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Article

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How does China's digital government construction affect enterprise exploratory innovation? Insights based on invention knowledge inertia

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ABSTRACT

Today, digital governments are creating novel digital business environments to promote enterprise innovation. How can enterprises benefit from this while minimizing the risks of working with the digital government?

We explored this issue using data from China's 1528 A-share firms over a decade. We find that China's digital government construction (*DGC*) significantly promotes firms' exploratory innovation (*EI*). Moreover, the enterprise's invention knowledge inertia (*IKI*) is an important mediation to develop its exploratory innovation in response to the construction of digital government. However, during this process, whether enterprises can maintain low risk and continuously promote *EI* by leveraging *IKI* is moderated by the extent of knowledge openness within the senior leadership team (*KOM*). For instance, the diversified knowledge of executives with financial backgrounds weakens the *DGC*→*IKI*, and the effect is obvious in state-owned and high-tech enterprises. In contrast, knowledge without such backgrounds strengthens the *IKI*→*EI*.

This study provides valuable insights into government-enterprise cooperation, emphasizing the role of innovation knowledge inertia and clarifying the debate on whether knowledge inertia has a positive or negative impact on innovation.

1. Introduction

The construction of digital government (*DGC*) serves as a new driving force to enhance the modernization of national governance by improving the innovative ecosystem (Bruton et al., 2013; GE et al., 2024; Tian et al., 2021). This process offers valuable opportunities for businesses to access and obtain resources fairly (Lazzarini, 2015). In light of the call from a digital government, there's a growing trend of enterprise exploratory innovation (Fig. 1). In this context, it's crucial to explore how businesses can maximize these opportunities while minimizing risks in working with the digital government (Nambisan et al., 2019).

While previous studies have examined the correlation between government and corporate innovation (Li et al., 2018; Ye et al., 2024), believing that the government can guide enterprises to "go global" (GE et al., 2024; Li & Zhang, 2024), improve financing constraints (Tian et al., 2021), reduce enterprise transaction costs to promote enterprise innovation. Nevertheless, few studies have answered the question of

whether there is a mechanism that digital government construction (*DGC*) to influence a firm's exploratory innovation (*EI*) by interfering with the invention knowledge inertia (*IKI*) of enterprises.

Particularly in China's socialist market economy system, businesses have a natural preference for experience and existing inventive knowledge to respond to digital government calls and solve problems. So, there remains a lack of consensus regarding whether engagement in *DGC* leads firms to inadvertently develop an *IKI* (Barr et al., 1992; Sydow et al., 2009) to impact the firms' *EI*? This gap hinders our understanding of the relationship between digital government and corporate innovation.

The academic significance of this work aims to uncover the intricate relationship between digital government construction and enterprise exploratory innovation. It offers a new perspective and deep insights into the innovation practices of enterprises in government-enterprise interaction. The in-depth exploration of these issues will enable enterprises to understand and appreciate the potential role of their invention

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knowledge inertia when interacting with the construction of digital government. This will also help in assessing whether the passive shaping of *IKI* aligns with the requirements for *EI*.

To address the aforementioned questions, resource dependence theory (Stern et al., 1979) was employed to elucidate the research. However, this theory primarily emphasizes the enterprises' aim to acquire government resources and the government's dominant position, without adequately considering the characterize in which enterprises engage in interactions. Therefore, a perspective on unilateral knowledge inertia (Zhang et al., 2023) within resource dependence theory is proposed to explain why enterprises exhibit inertia in invention knowledge when confronted with digital government initiatives.

Furthermore, enterprise's *IKI* is easy to fall into the dilemma of strategic attention contradiction (Raisch et al., 2018). Under such circumstances, if managers (from diverse knowledge backgrounds) exchange information and collide with their expertise, it may help to weaken the negative impact of the *IKI*, and even promote the positive transformation of the *IKI* to *EI*. So, we also empirically investigated whether the senior leadership team's openness to knowledge can be considered a critical factor in managing *IKI*.

The rest of the paper is structured as follows: Section 2 presents the theoretical development and hypothesis development. Section 3 presents the research methodology adopted in the study. Sections 4 to 5 presents a detailed description of the data sources, and the variables'

measurement included in the analysis and Section 6 presents the results and the robustness tests, with Section 7 discussing the implications, limitations, and future research to conclude the paper. The whole analysis is conducted based on annual data from 12,668 companies of 1528 A-share listed companies from 2013 to 2022.

2. Theoretical development and hypothesis development

2.1. Introduction of the institutional background

In China, with a socialist market economy, digital government plays a pivotal role in managing key resources such as data, investment projects, and business planning. It is rather a novel strategic entity within the existing government framework. Unlike government digitization, the *DGC* involves multiple dimensions, including digital equipment, online processing, institutional arrangement, data governance, technology leadership, and strategy (Fig. 2). That means *DGC* is a Pareto-optimal, integrated invocation for multiple departments. It focuses on fostering collaboration between enterprises and capital, technology, talent, and other resources to facilitate the transformation of digital economy knowledge into enterprise innovation and stimulate specific knowledge resource accumulation in the region (Lazzarini, 2015).

Since 1979, the government has delegated powers, and provincial governments have greater discretion in many areas (Jia et al., 2019).

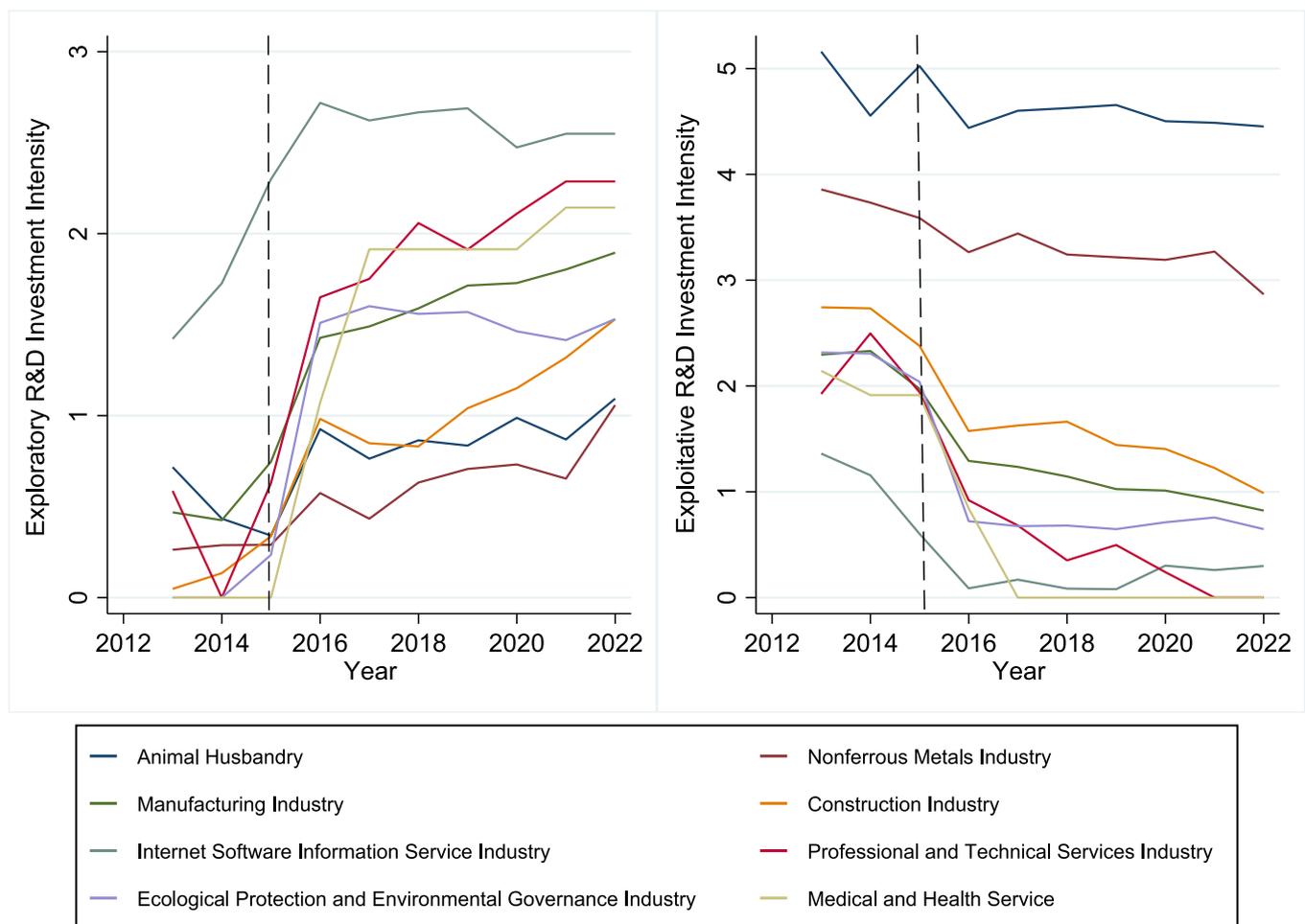


Fig. 1. China's A-shares exploratory R&D during the 2012 to 2022.

Note: The data presented in the figure represents the outcome of a two-step process. Firstly, the average ratio of annual R&D investment to annual operating income of listed enterprises in mainstream industries during 2010–2022 was extracted from the *CSMAR Database* as the R&D investment intensity data source. Secondly, the GARCH model (Mudambi & Swift, 2014) was employed to calculate the annual mean autoregressive residual, which reflects the degree of drastic changes in industrial R&D investment intensity (enterprises with small residuals exhibit a very stable intensity curve), thus illustrating the trend of industrial R&D investment intensity over time.

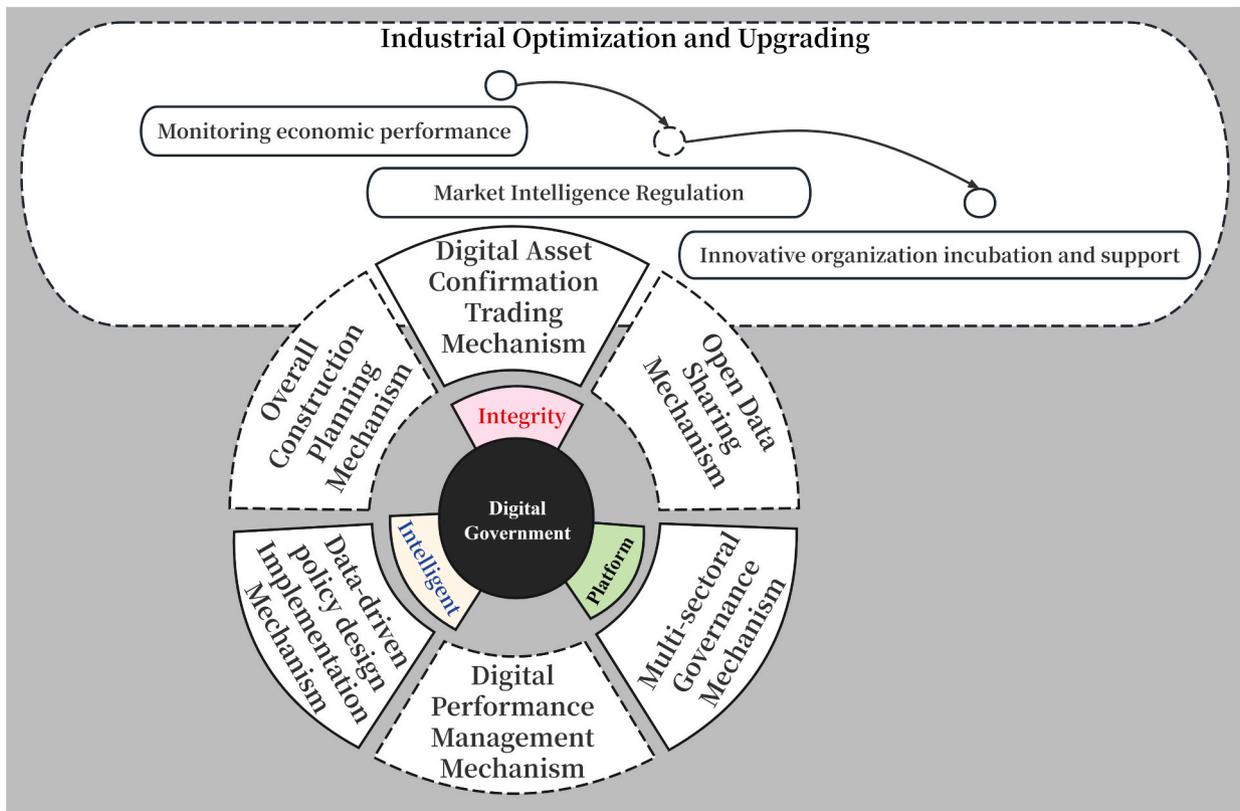


Fig. 2. China’s digital government governance system source: H3C.com.

Note: This picture comprehensively illustrates the functional positioning of China’s *DGC* within the digital economy, outlining a comprehensive and systematic framework that ranges from macro-level industrial strategic planning to specific functional mechanism deployments. At the macro-level, the focus is on Monitoring Economic Performance, Market Intelligence Regulation, and Innovative Organization Incubation and Support. Specifically, at the functional end, the deployments center around the Digital Asset Confirmation Trading Mechanism, Open Data Sharing Mechanism, Multi-sectoral Governance Mechanism, Digital Performance Management Mechanism, Data-driven Policy Design and Implementation Mechanism, and Overall Construction Planning Mechanism.

The coordination of local digital government resources has had a positive effect on the utilization of credit resources by financial institutions, regional financial development, and corporate financing, promoting the sound development of the financial system. The digital government has established a new modern superstructure and economic foundation relationships, enabling more timely two-way interaction, but requires continued investment from the provinces.

2.2. Resource dependency theory from unilateral knowledge inertia perspective

The research incorporates the concept of knowledge inertia into resource dependence theory to better suit the research context. Firstly, resource dependence theory offers a theoretical framework for understanding the interaction between enterprises and digital government, as well as defining the roles of both parties in this interaction. Secondly, the fundamental assumption of resource dependence theory is that organizations must acquire resources from their environment to ensure their survival, highlighting the reliance of organizations on external resources (Stern et al., 1979).

However, the current theory overemphasizes the role of resources but does not fully consider the other strategic states of enterprises in improving the reliability of resources. For example, when faced with new situations, enterprises find it difficult to change rapidly due to their existing cognitive structure, knowledge system, and experience (Rosenkopf & Nerkar, 2001; Shimizu & Hitt, 2005), namely knowledge inertia. Enterprises will choose to spontaneously get closer to the resource owners and obtain the support of these resource owners through non-market behaviors such as political behavior, private

strategy, or market behaviors such as R & D and innovation. Such as, Tencent has collaborated and compromised with the government on issues surrounding digital cultural governance by both precautions and remedies (Guo & Liu, 2021).

Therefore, we propose a unilateral perspective on resource dependence theory based on knowledge inertia. In this theory framework, firms need to consider the digital government’s goals and regulations when it comes to their research and development (R&D) and innovation efforts. This is necessary to secure necessary resources, ensure compliance, and take advantage of opportunities for exploratory innovation. To effectively participate in the construction of digital government, with low risk and low access to the dividend resources of new quality productivity and the recognition of other stakeholders, enterprises prefer the existing invention knowledge to participate in the government-enterprises interaction.

However, due to knowledge inertia, innovation decisions are often limited to core areas of concern (Joseph & Wilson, 2018; Ocasio, 1997; Tuggle et al., 2010), resulting in a lack of awareness of external innovative solutions and difficulty in quickly adapting to the environment and adjusting business models and knowledge systems promptly (Godkin & Allcorn, 2008). Under such circumstances, if managers (from diverse knowledge backgrounds) exchange information and collide with their expertise, it may help to weaken the negative impact of the invention knowledge inertia, and even promote the positive transformation of the invention knowledge inertia to exploratory innovation.

2.3. Digital government construction (DGC) and Firms' exploratory innovation (EI)

The *DGC* includes online innovation platforms, e-taxation systems, cutting-edge think tanks, and the comprehensive "OneNet" service platform et al. That effectively reduces the transaction costs associated with innovation activities and shortens the time and expenses related to business establishment and operation (Almeida & Zouain, 2016). The government supports collaborations between industry, universities, and research institutions to boost technical level, and innovation potential, reduce costs, foster knowledge exchange, and accelerate knowledge creation (Steinmueller, 2001). Additionally, the *DGC* has made it difficult and costly for local government officials and entrepreneurs to engage in rent-seeking behaviors (Mouna et al., 2020; Piatkowski, 2006). The *DGC* establishes a more equitable and conducive environment for innovation, further promoting sustainable economic development (Kong & Qin, 2021).

Therefore, we anticipate the following assumptions:

H1. *DGC* is positively related to Firms' *EI*.

2.4. Digital government construction (DGC) and Firms' invention knowledge inertia (IKI)

Knowledge inertia is the natural tendency of enterprises to rely on experience and knowledge to solve problems (Barr et al., 1992; Sydow et al., 2009). To gain policy dividends and competitive resources from digital government construction, enterprises are concurrently building their digital capabilities. It is evident that the technical knowledge and experience accumulated in the past still hold significant value in digital transformation. Like adapting to new policy environments and reducing trial-and-error costs. Through that interaction, enterprises gradually shape the *IKI*.

The *DGC* reflects the government's clear policy guidance in digital transformation (Wang et al., 2022), driving business environment optimization (Gan et al., 2023), and providing high-quality knowledge and resources (Steinmueller, 2001). Companies increasingly recognize the policies supported in government construction as valuable scientific resources (Fleming et al., 2019). Additionally, the State Council of China acknowledges the role of digital government construction in enhancing government information transparency. The cost and difficulty of rent-seeking by officials or entrepreneurs have increased (Mouna et al., 2020; Piatkowski, 2006). It is challenging for enterprises to conceal their activities and manipulate information for profit-seeking. As a result, they need to depend on existing technological knowledge to engage in innovative collaboration. Consequently, invention knowledge inertia is nourished.

To sum up, in the interaction of government and enterprise transformation guided by the digital government, firms passively shape the invention knowledge inertia. Based on this, we anticipate the following assumptions:

H2. *DGC* is positively related to *IKI*.

2.5. Firms' invention knowledge inertia (IKI) and exploratory innovation (EI)

Utilizing and depending on existing knowledge to implement innovation makes knowledge inertia a crucial factor influencing innovation (Zhang et al., 2023). Firm's exploratory innovation necessitates the capacity for absorbing knowledge and the collision of expertise (Jansen, Van Den Bosch, & Volberda, 2006; Benner et al., 2003).

The *IKI* is beneficial for companies to conduct comprehensive research. This includes deepening their understanding of their knowledge base (Howard et al., 2017; Stuart & Podolny, 1996; Sydow et al., 2009), improving organizational absorption capacity, and speeding up the innovation process (Sorensen & Stuart, 2000).

What's more, firm's *EI* requires the guidance of star scientists, many of whom are part of the Senior Leadership Team (*SLT*). Through socialization and induced learning, these prominent scientists utilize their authoritative knowledge and experience to drive more valuable innovation and broader product development through collaboration (Jain, 2016; Zucker & Darby, 1996). Relocation can optimize knowledge inertia following the establishment of new departments (Campbell et al., 2014). Because, following the establishment of new departments, scientists are willing to integrate existing knowledge of inventions, encourage new collaborations to enhance knowledge absorption capacity, and endeavor to explore novel innovation (Boeker, 1997; Jain and Huang, 2022). The duplication and uncertainty in *EI* are minimized (Rosenberg, 1990).

In summary, the *IKI* of enterprises can meet the required elements of *EI*. Therefore, our hypothesis is:

H3. *IKI* is positively related to *EI*.

2.6. The mediating role of enterprises' invention knowledge inertia

Integrating hypotheses 1, 2, and 3, we suggest that the enterprise's *IKI* may be a mediating mechanism between *DGC* and firms' *EI*. The *DGC* signifies a clear and robust policy direction in digital transformation (Gan et al., 2023), facilitating the conversion of digital economy knowledge into enterprise innovation. Within such an interactive environment, enterprises tend to rely more on existing technical knowledge to make innovative decisions, aiming to minimize costs of experimentation and risks (Cohen & Levinthal, 1990). The passively formed enterprises' *IKI* not only expands and deepens the enterprise's knowledge base but also effectively enhances the organization's absorptive capacity, driving *EI* to fit the interactive environment.

H4. *IKI* mediates the relationship between *DGC* and the *EI*.

2.7. The moderating effect of SLT's knowledge openness (KOM)

However, if the mediating role of *IKI* is not based on the context of knowledge sharing among executives, it will be magnified. Because an enterprise's *IKI* can easily trigger a split strategic focus among senior executives and become a victim of strategic differences (Raisch et al., 2018). Considering the impact of this realistic factor, based on the above theory and the hypothesis, this part extends and focuses on the effects of the senior leadership team's knowledge openness (*KOM*) on the relationship of "*DGC*→*IKI*→*EI*".

The *KOM* reflects the organization's ability to share knowledge based on cognitive diversity. The *KOM* enhances innovation capability (Tang, Zheng, Yan, & Dong, 2023; Yu, Liu and Chen, 2020; Liang et al., 2010; Seong et al., 2015; Amason & Sapienza, 1997) and strengthens problem-solving skills (Açikgöz et al., 2016; Liang et al., 2007). It acts as a bridge (Yun et al., 2020) between minds, enhancing efficiency and facilitating knowledge sharing (Lam et al., 2021) with external digital governments. When an enterprise's senior leaders embrace knowledge openness (Hambrick, 2007; Hambrick & Mason, 1984), the entire *SLT* becomes more proactive and forward-thinking (Li et al., 2021). This helps optimize the effectiveness of *IKI* and drives exploratory innovation (Ko & Liu, 2018; Lane & Lubatkin, 1998).

Meanwhile, *KOM* is crucial for nurturing organizational creativity, and accelerating innovation in the contemporary economy (Lin, 2006). *KOM* empowers the senior leadership team to maximize the utilization of invention knowledge and resources, cultivate a sense of value and presence among members, direct management attention towards specific innovations, and propel *EI*. With *KOM* in place, *IKI* is more likely to serve as a favorable starting point for *EI*. In conclusion, we put forward the following hypothesis:

H5. *KOM* positively moderates the relationship between *IKI* and *EI*.

Senior executives in enterprises are valuable human capital

resources with a robust internal social network of relationships, trust, and norms that directly impact knowledge sharing and trust among leaders (Tseng et al., 2014; Yen et al., 2015). So, it is important to further examine whether the diverse knowledge sources within *KOM* will have different effects on “*DGC*→*IKI*→*EI*” in this study context. These sources include expertise from executives with a financial professional background (PPRPEF) and those without such a background (NPPRPEF).

However, executives with a financial background prefer to focus on future risks and profits, and more sensitive to digital government policies. The past environment they worked in emphasized investment in the future and involved rigorous training in financial thinking mode (Liu et al., 2020). So, they will facilitate the transition from short-term invention knowledge inertia to long-term high-quality knowledge acquisition, absorption, and storage within the digital government environment.

Conversely, executives without a financial background (NPPRPEF) possess diverse knowledge that is focused on specific innovation practices, driving the exploratory innovation and accelerating its progress. Their decision-making may be less influenced by financial considerations compared to executives with a financial career background (PPRPEF). Based on this, we propose the following hypothesis:

H6a. PPRPEF negatively moderates the relationship between *DGC* and *IKI*.

H6b. NPPRPEF positively moderates the relationship between *IKI* and *EI*.

Our study model is shown in Fig. 3.

3. Methodology

The paper uses the Least Squares Dummy Variables (LSDV) method to conduct hypothesis tests. This is based on the results of heteroscedasticity and the Hausman test, as well as the empirical methods proposed by Zhong et al. (2021) and Wang and Wei (2018).

The regression includes (a) *DGC*→*EI*, (b) *IKI*→*EI*, and (c) *DGC*→*IKI*→*EI*. The presence of intermediary *IKI* was confirmed through Sobel-Goodman Mediation Tests and bootstrapping analysis. Furthermore, the moderating effect and mechanism of *KOM* pairs were examined while considering random error terms clustered at the city level. Each model includes virtual province- and industry-specific models representing their respective fixed effects.

3.1. Main effect model & mediation model

Following the methodology of Wang, Li, Tian and Hou (2022), this study aims to substitute this year’s data with a source of exploratory innovation-oriented data for the following year. It aims to deduce the interactive activities of enterprises participating in the construction of local digital government, promote the exploration of the delay effect of innovation, and improve the logic and tenacity of causal inference.

$$EI_{i,t+1} = \alpha_0 + \alpha_1 DGC_{i,t} + \alpha_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (1)$$

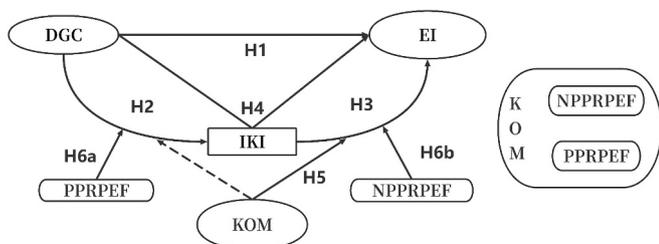


Fig. 3. Research model.

The response variable is represented by *EI*. The primary explanatory variable is digital government construction, denoted as *DGC*; control variables include enterprise characteristics, corporate governance, provincial social and economic development, as well as provincial and industrial fixed effects; ϵ represents random disturbance term; *c* denotes city. The main focus is on the coefficient α_1 , which reflects the relationship between the *DGC* and *EI*.

Based on the research of Wen & Ye, 2014, stepwise regression was used to test the mediating effect, and the model was set as follows:

$$IKI_{i,t} = \beta_0 + \beta_1 DGC_{i,t} + \beta_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (2)$$

$$EI_{i,t+1} = \gamma_0 + \gamma_1 IKI_{i,t} + \gamma_2 DGC_{i,t} + \gamma_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (3)$$

Where, the mediator variable is the knowledge path dependence of the management layer, referred to as Enterprises’ Invention knowledge inertia, which is *IKI*.

3.2. Moderated mediation model

$$EI_{i,t+1} = \alpha_0 + \alpha_1 DGC_{i,t} + \alpha_2 KOM_{i,t} + \alpha_3 DGC_{i,t} * KOM_{i,t} + \alpha_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (4)$$

$$IKI_{i,t} = \beta_0 + \beta_1 DGC_{i,t} + \beta_2 KOM_{i,t} + \beta_3 DGC_{i,t} * KOM_{i,t} + \beta_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (5)$$

$$EI_{i,t+1} = \gamma_0 + \gamma_1 IKI_{i,t} + \gamma_2 DGC_{i,t} + \gamma_3 KOM_{i,t} + \gamma_4 IKI_{i,t} * KOM_{i,t} + \gamma_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (6)$$

Among them, the moderating variable *KOM* represents the knowledge openness of the senior leadership team.

$DGC_{i,t} * KOM_{i,t}$ is the interaction between the core independent variable digital government construction and the moderator variable SLT’s knowledge openness within enterprises; $IKI_{i,t} * KOM_{i,t}$ is the interaction between the mediator variable invention knowledge inertia and the moderator variable; given that all variables in this paper are continuous variables, the core independent variable, the mediator variable and the moderator variable are first decentralized, and then the moderating effect is examined.

Given the heterogeneous knowledge sources within *KOM* in this study context, these sources encompass varied expertise from executives with a financial professional background (PPRPEF) and those without such a background (NPPRPEF). We examine whether they will yield different effects on “*DGC*→*IKI*→*EI*”.

$$EI_{i,t+1} = \gamma_0 + \gamma_1 IKI_{i,t} + \gamma_1 DGC_{i,t} + \gamma_2 NPPRPEF_{i,t} + \gamma_3 IKI_{i,t} * NPPRPEF_{i,t} + \gamma_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (7)$$

$$EI_{i,t+1} = \gamma_0 + \gamma_1 IKI_{i,t} + \gamma_1 DGC_{i,t} + \gamma_2 PPRPEF_{i,t} + \gamma_3 IKI_{i,t} * PPRPEF_{i,t} + \gamma_n control_{i,t} + \sum province + \sum industry + \epsilon_{i,t,c} \quad (8)$$

4. Data

To ensure the realizability of the study, data was collected from several sources. Firstly, the *DGC* indexes of cities across the country were manually collected from the Information Research Center of the Chinese Academy of Social Sciences and the authoritative website of Xinhua Three (H3C). These data are used to represent the construction

level of digital government in each city. Second, *IKI* is measured by the strength of patented technologies, which are collected from the **Incopat database and classified by IPC**, one of the most comprehensive databases covering patent information published in more than 120 countries. Thirdly, *KOM* and other control variables were obtained from the **China Securities Market and Accounting Research Database (CSMAR)**, which provides comprehensive historical information on corporate financial statements and corporate governance of companies listed on the Shanghai and Shenzhen Stock Exchanges, such as executive characteristics data, firm age, firm size, firm profit, senior leadership team position, family influence, curriculum vitae, political relationships, industry concentration, etc. Further mining from executive characteristics data & career background, resume, and other company positions and other data.

Provincial Science and Technology Innovation Index Level Data, and Proportion of Higher Education Students collected from **National Bureau of Statistics of China (YearBook)**. After excluding observations with missing key values, our final sample data consisted of 12,668 company-year observations of 1492 A-share listed companies from 2013 to 2022.

What's more, the research focuses on enterprise responses to government digital initiatives. However, the primary business of the concept company in question involves supporting the implementation of *DGC*. Its innovation efforts are primarily directed towards advancing digital government, and its main business is to support the construction of digital government. So, our sample excludes leading stocks (concept stocks) that contribute to digital government and smart cities. The inclusion of these companies could compromise research transparency and raise concerns about mutual causation.

5. Measurement

5.1. Digital government construction (DGC)

In 2014, the Chinese government launched the Digital Government Construction. The institute (CIS, See [Table 1](#)) has been conducting research and data disclosure in this area since 2011, which is more in line with this research. So, we take the smart city development index published in the fourth report as the measurement of digital government construction (match *DGC* by the registered place of enterprises).

The Chinese Smart City Development Level Assessment Report focuses on the development level index of China's smart city and comprehensively discusses the development status of China's city-level digital government construction ([Table 9](#) in [Appendix](#)).

In addition, we did not refer to past scholars who used **text mining**

Table 1
Data Sources for digital government construction.

Data Subject	Institution	Database	Issues Opened
UN E-Government Surveys	UN	UN E-Government Knowledgebase	11
The Research Report On Digital Government Development In China	THU	Center on Data and Governance	3
Chinese Government Cloud Market Share Series Study	IDC	IDC Tracker	4
Chinese Smart City Development Level Assessment Report	CIS	Guomai Research Institute & H3C.com	13

Note: The first research publishes an e-government Development Index every two years, analyzing the future of digital government in each country. The second research focuses on digital government evaluation at the city level in China. The third research focuses on the supply and demand of digital government equipment in China, especially the government cloud dedicated cloud infrastructure, public cloud IaaS et al. **However, the sample size is insufficient to support a 10-year study or macro evaluation.**

methods of government work reports to track the focus and initiative of government construction ([Jiang & Zhang, 2020](#); [Gan et al., 2023](#)) to further test our research hypothesis. We have considered that the disclosure of local government work reports may be distorted by deliberate propaganda of digital government construction achievements due to information preference motivation, resulting in an inaccurate assessment of digital government through government reports.

5.2. Enterprise's invention knowledge inertia (IKI)

[Liao et al. \(2008a\)](#) initially defined *IKI* as the utilization of traditional problem-solving methods, existing knowledge, or experiences to address issues and pursue new knowledge ([Sydow et al., 2009](#)). We apply the notion of technological proximity ([Byun et al., 2021](#)) to illuminate this. Utilizing data from Chinese patent IPC national patent classification main categories [<https://ipc.incopat.com/index>], companies applying for an IPC four code patent in their first year are locked as evaluation subjects ([Zhang et al., 2023](#)).

If these evaluation subjects have appeared within the six years before the first year, their invention application is deemed indicative of a tendency towards knowledge inertia with a code of 1; while a code of 0 represents a novel invention application that has not previously surfaced. To ensure unique panel data matching, stock codes are combined with the first four digits of IPC for matching purposes ([Table 2](#)).

After completing the aforementioned identification work, the ratio of applications for repeated inventions (the top four codes of IPC) to the total number of applications in the year is utilized as a measure of inertia for invention knowledge in that year. A higher measure indicates greater reliance on past knowledge and experience of invention by an organization.

5.3. SLT's knowledge openness (KOM)

In our research context, *KOM* is defined as the proportion of executives with varied professional backgrounds in the executive team, which can be included in the numerator based on a condition specified in [Table 3](#).

These types of knowledge reflect the senior leadership team's extensive experience and practical understanding across various fields, cultures, values, and thinking patterns. This serves as the foundation for embracing and integrating diverse knowledge within the organization, offering crucial guidance and support for organizational innovation and development. **K code** ([Table 3](#)) is utilized to distinguish between these two types of knowledge to avoid redundant data.

Finally, the **CSMAR** database provides information about company executives, such as name, age, academic background, financial background, career background, resume, and other company positions.

5.4. Firm's exploratory innovation (EI)

To mitigate data collinearity, exploratory innovation no longer focuses on output-level measurement methods such as IPC or statistics on invention patents ([Hu & Yu, 2022](#); [Zhang et al., 2023](#)) and non-invention patents but focuses more on R&D expenditure tendencies.

Unless the company's management recognizes the necessity of altering the company's R&D, there will be a small yet significant shift in R&D spending within a limited timeframe. If a substantial increase in R&D expenditure indicates a transition from development to exploration for firms, then this alteration in R&D spending would correlate with a notable expansion of firms' technological creation activities ([Mudambi & Swift, 2014](#)).

Drawing upon [Minhui et al.'s \(2023\)](#) adoption of the GARCH model, this paper defines exploratory innovation measurement as follows: A sharp rise in R&D investment signifies exploratory innovation (i.e., shifting strategy to exploratory).

The measurement process consists of three steps:

Table 2
IKI data measurement part details display.

Stock Code	Fiscal Year	IPC Code	IPC & Stock Code	Number of applications	Whether to repeat	Number of repetitions
63	2019	H03M	63H03M	3	1	3
63	2020	H03M	63H03M	4	1	4
63	2021	H03M	63H03M	2	1	2
70	2016	H03M	70H03M	2	0	0
70	2017	H03M	70H03M	2	1	2
90	2021	H03M	90H03M	6	0	0
100	2007	H03M	100H03M	1	0	0

Note: The assessment of knowledge inertia in literature over the last decade has predominantly relied on questionnaire-based research (Fu et al., 2021; Lee & Chen, 2023; Liao et al., 2008b; Xie et al., 2016). This study concentrates on innovation-related knowledge inertia and posits that invention patents and utility models better reflect technical expertise and experience compared to design patents.

Table 3
Details of KOM measure.

SLT's knowledge openness	K Code	Abbreviation
One professional background	0	
More than 2 professional backgrounds (excluding financial background)	1	NPPRPEF
More than 2 professional backgrounds (including financial background)	2	PPRPEF

Step 1: taking the ratio of enterprise R&D investment and operating income from 2010 to 2022 as the R&D investment intensity data, the GARCH model (Mudambi & Swift, 2014) is used to calculate the residual of the auto-regression model of the i^{th} enterprise in the t^{th} year (observed - predicted y) to estimate the trend of enterprise R&D investment over time, reflecting the degree of dramatic and compact changes in the intensity of enterprise R&D investment (enterprises with smaller residuals can be considered to have a very smooth intensity curve of R&D investment).

Step 2: The residuals are normalized to obtain the studentized residuals.:

$$e_{it}(stud) = \frac{e_{it}}{s_i \sqrt{1 - h_{it}}} \tag{1}$$

Where s_i is the square root of the mean square error of the regression model after deleting the data; $s_i = \sqrt{\sigma(e_{it})}$ is the ordinary residual, and h_{it} is the leverage value of s_i .

Step 3: Take the maximum value of the absolute value of the studentized residuals, that is, $e_{it}(max) = MAX_t |e_{it}(stud)|$, $2013 \leq t \leq 2022$, the maximum value of the absolute value. The larger the absolute value of the residual, the farther away the point is from the regression line.

Step 4: Measure the of exploratory innovation.

$$EI = \begin{cases} e_{it}max, e_{it}(stud) > 0 \\ 0, e_{it}(stud) \leq 0 \end{cases} \tag{2}$$

If the original value of the absolute maximum of the studentized residual is positive, it is considered that there is a sharp increase in R&D investment, that is, the enterprise's technological innovation strategy is transformed to the exploratory type, denoted by *EI*. In the years before the most significant change in the company's R&D expenditure, the indicator is set to zero. For the year of transition and the subsequent year of sustained growth, the construction variable is assigned the value derived from the aforementioned three-step process.

5.5. Control variables

According to the existing literature (Jia et al., 2019; Li et al., 2021), the study controls the variables that could potentially impact the

construction of digital government and exploratory innovation of firms, which are key data points at company, provincial, and industry levels. The specific 12 control variables are as follows:

The **Enterprise Digitization Level (Digital_MMT)** affects its innovation efficiency, we need to control it. Referring to the mature practices of existing literature (Wu et al., 2021), the firm of the digital level uses the five-dimensional **word frequency mining** of management meeting documents, which is more truthful and reliable. The sum of the above five dimensions **word frequency counts** increased by one and the natural logarithm is taken. Large, established companies may have more resources to make substantial innovations. Therefore, we control for enterprise **scale** (natural logarithm of annual total assets), **firm leverage** (long-term debt as a proportion of total assets, *FL*), and return on assets (*ROA*).

Additionally, corporate governance significantly influences corporate decision-making and innovation (Eklund & Mannor, 2020). Therefore, we control for the average age of TMT and the proportion of women in TMT. The equity balance degree is the sum of the shareholding ratio of the second to the fifth major shareholder divided by the shareholding ratio of the first major shareholder. In Chinese enterprises, at least one related family member, in addition to the actual controller, holds/manages/controls a listed company or a controlling shareholder company (Wang & Hu, 2008). Hence, we controls for family influence and measures the proportion of the public companies owned by all actual controllers among family members (La Porta, López de Silanes, & Shleifer, 1999; Claessens, Djankov, Fan and Lang, 2002).

To test the transparency of the KOM's moderation effect, we need to control the number of potential significant knowledge transactions (*NPSKT*) for other elements that may achieve significant knowledge flows. The data for corporate acquisitions involves multiple types, and the first two digits of the business code for each transaction are different, as shown in Table 4.

To analyze the heterogeneity of China's provincial level, we controlled for provincial special financial expenditure on science and technology and the proportion of provincial higher education students (*P_HE*). These elements have a direct impact on scientific and

Table 4
Details of potentially significant knowledge transaction amounts.

Restructuring Type	Top Two Business Codes	Restructuring Type	Top Two Business Codes
Asset acquisition	20	Absorption & merger	23
Asset divestment	21	Debt restructuring	24
	22	Equity transfer	26
		replacement	

Note: The database shows that intellectual property mergers and acquisitions are mainly concentrated in the three categories of 20, 21, and 23. Therefore, we select the total number of successful transactions in the three categories 20, 21, and 23 as the number of potential major knowledge transactions in that year.

technological innovation as well as achievement transformation, thus necessitating control measures.

The level of fiscal expenditure on science and technology is reflected in $\ln(1 + TII)$, while the proportion of the population with higher education is derived from public data provided by the National Bureau of Statistics (proportion of individuals aged 6 and above with a college degree or above). To mitigate any disequilibrium effects, we also controlled for industry concentration and industry fixed effect using sales proportion data from the top ten enterprises (*HYJZ_10A*).

Furthermore, since our provincial control variable *TII* exhibits linearity concerning time changes, it is not suitable to control for time-fixed effects. To enhance result effectiveness, we referenced Wang et al. (2022) practice in studying and controlling for province- and industry-specific fixed effects.

Table 5
Main effect & mediation results & moderation of *KOM*, *NPPRPEF*, and *PPRPEF*.

VARIABLES	DV: IKI				DV: EI				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DGC × KOM			-0.153 (-1.46)				0.414 (0.90)		
KOM × IKI (H5)								1.230* (1.93)	
DGC × PPRPEF(H6a)				-0.130** (-2.11)					
NPPRPEF × IKI (H6b)									0.485* (1.81)
PPRPEF				0.062*** (3.77)					
NPPRPEF									0.013 (0.17)
DGC		0.084*** (5.63)	0.078*** (5.23)	0.076*** (5.02)	0.296*** (3.20)	0.270*** (2.92)	0.354*** (3.50)	0.265*** (2.87)	0.267*** (2.90)
IKI						0.317*** (5.35)		0.344*** (6.11)	0.321*** (5.47)
KOM			0.104*** (3.91)				0.312* (1.69)	0.194 (0.99)	
FL	-0.043 (-0.88)	-0.042 (-0.87)	-0.039 (-0.81)	-0.045 (-0.94)	0.251 (0.85)	0.264 (0.89)	0.262 (0.88)	0.265 (0.89)	0.269 (0.91)
Scale	0.054*** (15.69)	0.053*** (15.46)	0.053*** (15.41)	0.052*** (15.13)	-0.033 (-1.42)	-0.050** (-2.05)	-0.026 (-1.15)	-0.051** (-2.09)	-0.050** (-2.05)
ROA	0.065 (1.42)	0.071 (1.54)	0.070 (1.53)	0.073 (1.56)	1.199*** (5.02)	1.177*** (4.99)	1.273*** (5.46)	1.167*** (4.90)	1.166*** (4.89)
NPSKT	-0.019*** (-3.37)	-0.018*** (-3.16)	-0.018*** (-3.18)	-0.019*** (-3.33)	0.110*** (3.31)	0.116*** (3.55)	0.104*** (3.19)	0.116*** (3.58)	0.114*** (3.49)
Digital_MMT	0.006** (2.20)	0.006* (1.95)	0.006* (1.87)	0.006* (1.82)	0.077*** (3.70)	0.075*** (3.67)	0.040** (2.16)	0.075*** (3.69)	0.075*** (3.63)
TMT_age	0.003** (2.37)	0.003** (2.23)	0.003** (2.38)	0.003** (2.53)	-0.000 (-0.00)	-0.001 (-0.13)	-0.000 (-0.07)	-0.001 (-0.10)	-0.001 (-0.10)
LnFI	-0.105*** (-5.04)	-0.107*** (-5.09)	-0.109*** (-5.17)	-0.107*** (-5.04)	0.051 (0.49)	0.085 (0.80)	0.034 (0.33)	0.078 (0.73)	0.087 (0.82)
P_Female	0.049 (1.33)	0.039 (1.04)	0.041 (1.10)	0.035 (0.93)	0.350** (2.07)	0.337** (2.02)	0.479*** (2.81)	0.337** (2.04)	0.339** (2.04)
EBD	-0.015*** (-3.72)	-0.015*** (-3.79)	-0.016*** (-4.00)	-0.015*** (-3.88)	0.110*** (3.56)	0.115*** (3.73)	0.093*** (3.03)	0.114*** (3.67)	0.115*** (3.73)
TII	0.102*** (11.87)	0.077*** (8.54)	0.071*** (8.03)	0.073*** (8.36)	0.826*** (15.84)	0.801*** (15.41)	0.831*** (14.58)	0.794*** (14.82)	0.803*** (15.35)
P_HE	0.012 (0.21)	0.015 (0.25)	0.013 (0.22)	0.008 (0.14)	0.557* (1.82)	0.553* (1.82)	0.946*** (2.87)	0.517* (1.71)	0.535* (1.75)
HYJZ_10A	-0.139 (-1.26)	-0.132 (-1.26)	-0.170 (-1.60)	-0.140 (-1.34)	5.041*** (7.42)	5.083*** (7.53)	1.726*** (3.22)	5.076*** (7.39)	5.088*** (7.45)
Constant	-2.122*** (-12.22)	-2.085*** (-12.60)	-0.153 (-1.46)	-1.996*** (-11.84)	-16.846*** (-16.51)	-16.185*** (-15.55)	-14.151*** (-13.88)	-16.134*** (-14.86)	-16.227*** (-15.47)
t-tests		***		**	***	***	*	*	*
Observations	12,668	12,668	12,668	12,668	12,668	12,668	12,668	12,668	12,668
R-squared	0.171	0.174	0.176	0.176	0.302	0.305	0.302	0.305	0.305
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters	271	271	271	12,668	271	271	271	271	12,668

Note: This table presents the results of the Main effect & Mediating effect test & Moderating effect. Robust t-statistics in parentheses are clustered at the city level ; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table of Wild Cluster Bootstrap *t*-tests displays the significance of the *KOM* × *IKI*, *DGC* × *PPRPEF*, *NPPRPEF* × *KI* effects. In addition, (2), (4), and (5) judged the validity of clustering robust parameters. T-tests are the Wild Cluster Bootstrap method. Repeated 1000 times, the confidence interval was set to 99 %. All significant results were validated by the Wild Cluster Bootstrap method recognized by Cameron et al. (2008).

Table 5). The results show that *DGC* had a significant positive effect on *IKI* ($\beta = 0.084, p < 0.01$), supporting H2. Secondly, it was observed that *IKI* has a significant positive impact on the *EI* ($\gamma = 0.317, p < 0.01$), supporting H3.

Regarding mediation testing, if *IKI* is a potential mechanism, adding this variable would partially mediate the impact of *DGC* on *EI* (Hayes & Preacher, 2014; Wen & Ye, 2014). When the mediator variable *IKI* was added to the equation, it was found that while the coefficient of *DGC* on *EI* still passed the 1 % significance level test ($\gamma = 0.270, p < 0.01$), its value decreased somewhat indicating that invention knowledge inertia plays a mediating role between *DGC* and enterprise *EI* and supporting H4.

To further validate *IKI* Mediation, Sobel-Goodman Mediation Tests and bootstrap analysis were conducted. The results are presented in Table 10 (See Appendix). Among the two indirect effect paths, the *IKI* mediation effect is statistically significant, explaining 9.80 % and 8.90 % of the total effect, respectively. This finding contributes new insights to the field of knowledge inertia compared to Xincheng Wang (2023) on digital attention of corporate executive teams in “Government Digital Initiatives on Corporate Digital Innovation” (0.0085 with bias-corrected 95 % confidence intervals) [0.0040, 0.0129]). Furthermore, the bootstrap analysis repeated 1500 times indicated that the indirect impact of *DGC* on *EI* through *IKI* was 0.027, with a bias-corrected 95 % confidence interval of [0.018, 0.041], excluding zero from its range value.

Regarding the moderating effect, the H5 posits that *KOM* positively moderates the relationship between the relationship between *IKI* and *EI*. Following Wen & Ye’s (2014) test method, Table 5 (3) presents the results of *KOM*’s front path moderation for the “*DGC*→*IKI*→*EI*”. The interaction coefficient of *DGC* × *KOM* is found to be not significant ($\beta = -0.153, p > 0.1$), indicating that *KOM* does not significantly impact the positive relationship between *DGC* and *IKI*. Maybe the knowledge openness of the senior leadership team is composed of different executives, the interweaving of these diverse energies may weaken the overall absorptive capacity of the entire *KOM* to “external radiation”. However, the interaction coefficient of *KOM* × *IKI* is significantly positive ($\gamma = 1.23, p < 0.1$), suggesting that *KOM* positively moderates the positive relationship between *IKI* and *EI*, thereby supporting H5 (see (7) & (8) in Table 5).

KOM includes the provision of practical knowledge openness to two types of executives, namely, the *PPRPEF* and the *NPPRPEF*. Table 5 (4) illustrates the moderating effect of *PPRPEF* on the “*DGC*→*IKI*”. The results indicate that the interaction coefficient of *PPRPEF*×*DGC* is significant ($\gamma = -0.130, p < 0.05$), suggesting that *PPRPEF* attenuates the “*DGC*→*IKI*”, thus supporting H6a. Additionally, *NPPRPEF*’s moderating role in the “*DGC*→*IKI*→*EI*” was demonstrated, with results showing a significant interaction coefficient of *NPPRPEF* × *DGC* ($\gamma = 0.485, p < 0.1$), thereby supporting H6b (see (9) in Table 5).

6.2. Robustness test

To make the conclusions reliable and rigorous, robustness tests were performed.

Alternative Measures of *EI*, *DGC*, and *IKI*. *EI* may be influenced by operating income as the denominator and does not accurately reflect the true level of fluctuation in R&D spending. Therefore, a direct introduction of research and development expenditure into the GARCH model was conducted, followed by benchmark regression analysis. We found that *IKI* and *DGC* coefficients remained significant ($\beta = 0.301, p < 0.01; \beta = 0.119, p < 0.05$), indicating robust conclusions. The stability test of the relationship between *DGC* and exploratory innovation, as well as the mediating role of *IKI*, was re-evaluated by replacing digital government construction with urban broadband Access users (UBroadband) provided by CSMAR. In Table 6 (1) ~ (2), it was found that both the *DGC* coefficient ($\beta = 0.001, p < 0.01$) and the *IKI* coefficient ($\beta = 0.304, p < 0.01$) were statistically significant, leading to a robust conclusion. It is important to acknowledge that there is a time lag for companies to initiate R&D and implementation. We substitute *IKI* with the ratio of repeated patent applications in the following year to the total number of patent applications over the entire study period. Table 6 (3) & (6) demonstrates continued support for H1~H4.

Narrow sample and Alternative measures of *KOM* & *NPPRPEF*. Given that 81.7 % of the sample consists of manufacturing industries, the sample was narrowed down to only 11,602 listed manufacturing companies for benchmark regression (refer to Table 6). H1~H4 are found to be robust compared with (4) and (5). Drawing on the approach of Xincheng Wang et al. (2022), *KOM* and *NPPRPEF* in Table 11 (See Appendix) are replaced by the number of executives who meet the corresponding conditions. (4) in Table 11 shows that the interaction of *IKI* × *KOM* is positively related to Exploratory ($\beta = 0.047, p < 0.01$). (5) shows that the interaction of *IKI* × *NPPRPEF* is positively related to Exploratory ($\beta = 0.038, p < 0.01$).

Refrain from the interference caused by the Broadband China policy. It is necessary to consider that the implementation of the “Broadband China” strategy will have an exogenous impact on our research on local digital government construction. To ensure a more robust conclusion, samples from pilot cities of the strategy were excluded, and the remaining samples were analyzed. In Table 11 (See Appendix), the coefficient of *DGC* in (1) ($\beta = 0.05, p < 0.05$), and the coefficient of *IKI* × *KOM* interaction in (3) ($\beta = 2.186, p < 0.1$) remained significant; while the interaction coefficients of *DGC* × *NPPRPEF* ($\beta = 0.038, p < 0.01$) and *DGC* × *PPRPEF* ($\beta = -0.267, p < 0.05$) also remained significant in (2).

Evaluation of missing variable bias using the ITCV method. Finally, to address the issue of missing variable bias, we utilized the impact of confounding variable (ITCV) analysis (Frank, 2000). The ITCV results indicate that to invalidate *DGC*’s estimation of *EI* and *IKI*, 38.72 % (4905) and 68.56 % (9731) of our observations would need to replace

Table 6 Robustness test summary 1.

VARIABLES	(1) Dv: EI	(2)	(3)	(4)	(5)	(6) IKI
IKI		0.304*** (4.86)	2.946*** (13.25)		0.337*** (4.36)	
DGC	0.001*** (16.71)	0.001*** (15.80)	0.475** (5.68)	0.328*** (3.25)	0.304*** (3.02)	0.052*** (11.62)
Control	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	/	/	YES
Province FE	YES	YES	YES	YES	YES	YES
Industry	All			Manufacturing		All
t-tests	***	***	***	***	***	***
Wild Cluster Bootstrap	1000 95 %					

Note: Robust standard errors in parentheses are clustered at the city level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table of Wild Cluster Bootstrap t-tests displays the significance of the *DGC* effects.

cases where there is no effect (Hill et al., 2019; Larcker & Rusticus, 2010). Furthermore, none of the covariates in our model exceeded a certain threshold, demonstrating robustness in our regression analysis. Table 12 (See Appendix) (2) and (5) display ITCV values for DGC, EI, and IKI while (3) illustrates the potential impacts of each control variable on regression outcomes. The most significant influence on regression results comes from provincial special financial expenditure on science and technology (TII), with coefficients at 0.1053 and 0.0816 respectively but less than 0.106 and 0.191 overall. Therefore, it can be concluded that endogenous issues with DGC, Exploratory, and IKI do not compromise result stability.

6.3. Heterogeneity test

The heterogeneity test can comprehensively analyze the impact mechanism of digital government construction on the exploratory innovation of enterprises, offering more effective policy recommendations and management practices for both governments and enterprises.

In Fig. 7 (See Appendix), we find that digital government construction plays a more critical role in promoting exploratory innovation in Western China than in Eastern China ($\alpha = 0.310, p < 0.05$). Cities with less external cultural influence benefit from reduced competition, strengthening the positive impact of digital government on innovation ($\alpha = 0.301, p < 0.01$). Open cities, however, face multicultural conflicts and increased foreign competition, affecting this impact. High-tech enterprises, with their digital technology foundation, are more responsive to digital government construction ($\alpha = 0.376, p < 0.01$), while low-tech enterprises may be less engaged. State-owned enterprises, due to their close relationship with the government, are more likely to comply with digital government policies and actively seek resources for exploratory development ($\alpha = 0.372, p < 0.01$), unlike non-state-owned enterprises, whose response is weaker ($\alpha = 0.276, p < 0.05$).

To detect the specific regions in which PPRPEF and NPPRPEF moderate the relationship between “DGC→IKI→EI”. In comparison to the low PPRPEF group, the positive impact of digital government construction on enterprise invention knowledge inertia is more easily weakened in the high PPRPEF group (Fig. 4 A). Similarly, compared to the low NPPRPEF group, the high NPPRPEF group is more likely to transform short-term invention knowledge inertia into long-term high-quality knowledge mining, absorption, and reserve, which are the best way to achieve exploratory innovation. (Fig. 4 B). This indicates that

non-financial executives’ diverse knowledge can help convert IKI into an advantage for exploratory innovation by focusing on specific innovative outcomes and demonstrating strong execution and flexibility.

In Fig. 5, we find that the relationship of “IKI→EI” is inconsistent in heterogeneous groups of different enterprise types and geographical areas. For instance, the construction of digital government has a weak impact on generating innovative knowledge inertia among enterprises in the Western region and open areas, as well as low-technology, non-state-owned, and low-pollution enterprises. On the contrary, the relationship effect of “DGC→KI” has little difference.

Fig. 6 illustrates that the impact of PPRPEF on attenuating the correlation between DGC and enterprise IKI is particularly pronounced in high-tech enterprises, state-owned enterprises, and enterprises with high pollution levels, aligning with current expectations.

7. Discussion

7.1. Theoretical implications

This work has made significant theoretical contributions.

Firstly, this paper proposes a perspective of unilateral knowledge inertia within the resource dependence theory (Stern et al., 1979) and seeks to integrate it with stakeholder theory, and upper echelon theory to uncover the intricate relationship between digital government construction and enterprise exploratory innovation.

Secondly, some scholars believe (Nelson, 1985) that IKI leads to cognitive constraints in organizations, which prevents them from generating and promoting new ideas; others believe that IKI enables organizations to focus on certain technical fields and enhance the accumulation of professional knowledge (Liao et al., 2008b; Xie et al., 2016), which encouraged the creation of new knowledge. Based on these debates, this study further explores the relationship between enterprises and government by inserting invention knowledge inertia (Shin & P’erez-Nordtvedt, 2020; Srinivasan et al., 2020). We provide empirical evidence to support the positive impact of invention knowledge inertia on exploratory innovation and clarify the debate on whether knowledge inertia has a positive or negative impact on innovation (Liao et al., 2008b; Nelson, 1985; Xie et al., 2016).

Finally, utilizing enterprise invention knowledge inertia and the senior leadership team’s knowledge openness to intensify exploratory innovation of digital government towards enterprises enriches Shimizu

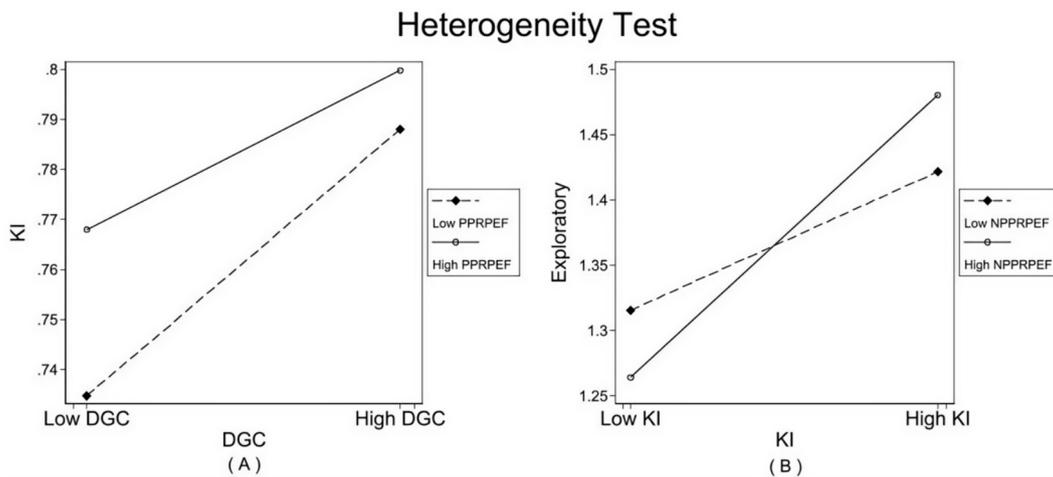


Fig. 4. Moderation effect plots for PPRPEF and NPPRPEF at high and low levels.

Note: In (A), the horizontal axis represents the invention knowledge inertia, and the vertical axis represents the digital government construction. In (B), the horizontal axis represents the exploratory innovation of the enterprise, and the vertical axis represents invention knowledge inertia. Under the guidance of Spiller, Fitzsimons, Lynch, & McClelland (2013) theory, we have made corresponding divisions for the three continuous variables KOM, NPPRPEF, and PPRPEF. The characteristics of the high moderator variable group are greater than the mean + standard deviation; the characteristics of the low moderating variable group are less than the mean + standard deviation.

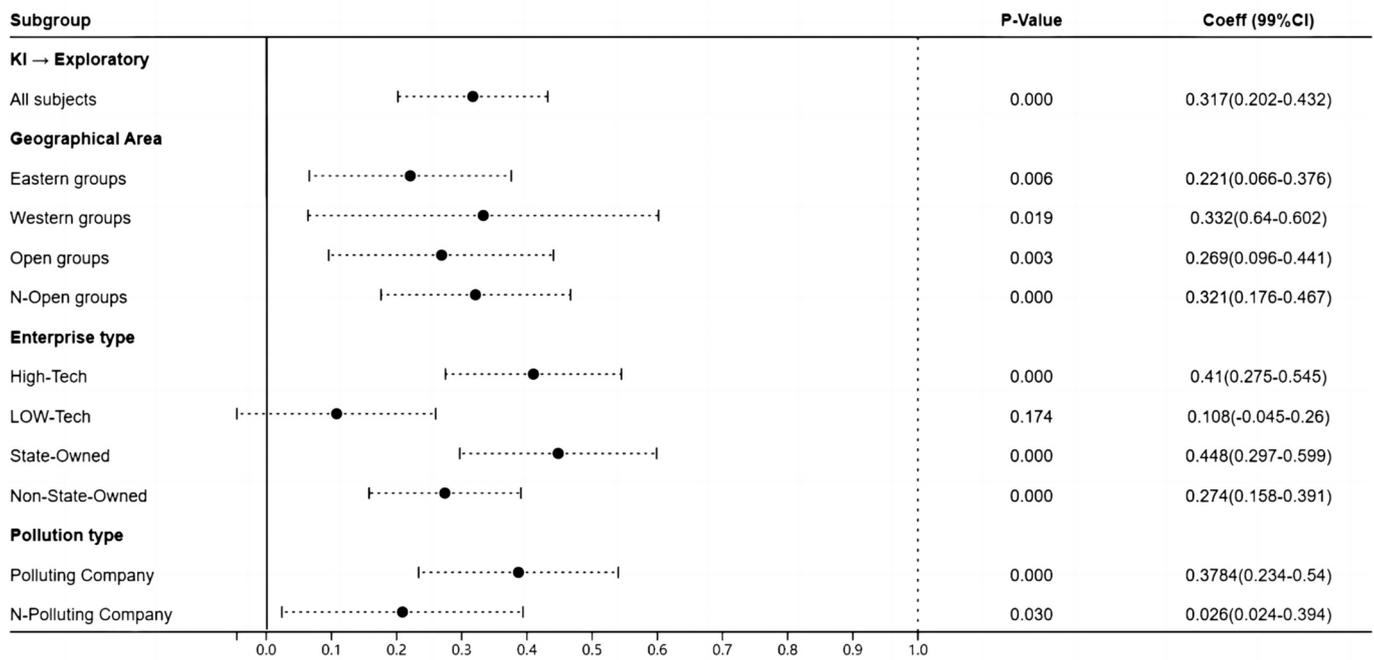


Fig. 5. Heterogeneous groups of "IKI → EI".

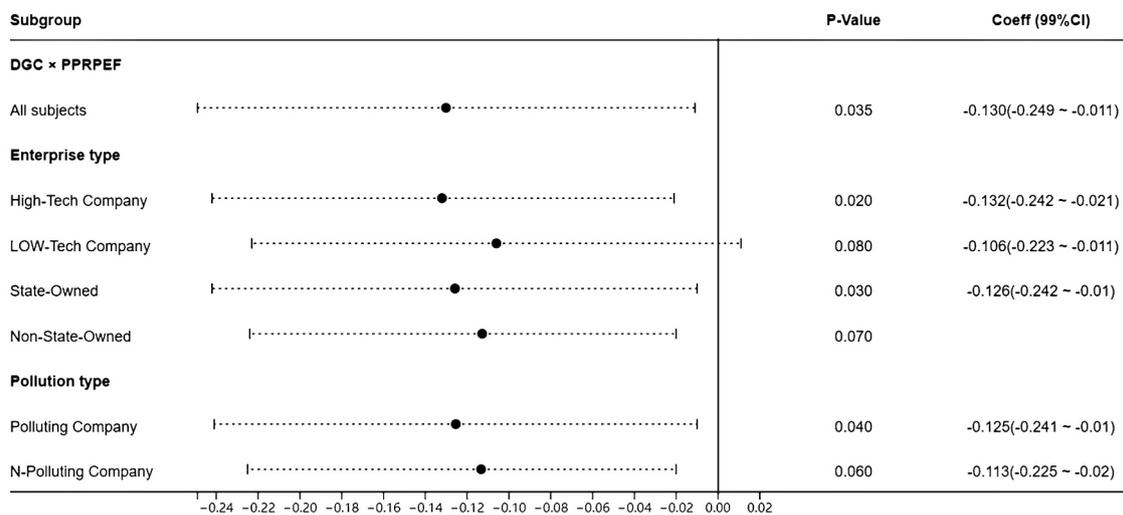


Fig. 6. Heterogeneity test of PPRPEF's moderation effect.

and Hitt's (2005) research path. This theme responds to Nambisan et al.'s (2019) call and develops Xincheng Wang et al.'s (2022) views.

7.2. Practical implications

Our findings have several implications for management.

At the policy-making level:

Policymakers should focus on managing granularity, safeguarding intellectual property rights, distinguishing between inert and substantive innovation at the source, and providing thoughtful guidance and support. Without proper guidance and management, firms may hinder their invention knowledge inertia towards exploratory innovation. Conversely, *IKI* can be leveraged by companies to access the innovation incentives provided by the government.

When advocating for digital government development, policymakers

must consider the cultural differences between regions and the influence of external factors. It's crucial to avoid standardized policy measures that could lead to digital government becoming mere cost centers and isolated information hubs. Specifically in regions like eastern China, where internal and external cultures have a significant influence, emphasizing diversity and inclusivity while enhancing resource allocation efficiency is paramount.

Giving more attention to the innovative advancement of non-state-owned and non-high-tech enterprises is vital. These companies often face greater market pressures and resource constraints, yet their potential for innovation cannot be overlooked. The digital government should cultivate the digital savvy and innovation readiness of these enterprises through fostering ingenuity and entrepreneurship (Ajah, 2023) to guide their passive inertia of innovation knowledge towards digital technology innovation and enhance the efficiency of exploratory

innovation.

Corporate executive team building:

When the corporate governance mechanism is not sound enough, the inertia of invention knowledge may make the enterprise fall into a position of complacency, unable to effectively drive exploratory innovation, and become a bad source of enterprises' excessive pursuit of short-term benefits and competitiveness.

The main way to strengthen the interpretation and understanding of government policies within senior leadership teams of low-technology, non-state-owned, and high-pollution enterprises is to appoint executives with diverse practical experience and cross-financial career backgrounds. This will also help in overcoming the inertia of innovation knowledge.

An open-minded and inclusive culture that promotes knowledge sharing and exchange among team members is essential. Incorporating knowledge from diverse sources can effectively optimize innovation. By absorbing knowledge and information from different fields and backgrounds, more comprehensive and in-depth innovative thinking can be developed to promote exploratory innovation within enterprises.

Creating a diverse knowledge base within senior leadership teams is crucial for high-quality exploratory innovation in the context of digital government construction (Zhang et al., 2018). Continuously enriching and improving the team's knowledge base helps enterprises to better respond to the opportunities and challenges presented by digital government, leading to a high-quality transformation of innovation knowledge from inertia to exploratory innovation.

8. Conclusions, limitations and future research

Based on the theoretical framework of unilateral knowledge inertia and resource dependence, this paper discusses the influence mechanism of digital government construction on enterprise exploratory innovation.

8.1. Main conclusions

First of all, the construction of digital government significantly fosters the exploratory innovation of enterprises. The enterprises in western regions and cities with less cultural influence, state-owned and high-tech enterprises play a more substantial role. **Secondly**, the mechanism of action demonstrates that when enterprises engage in government-enterprise interaction, they passively cultivate invention knowledge inertia to meet the requirements of exploratory innovation. However, during this process, whether enterprises can maintain low risk and continuously promote *EI* by leveraging *IKI* is moderated by the extent of knowledge openness within the senior leadership team (*KOM*).

What's more, due to the SLT's *KOM* being a result of colliding knowledge from different executives, this force is fueled by diverse energy sources which weaken the absorption capacity of the *KOM* towards "external radiation". Therefore, the moderating effect study reveals that *KOM* only moderates the relationship between *IKI* and *EI*.

Interestingly, diversified knowledge from executives with financial backgrounds significantly weakens the positive relationship between

Appendix A. Appendix

A.1. Descriptive statistics

Table 7 presents the definitions, observed values, mean values, median values, standard deviations, and extreme values of the primary variables in this study. All observed values are 12,668. Table 8 lists the correlation coefficients of the main variables. It can be seen that the phase (*IKI*) relationship between digital government construction and the inertia of invention knowledge is positive and significant ($\beta = 0.174, p < 0.001$). The correlation coefficient between invention knowledge inertia and Exploratory innovation was positive and significant ($\beta = 0.134, p < 0.001$), initially supporting **H1&H2**. We control 10 variables highly correlated with exploratory innovation, as well as return on assets (*ROA*) and proportion of provincial higher education students (*P_HE*), which are not directly correlated.

DGC and *IKI*; whereas diversified knowledge from executives non-financial backgrounds strengthens the relationship between *IKI* and *EI*. The latter is less constrained by financial thinking, focuses on specific innovative outcomes, and drives exploratory innovation.

8.2. Limitation and future research

The study is subject to certain limitations.

While the concept of firms' *IKI* as a mediator may not be groundbreaking in theory, there remains a question of whether there are other potential channels to influence companies' exploratory innovation in a digital government environment. It may be more insightful to consider cultural path dependence and the customer knowledge management (Chaithanapat et al., 2022; Wang et al., 2020).

The focus on China's A-share companies might limit the generalizability of the findings. Future researcher can examine different economic contexts or extend the model to include other aspects of digital transformation. We did not provide positive evidence on whether this invention knowledge inertia improves firm or industry value chain climbing. Whether the *EI* under the influence of the *IKI* is conducive to the creation of digital derivative value. Therefore, it will be valuable for future research to study how firms can gain value chain upgrades by using invention knowledge inertia (Meng & Wang, 2023).

External knowledge serves as a crucial source of innovation (Nigg-Stock et al., 2023). This paper only examines the moderating effect of knowledge openness within the executive team, without discussing whether the external knowledge sources supports exploratory innovation (Wang et al., 2020).

CRedit authorship contribution statement

ZhaoShuai Ren: Writing – review & editing, Writing – original draft, Data curation. **QiaoYi Gao:** Writing – original draft, Resources, Project administration, Data curation. **Tong Sun:** Software, Funding acquisition, Formal analysis. **Min Sun:** Writing – original draft, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 7
Descriptive statistics.

Variable	N	Mean	p50	SD	Min	Max
EI	12,668	1.230	1.307	1.325	0	13.373
DGC	12,668	4.174	4.221	0.252	2.868	4.527
IKI	12,668	0.772	0.853	0.246	0	1
KOM	12,668	0.401	0.417	0.101	0	0.571
Scale	12,668	22.54	22.34	1.303	19.590	26.45
FL	12,668	0.0560	0.0400	0.0590	0	0.730
ROA	12,668	0.0400	0.0370	0.0630	-0.373	0.247
LnNPSKT	12,668	0.228	0	0.439	0	3.091
Digital_MMT	12,668	0.848	0	1.091	0	5.481
lnFI	12,668	49.91	50	3.124	39.330	57.79
TMT age	12,668	0.182	0.190	0.178	0	0.642
P_Female	12,668	0.178	0.167	0.109	0	0.563
EBD	12,668	0.741	0.568	0.609	0.019	2.963
lnTII	12,668	14.68	14.87	0.957	10.640	16.28
P_HE	12,668	0.192	0.164	0.102	0.024	0.505
HYJZ_10A	12,668	0.784	0.774	0.062	0.590	0.997

Note: lnTII, lnDGC, and Scale are logarithmic based on the original data, while lnFI, Digital_MMT, and LnNPSKT are logarithmic based on the original data plus 1. The EI arises from the results of the GARCH model measurement scheme, with a mean of 1.282, a median of 1.307, and a variance of 1.325. The occurrence of “1” indicates that the first four digits of the IPC code patented in the current year have occurred within the previous six years. The independent and moderated variables to mitigate the potential multiple collinearity problem.

Table 8
Correlations.

Variable	1	2	3	4	5	6	7
1 EI	1						
2 DGC	0.250***	1					
3 IKI	0.134***	0.174***	1				
4 KOM	0.114***	0.135***	0.101***	1			
5 FL	-0.078***	0.018**	0	-0.032***	1		
6 Scale	-0.069***	0.116***	0.231***	-0.0120	0.312***	1	
7 ROA	-0.00500	-0.028***	0.022**	-0.00300	-0.117***	0.032***	1
8 LnNPSKT	0.030***	0.00600	-0.042***	0.0100	0.00300	-0.038***	0.019**
9 Digital MMT	0.228***	0.206***	0.084***	0.054***	-0.095***	0.00700	-0.00800
10 TMT age	-0.029***	0.059***	0.121***	-0.034***	0.092***	0.372***	0.049***
11 lnFI	0.039***	0.021**	-0.096***	0.033***	-0.135***	-0.322***	0.116***
12 P_Female	0.102***	0.122***	-0.033***	0.031***	-0.062***	-0.222***	0.034***
13 EBD	0.128***	0.078***	-0.025***	0.068***	-0.027***	-0.090***	-0.027***
14 lnTII	0.184***	0.598***	0.126***	0.117***	-0.055***	0.00100	0.021**
15 P_HE	0.103***	0.393***	0.076***	0.036***	0.084***	0.197***	-0.029***
16 HYJZ_10A	-0.107***	0.039***	-0.048***	-0.083***	0.207***	0.231***	-0.069***
Variable	8	9	10	11	12	13	14
8 LnNPSKT	1						
9 Digital MMT	0.054***	1					
10 TMT age	-0.094***	-0.102***	1				
11 lnFI	0.064***	0.039***	-0.321***	1			
12 P_Female	0.032***	0.098***	-0.279***	0.258***	1		
13 EBD	0.046***	0.098***	-0.117***	-0.00400	0.065***	1	
14 lnTII	0.037***	0.191***	-0.057***	0.123***	0.092***	0.105***	1
15 P_HE	0.0130	0.090***	0.147***	-0.162***	-0.026***	-0.00600	0.214***
16 HYJZ_10A	-0.00500	-0.156***	0.103***	-0.093***	-0.052***	-0.059***	-0.0110
Variable	15	16					
14 TII	1						
15 P_HE	0.106***	1					

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. The correlation coefficient between the general variables was below 0.6, with an average VIF value of 1.24 and a maximum VIF value for both the explanatory and control variables below 2, indicating no significant multicollinearity among the study’s variables.

A.2. Digital government construction (DGC)

Table 9
Interpretation of DGC in “Chinese Smart City Development Level Assessment Report”.

Core indicators	Connotation
Institutional Framework	Leadership organizations, government agencies, social organizations, etc. related to the development of digital government; Measuring the level of development and completeness of different types of organizations in the digital government development process.
Governance System	Policies and regulations related to the development of digital government, such as government governance, data governance, economic governance, and people’s livelihood services; Measuring the level of development and completeness of policies and regulations in different areas of digital government.

(continued on next page)

Table 9 (continued)

Core indicators	Connotation
Governance Capacity	Improvements in government digital transformation in information acquisition, data governance, data opening, platform governance, government-public interaction, and online government services; Measuring the overall improvement in governance capacity driven by government digital transformation.
Governance Effectiveness	The situation of digital government promotes governance modernization and improves the quality and effectiveness of government services, as well as the corresponding public evaluation; Measuring the effectiveness of digital government promoting governance modernization.

Note: Renteria et al. (2019) proposed the Enabler-Based digital government construction Framework, which helps decision-makers clarify actions and resource requirements, and evaluate the organizational capacity and governance capacity of information technology to provide public services. Therefore, digital technology is only one dimension of building a digital government, and government digitization is not equivalent to digital government.

A.3. Sobel-Goodman Mediation Tests & Bootstrap results

Table 10
Sobel-Goodman Mediation Tests & Bootstrap results (Replications = 1000).

Sobel-Goodman	Indirect Effect Path	Z	% total effect that is mediated
Sobel	DGC— > KI— > Exploratory	3.878***	9.80 %
Indirect Effect Path	Coef.	Deviation correction 95 % confidence interval	
		LLCI	ULCI
DGC— > IKI— > EI	0.027	0.014	0.038
	0.084	0.047	0.120

Note: This table presents the results of the mediating role of KI in the relationship between DGC and Exploratory. Robust t-statistics in parentheses are clustered at the city level ; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The last line is the results of a robustness test in Alternative methods of *IKI* measurement.

A.4. Refrain from the interference caused by the broadband China policy

Table 11
Robustness test summary 2.

VARIABLES	(1) DV: IKI	(2)	(3) DV: EI	(4)	(5)
DGC × PPRPEF (H6a)		-0.267** (-2.17)			
IKI × KOM (H5)			2.186* (1.66)	0.047*** (3.32)	
IKI × NPPRPEF (H6b)					0.038*** (2.61)
KOM			0.257 (0.59)	0.002 (0.24)	
PPRPEF		0.094*** (3.12)			
NPPRPEF					-0.002 (-0.35)
IKI			0.239* (1.87)	0.294*** (4.73)	0.291*** (4.49)
DGC	0.05** (22.20)	0.041* (1.70)	0.241* (1.75)	0.265*** (2.87)	0.265*** (2.88)
Control	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
t-tests	**	**	/	***	***
Wild Cluster Bootstrap	1000 95 %	1000 95 %	/	1000 95 %	1000 95 %

Note: Robust standard errors in parentheses are clustered at the city level, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; In addition to (4), we conducted a study using the Wild Cluster Bootstrap method for 1000 repetitions, with a confidence interval set at 95 %. The table of Wild Cluster Bootstrap t-tests displays the significance of the *DGC*, *IKI* × *NPPRPEF*, and *DGC* × *PPRPEF* effects.

A.4.1. Evaluation of missing variable bias using the ITCV method

Table 12
ITCV results.

	(1)	(2)	(3)	(4)	(5)	(6)
	EI	ITVC	impacts	IKI	ITVC	impacts
DGC	0.296*** (3.20)	0.106		0.084*** (5.63)	0.191	
FL	0.251 (0.85)		-0.0017	-0.042 (-0.87)		0.0000
Scale	-0.033 (-1.42)		0.0114	0.053*** (15.46)		0.0289
ROA	1.199*** (5.02)		-0.0012	0.071 (1.54)		-0.0009
lnNPSKT	0.110*** (3.31)		0.0004	-0.018*** (-3.16)		0.0003
Digital_MMT	0.077*** (3.70)		0.0452	0.006* (1.95)		0.0073
TMT_age	-0.000 (-0.00)		-0.0025	0.003** (2.23)		0.0092
lnFI	0.051 (0.49)		0.0011	-0.107*** (-5.09)		-0.0006
P_Female	0.350** (2.07)		0.0125	0.039 (1.04)		-0.0035
EBD	0.110*** (3.56)		0.0095	-0.015*** (-3.79)		-0.0017
lnTII	0.826*** (15.84)		0.1053	0.077*** (8.54)		0.0816
P_HE	0.557* (1.82)		0.0353	0.015 (0.25)		0.0349
HYJZ_10A	5.041*** (7.42)		-0.0041	-0.132 (-1.26)		-0.0008

Note: Robust standard errors in parentheses are clustered at the city level ; *** p < 0.01, ** p < 0.05, * p < 0.1. The impact threshold of omitted confounding variables can be implemented through the “konfound” command. The value in the parentheses is the t-value. ITCV measures the partial correlation between the dependent variable and the unobserved variable multiplied by the partial correlation between the dependent variable and the unobserved variable, i.e. assessing the minimum change in the significance of results.

A.4.2. Heterogeneity test of “DGC → exploratory”

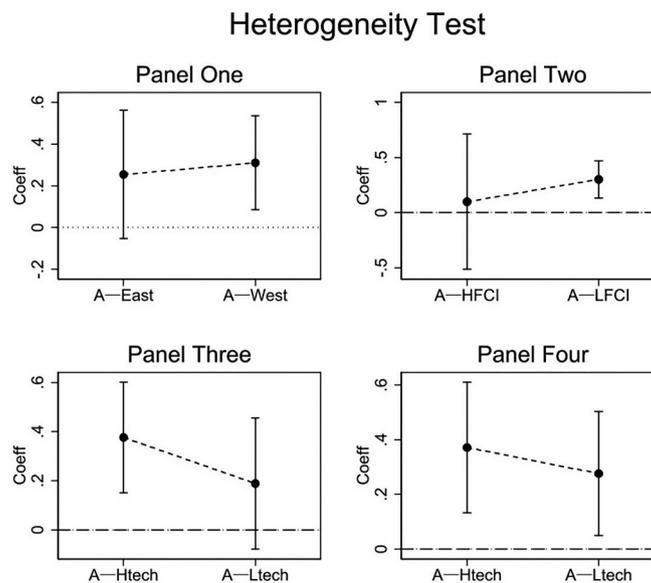


Fig. 7. Coefficients of four heterogeneous groups about “DGC → Exploratory”.

Note: A represents the variable to be explained, which is exploratory; HFCI: High Foreign Culture Influx; LFCI: Low Foreign Culture Influx, Htech: High-tech Company, Ltech: Low-tech Company; SOE: State-owned enterprises, NSOE: Non-State-owned enterprises, Robust t-statistics in parentheses are clustered at the city level; The classification criteria are as follows: 1) The geographical area is divided into eastern and western groups; 2) If the enterprise is registered in provinces and cities that were at the forefront of China’s early reform and opening up, such as Shenzhen, Zhuhai, Shantou, Xiamen, Hainan, Dalian, Qinhuangdao, Tianjin, Yantai, Qingdao, Lianyungang, Nantong, Shanghai Hai, Ningbo, Wenzhou, Guangzhou, Zhanjiang, Beihai, Yingkou. These regions have a higher degree of openness to foreign cultures and are assigned a value of 1 for “Open”, otherwise it is 0. 3) If the enterprise type is a High-Tech Company, then the value is 1; Otherwise, it will be assigned a value of LOW-Tech Company which equals 0. 4) For state-owned enterprises the value will be set to 1; Otherwise, it will be set to 0.

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