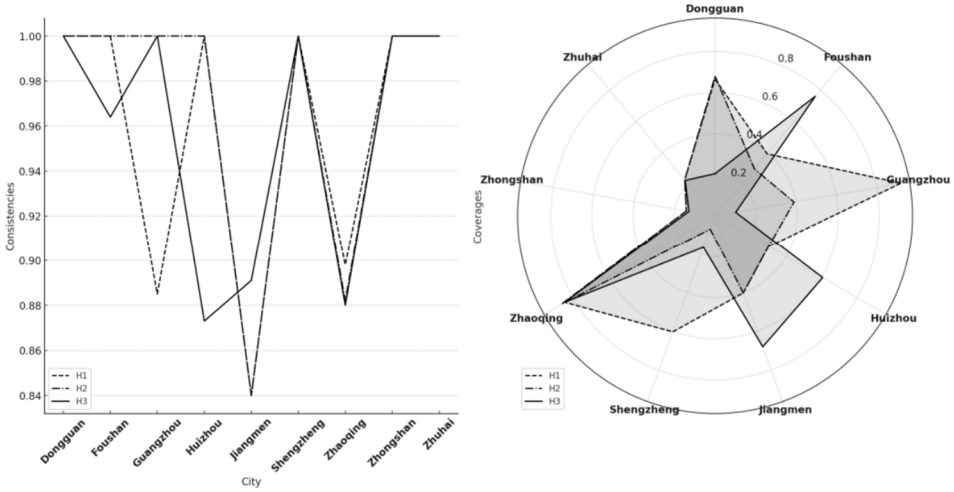



**Figure 10.** Variation of within-group consistency and within-group coverage for each configuration. Source: Compiled by the authors.

Given the high levels of consistency, the next step is to discuss the within-group coverage of each configuration. Higher within-group coverage indicates a stronger impact of the innovation ecosystem on a city's innovation performance, allowing for a more precise identification of the GBA cities that correspond to each of the three innovation ecosystems. The variation in within-group coverage is illustrated by the radar chart in Figure 10.

The radar chart indicates the following:

- Configuration H1 has higher coverage for Guangzhou and Shenzhen;
- Configuration H2 has higher coverage for Dongguan and Zhaoqing;
- Configuration H3 has higher coverage for Foshan, Huizhou, and Jiangmen;
- Additionally, Zhongshan and Zhuhai have the same level of coverage under both H1 and H2 configurations.

### *5.4. Robustness Test*

The dynamic QCA method accounts for both time and individual effects, making its results more robust compared to QCA analyses based on cross-sectional data. In this study, the between-group and within-group consistency-adjusted distances for the configurational analysis results are all less than 0.1, indicating high robustness of the configurational results across both temporal and spatial dimensions [62]. To further validate robustness, we

conducted additional tests by increasing the PRI threshold and the consistency threshold, as suggested by related research [63].

As shown in Table 8, when the PRI threshold was increased from 0.8 to 0.85, the configuration results remained unchanged. Similarly, when the consistency threshold was increased from 0.7 to 0.75, the configuration results still did not change. This further confirms the robustness of the original configuration results.

**Table 8.** Results of the robustness test.

| Original Configuration Analysis Settings Case Frequency/PRI Threshold/Consistency Threshold | Increase PRI Threshold | Increase Consistency Threshold |
|---|---|---|
| 1/0.8/0.7 | 1/0.85 ↑/0.7 | 1/0.8/0.75 ↑ |
| Change in Configuration Results | No Change | No Change |

Source: Compiled by the authors. Note: ↑ indicates the uplift threshold.

## 6. Research Conclusions and Discussion

### *6.1. Research Conclusions*

Based on the theory of the innovation ecosystem, this study constructed an "Actors-Resources-Environment" analytical framework. Using the nine mainland cities in the GBA as case studies from 2012 to 2022, the development level of the GBA's innovation ecosystem was measured using a comprehensive evaluation model. This study employed a mixed-method approach combining dynamic QCA and NCA to further address the following research question: what kind of innovation ecosystem leads to sustainable high innovation performance in the GBA? The following conclusions were drawn:

1. Overall Development Trend: From 2012 to 2022, the comprehensive scores of the innovation ecosystems in the GBA cities showed a continuous upward trend. Particularly after the establishment of the GBA in 2017, the rate of score growth significantly accelerated. The development levels of the nine cities can be divided into three tiers. Additionally, the GBA's innovation ecosystem exhibits characteristics such as multi-polarization, a "head effect", and a "strong-get-stronger" dynamic.
2. Necessary Conditions: Technological innovation actors and the digital economy environment are identified as necessary conditions for achieving sustainable high innovation performance in the GBA. Between-group results indicate that the time effects of technological innovation actors, personnel input in R&D, and the public service environment are significant, showing S-shaped, W-shaped, and U-shaped patterns, respectively. Within-group results reveal that the necessity levels of the seven conditional variables show significant regional differences within the GBA cities.
3. Three Innovation Ecosystems: There are three distinct innovation ecosystems in the GBA that lead to sustainable high innovation performance. These can be further classified into two types based on core conditions: innovation actor-driven and resource–environment linkage. There are no significant cross-temporal or cross-case effects among the three ecosystems. However, the between-group consistency variation indicates that the innovation ecosystems in the GBA have become more mature and stable since the establishment of the GBA in 2017.

### *6.2. Theoretical and Practical Contributions*

This study, through systematic analysis and empirical research, reveals the complex ecosystem behind the high innovation performance in the GBA, making significant contributions on theoretical, methodological, and practical levels.

(1) The study constructs an "Actors-Resources-Environment" analytical framework based on innovation ecosystem theory. This framework, from a systematic perspective,

thoroughly explores the core elements of the GBA's innovation ecosystem and their interactions. Through this framework, the study provides a deeper understanding of the internal mechanisms of regional innovation, particularly regarding how the synergistic interactions among different actors and the effective allocation of resources drive the sustained enhancement of regional innovation performance. This theoretical contribution offers a powerful analytical tool for future regional innovation research and expands the application scope of innovation ecosystem theory.

(2) From a configurational perspective, the study identifies and reveals three typical innovation ecosystem models that lead to sustainable high innovation performance in the GBA. Unlike traditional analyses that focus on single elements, this research demonstrates how multiple elements, through specific combinations, jointly promote the enhancement in regional innovation capacity. The discovery of these models not only enriches empirical research on innovation ecosystems, but also provides valuable insights for other regions in formulating innovation policies and constructing innovation systems.

(3) By employing the dynamic QCA method, the study examines the variations in the GBA's innovation ecosystem across three dimensions: aggregate, between-group, and within-group, over time and across cases. This method not only effectively addresses the limitations of traditional fsQCA methods concerning the temporal dimension, but also allows more precisely capturing the dynamic characteristics and evolutionary paths of innovation ecosystems. Through dynamic QCA analysis, the study further deepens the understanding of the evolution of complex systems and provides new analytical tools and methodological references for research on other complex social systems.

### *6.3. Implications of the Study*

Based on the research findings, the following implications are drawn:

(1) Effective regional collaboration and the implementation of innovation policies play a crucial role in enhancing regional innovation capacity. The study shows that since the establishment of the GBA in 2017, the development of innovation ecosystems across its cities has accelerated significantly. This indicates that collaborative efforts within the region, coupled with the implementation of innovation policies, can greatly promote regional innovation levels. Other regions should draw on the successful experiences of the GBA when formulating innovation development strategies, strengthening inter-city collaboration and policy guidance to continuously improve overall regional innovation capacity.

(2) Technological innovation actors and the digital economy environment play pivotal roles in driving regional innovation. The study reveals that these two factors are necessary conditions for achieving sustainable high innovation performance in the GBA. Therefore, future regional innovation policies should focus more on supporting and nurturing technological innovation actors, as well as optimizing the digital economy environment. This includes enhancing the development of technology enterprises, cultivating research personnel, and building digital infrastructure to further invigorate regional innovation.

(3) The dynamic and sustainable development characteristics of innovation ecosystems impose higher demands on policymaking. This research finds that the GBA's innovation ecosystem has further matured and stabilized since 2017, highlighting the dynamic nature of innovation ecosystems and the need for sustainable development. Thus, regional innovation policies should adopt a long-term perspective, focusing on the continuous optimization and evolution of the innovation ecosystem. Policies should be regularly evaluated and adjusted to ensure the long-term health of the innovation ecosystem. This also suggests that future research and practice should pay more attention to the dynamic changes in innovation ecosystems to better inform the formulation and implementation of innovation policies.

### *6.4. Research Limitations*

This study has several limitations that warrant improvement and further exploration in future research:

(1) Like many QCA studies, this research faces limitations in the selection of conditional variables. Due to the complexity and diversity of innovation ecosystems, it is challenging to exhaustively include all potential influencing factors in the analysis. This means that the current analysis may not fully capture all critical variables and combinations of factors, thereby limiting a comprehensive understanding of the innovation ecosystem. Future research could consider integrating QCA with other quantitative or qualitative research methods to include a broader range of conditional variables. Such a multi-method research strategy would help to explore the complexity of innovation ecosystems and reveal the hidden interactions and mechanisms within them, providing richer insights for both theoretical development and practical application.

(2) This study focuses on the GBA, and while the findings offer valuable regional insights, the uniqueness of this region may limit the generalizability and applicability of the results. Therefore, future research could expand the scope of analysis to include comparisons with other globally renowned innovation bay areas, such as the San Francisco Bay Area, Tokyo Bay Area, and New York Bay Area. Comparative analysis could lead to a deeper understanding of the commonalities and differences among innovation ecosystems in different regions, providing broader references and guidance for the formulation of innovation policies across diverse global regions.

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