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Research article

Digital transformation, productive services agglomeration and innovation performance

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ABSTRACT

Innovation is a necessary guarantee for sustainable development. Stepping into the digital age, digital transformation has triggered the innovation revolution. This paper takes 30 provinces in China from 2012 to 2022 as the research sample, we verify whether digital transformation has improved innovation performance. Based on the Solow growth model and agglomeration economics theory, we also explore the moderating role and threshold effect of agglomeration in productive service industry between digital transformation and innovation performance. To achieve this, we apply the methods of machine learning and text analysis to construct an evaluation index of regional digital transformation and measure it. The paper finds that China's digital transformation index is increasing, but there is a digital divide between regions. We also determine that digital transformation significantly and positively contributes to the level of innovation performance. Considering the threshold effect of agglomeration in productive service industry, the impact of digital transformation on innovation performance exhibits non-linear characteristics, As the level of agglomeration continues to exceed the threshold, the innovation-driven effect of digital transformation increases. The research results help clarify the relationship between digital transformation and innovation performance, and provide favorable policy directions for regional governments to identify digital divides and make reasonable industrial layouts. Thus, it can promote the construction of digital China and innovation power, injecting strong innovation force into the realization of SDGs.

1. Introduction

In 2015, the United Nations set 17 Sustainable Development Goals (SDGs), which point a clear direction for the international community to achieve balanced economic, social, and ecological development. The achievement of these SDGs is inextricably linked to the level of technological innovation in the economy [1]. Whether it is overcoming the predicament of external technology dependence faced by SDG1 (No poverty), breaking through the obstacles of energy technology innovation to promote renewable energy substitution for SDG7 (Affordable and clean energy), or maintaining the supply of innovation momentum for sustainable economic growth of SDG8 (Decent work and economic growth), the improvement of innovation level plays a pivotal role. It is worth noting that the digital

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economy has broken the constraints of material factors on traditional economy development, and fundamentally changed the way of economic and social value creation, which has become a kinetic driving force for technological innovation. According to data released by the China Academy of Information and Communications Technology, China's digital economy achieved significant breakthrough in 2022, reaching 50.2 trillion yuan, accounting for 41.5 % of GDP [2]. Over half of the world's top 1000 companies have made digital transformation as the core of their strategy development [3]. In the digital age, digital transformation has become the consensus of all walks of life. Digital transformation has gradually penetrated into all aspects of enterprise production, management and development. It is manifested in the transformation of production process driven by digital technology and the implementation of enterprise strategy based on digital management. To seize development opportunities and achieve the goal of being a digital China, the14th Five-Year Plan regards digital transformation as strategic to promote production, lifestyle, and governance changes, and proposes to "accelerate digital development". The report of the 20th CPC National Congress presented that China shoulders its responsibility in the digital era, acceleratesthe digital innovation drive, eliminates the "digital divide", and boosts the digital economy's healthy and orderly growth. Combining digitalization with industrial development, promotes the reconstruction of the innovation ecosystem, enhances enterprises' capacity to digest, absorb, and reinvent, digital transformation goes beyond simply replacing original production methods with digital technology and intelligent manufacturing, thereby enhance enterprise performance and competitive advantage. The development model of digitally-driven innovation can infuse a steady stream of technological impetus for sustainable development of China and the world. Relying on digital transformation to develop new types of products and technology is of great significance in realizing SDGs. Therefore, in the age of digital economy and sustainable development, it has become a significant research topic through digital transformation to stimulate the endogenous driving force of development, promote technological innovation, and enhance competitive strength.

With the deepening of the labor social divisions and the continuous improvement of specialization levels, the producer services sector has gradually been separated from the manufacturing sector. It has developed into a modern service industry that provides technical assistance and intermediary services for industrial output, development, and transformation, with high industrial correlation and technological intensity, and exhibits significant agglomeration effects [4]. According to the theory of New Economic Geography, the agglomeration of producer service industries can demonstrate the linkage effect of agglomeration through the connection of the entire industrial chain. It can improve the quality of intermediate input products and services, and the layout of supporting industries. It also guides the digital transformation of traditional industries, promotes the expansion of digital industries, and provides industrial integration services for the innovative effect of digital transformation [5]. The technology diffusion theory suggests that producer services can actively promote technological exchange and knowledge integration between different enterprises and regions, provide a platform for sharing innovative resources, unblock the channels for the circulation of new technologies [6], and strengthen the innovation effect of digital transformation. Furthermore, in the process of enterprise digital transformation, the "self-reinforcing" effect can blur the technological boundaries, eliminate the technological entry barriers between regional enterprises, and play an important role in reinforcing the complementary advantages and promoting the in-depth development of scientific and technological innovation [7]. Thus, based on regional differences in the producer services, pay more attention to the innovation-driven role of digital transformation under the antecedents of China's digital strategy. This is also a timely response to the urgent need to "accelerate the deep integration of the digital economy and the real economy", as proposed in the 20th National Congress Report.

In academic research, some studies have generally confirmed the innovation-driven role of digital transformation. However, the current research lacks the test of the non-linear relationship between the two, let alone the discussion of industrial agglomeration regulation. Using the data from 30 provinces in China from 2012 to 2022, this paper aims to explore the impact of regional digital transformation on innovation performance. Based on natural language processing of machine learning, we first construct a digital transformation index, and use the patent accumulation method to measure innovation performance. Furthermore, the benchmark regression model between the two core variables is constructed to provide convincing evidence for the innovation-driven role of digital transformation. Subsequently, the paper introduces the threshold variable of producer services agglomeration, constructs a dynamic threshold model, and discusses their nonlinear relationship under the regulation of producer services in detail.

This paper mainly has three marginal contributions, as follows. (1) This paper analyses the annual reports of listed companies from each province through machine learning and natural language processing and uses "digitalization" related word frequency science to measure regional digital transformation indicators. (2) The dynamic panel threshold model effectively addresses the early dependency and dynamic features of innovation performance while considering the dynamics of innovation performance and the model's endogeneity. (3) This paper broadens the study scope of innovation-driven digital transformation, incorporating for the first time the non-homogenous threshold characteristics of regional producer services agglomeration, investigates the impact of digital transformation on enterprise innovation performance. It provides reference value for the path selection and policy design of the digital enabling of innovation performance. The research results provide theoretical support and micro-evidence for regional governments to identify the digital divide, rationally distribute producer services, and further improve regional innovation performance. Further, it will contribute to China implement the innovation powerhouse strategy, enhance its national competitiveness in science and technology, and inject strong innovation into the realization of sustainable development goals (poverty alleviation, renewable energy and sustainable economic growth, etc.). The proposed policy recommendations provide a practical basis for developing countries to drive innovation and achieve SDGs through digital transformation.

The subsequent sections as follows: Section 2 reviews relevant literature on digital transformation, innovation performance, and machine learning; Section 3 conducts the theoretical analysis and research hypotheses; Section 4 describes the model setting and relevant variables; Section 5 reports the empirical results and Section 6 gives a detailed discussion. Finally, Section 7 concludes and proposes policy recommendations.

2. Literature review

A new round of scientific and technological revolution and industrial transformation continues to unleash momentum, and promoting the shift from transformation factor-driven to innovation-driven has become an important starting point for China's high-quality development. More and more regions and enterprises are taking innovation performance improvement as a development strategy. At the same time, the role of digital transformation in promoting technological innovation has received extensive attention from scholars at home and abroad. The content related to the topic involves three aspects: research on digital transformation, research on digital transformation and innovation performance, and research on digital transformation and machine learning.

2.1. Research on digital transformation

The existing research mainly includes three aspects: the concept, measurement and impact effect. ①Concept. The concept of digitization was first explained and conceived in Wilhelm's Explanation of Binary Arithmetic in 1703. Digital transformation as a unique phenomenon of economic development in the digital era, mainly refers to the transformation and innovation of backward economic forms by economic entities through digitalization, to become a more advanced economic form [8]. In terms of the evolution process, Verhoef et al. (2021) proposed to divide it into three processes: informatization, digitalization, and digital transformation [9]. For transformation subjects, the research addresses concepts at the business level [10], supply chain [11,12], and government [13]. ② Measurement. Scholars have shifted their research on digital transformation indicators from qualitative to quantitative, facing many shackles. The measurement methods mainly include the entropy method and principal component analysis method,but there is no unified standard. ③Influence effect. With the continuous development of the digital economy theory, the critical role of digital transformation in alleviating information asymmetry [14], optimizing production and management processes [15], innovating business models [16], and promoting economic growth [17] has been verified.

2.2. Research on digital transformation and innovation performance

As to whether digital transformation can promote innovation, scholars have conducted relevant research based on different perspectives, and the conclusions are inconsistent. ① View of promotion. Some studies hold that digital transformation has a significant innovation effect, and its driving path mainly include expanding innovation opportunities, improving innovation efficiency, and reducing innovation costs [18,19].② View of inhibition. Scholars have proposed the innovation paradox of digital transformation, that is, the innovation effect of digital transformation is not significant [20]. Specifically, according to the "China Enterprise Digital Transformation Index Report (2022)", only 11 % of enterprises have performed outstandingly after digital transformation, and the majority of enterprises' digital transformation investment has not brought substantial innovation performance or productivity improvement, namely the "IT productivity paradox". ③ View of indeterminacy. Based on Metcalfe's Law and Davido's Law, some scholars argue that digital transformation is characterized by economies of scale and scope. Meantime, combined with the creation of economic environments under the Matthew effect [21,22] and the Long Tail effect [23], it exhibits a nonlinear effect on innovation.

2.3. Research on digital transformation and machine learning

In recent years, machine learning has gained prominence in the fields of information systems [24], finance [25], and management [26], where its function is reflected in improving prediction accuracy and technical operational efficiency. Some scholars have also noticed the potential value of machine learning in the field of digital transformation research, and tried to adopt machine learning methods in the measurement and empirical research on digital transformation. ①Measurement of digital transformation. Wu et al. (2021) first proposed a digital transformation measurement method based on text analysis of machine learning [27]. On the basis of his research, some scholars use the Java pdfbox class library for text transformation [28], some adopt the word embedding neural network language model to conduct vectorization representation of words and others apply Word2vec model in extracting similar words [29, 30]. Besides, some studies combine manual reading with machine learning and use ERNIE (Enhanced representation through knowledge integration) to identify corporate annual report texts and then build 0–1 indicators of digital transformation [31]. ② The relation between digital transformation and other variables. In the empirical analysis, machine learning is regarded as a perfect supplement to econometrics for testing statistical relationships between variables. For instance, Li et al. (2022) uses DBSCAN and CART to explore the complex impact of enterprise digital feature configuration on green innovation performance [32]. Zhang et al. (2023) adopts the random forest model and the CatBoost model to identify the degree and ranking of the impact of digital finance on green development [33]. Ballestar et al. (2021) constructs an innovative machine learning (ML) model that includes automatic nested vertical clustering (ANLC) executed in two stages, to explore the relationship between corporate performance and robot adoption [34].

Existing studies have focused on the innovation effects of digital transformation, which has laid a solid theoretical foundation for this paper. However, there are still some shortcomings, which can be improved from the following three aspects, (1) Digitalization is a systematic process, and how to accurately describe the digitalization at the micro enterprise level is a challenge. The existing research is mainly carried out from a macro perspective, using the regional or industry level digital economyindicators, such as IT investment scale and informatization investment. This has the defects of a single indicator dimension and low representativeness. (2) Existing studies mainly explore the innovation effect of digital transformation from a static perspective, ignoring that digital transformation is an essential feature of dynamic accumulation. This makes it difficult to accurately reflect the innovation performance and expectation of digital transformation and offers limited guidance for regional or enterprise digital practice. (3) Presently, most literature focuses more on the linear empowerment effect of digital transformation, while ignoring the possible suitability problems between digital transformation and industrial agglomeration, and fails to fully reveal the nonlinear characteristics of the innovation effect of digital transformation. Due to China's regional heterogeneity, it is essential to introduce producer service aggregation into the research on the innovation effect of digital transformation from the perspective of industrial linkage theory and technological support.

On this basis, this paper takes the provincial data of China from 2012 to 2022 as the research sample, conducts empirical tests based on theoretical analysis to explore the complex relationship between digital transformation and technological innovation in detail. The benchmark regression model and dynamic threshold model are adopted to analyze the innovation-driven effect and complex nonlinear relationship of digital transformation under the heterogeneity of producer services agglomeration.

3. Theoretical analysis and assumptions

According to the examination of literature, this paper discovers that the relationship between digital transformation and innovation performance has not achieved a unified conclusion, and the adaptation relationship between digital transformation and producer services is disregarded. Therefore, in the strategic convergence period of the digital economy and innovation-driven development, this paper focuses on the following two research questions around the research theme. First, does digital transformation help drive innovation performance? Second, does producer services agglomeration play a significant threshold role in the process of digital transformation affecting innovation performance? Based on this, this paper will conduct a theoretical analysis of the above two questions, and put forward research hypotheses.

3.1. Digital transformation and innovation performance

Based on Solow's growth model, enterprises examine and adjust their development strategy and organizational structure based on digital technology, which helps realize the interaction effect between innovation supply and demand, by precisely positioning the innovation content and deepening innovation cooperation. This reduces innovation costs and improves innovation performance [35].

First, based on the supply-side perspective, enterprises use digital technology and digital empowerment to form dual organizational capabilities in the digital transformation process. This covers both use-based innovation to increase existing organizational capabilities and exploration-based innovation to help enhance the construction of new skills. Specifically, digital technology can provide real-time and accurate information for enterprises [36]. Companies can accurately forecast market demand, improve the market fit of research and development products, and boost innovation efficiency with low innovation costs aided by digital information dissemination and online transactions [37]. Additionally, digital transformation may increase innovation performance at the scale level, foster cooperative relationships, deepen collaboration throughout the industrial chain, and stimulate innovation.

Second, form a demand-side perspective, digital transformation may blur the boundaries of time and space, break organizational boundaries, integrate consumers' personalized needs, and provide innovative ideas for enterprises by establishing an "enterprise-consumer" interaction model [38]. In increasingly fierce market competition, quickly responding to consumer demand and accurately implementing policies is critical for enterprises to enhance their ability to create value together and realize endogenous innovation. In addition, digital transformation has also created new business models, such as service-oriented manufacturing and personalized customization, which improve innovation performance through the synergy of technological innovation and business model innovation [39].

Thus, this paper proposes Hypothesis 1: Innovation performance is improved by digital transformation.

3.2. Productive services agglomeration, digital transformation and innovation performance

Marshall's scale economy theory, Weber's location theory the new Economic geography theory represented by Krugman proposed that industrial agglomeration has an important platform and driving force for regional economic output and innovation sources, strongly affects technological progress, the factor allocation optimization and output multiplication [40,41]. In the current context of the deepening social division of labor and improving specialization levels, the productive service industry, with its high industrial correlation and knowledge intensity characteristics, has gradually shown agglomeration effects [4]. Theoretical and practical circles have frequently stressed the importance of regions completely using the benefits of knowledge spillover and technology diffusion in the agglomeration of productive service sectors, as well as promoting digital development and innovation efficiency improvement [42]. This paper will try to analyze the impact of producer services agglomeration on the innovation effect of digital transformation from the perspective of forward, backward and side all-round linkages using industrial linkage theory.

Firstly, based on a forward perspective, the agglomeration of productive service industries helps to increase effective digital supply. Furthermore, it can provide digital services and technical support at a lower cost. Specifically, digital transformation is typically dynamic and high-tech, requiring advanced elements such as technical resources, knowledge accumulation, and human capital as basic support [43]. The knowledge accumulation and human capital reserve caused by the agglomeration of producer services become necessary for digital transformation, which can form a cost saving mechanism and scale effect, thus fully stimulating the innovation effect of digital transformation [44].

Secondly, based on a backward perspective, the consolidation of productive service industries can help generate digital demand and strengthen the driving force of digital development. Specifically, digital transformation is characterized by high risk and investment, and it requires strong market expectations to enhance enterprise transformation confidence. The producer service industry gathers new demands for data elements and digital technology, injects continuous power into digital transformation, and promotes the cultivation of new business types and models [45]. This can serve as an innovation transmission mechanism, guiding enterprises through transformation and digital investment and influencing the innovation effect of digital transformation.

Finally, from a the side perspective, the agglomeration of producer services contributes to the construction of a radiation impact throughout the entire industry chain and region, broadens technological limits, and strengthens the innovation effect of digital transformation. Specifically, according to Marshall and Jacobs' agglomeration economics theory, producer services agglomeration can improve the quality of intermediate input products and services, promote the sharing of innovative resources, stimulate the spatial spillover of innovative knowledge and digital technology, and further strengthen the innovation effect of digital transformation [46]. Furthermore, due to the knowledge spillover effect in the agglomeration process of productive service sectors, there is a continuous flow of new technologies among the upstream and downstream industries, which has had a "creative destruction" on the overall industry development [6]. Based on Schumpeter's innovation theory, this "creative destruction" plays a vital role in improving innovation performance, and further provides a reliable theoretical basis for the innovation effect of producer services agglomeration in promoting digital transformation.

Besides, it is worth noting that the agglomeration of producer services can impact the innovation effect of digital transformation through forward, backward and sideways aspects. However, this is influenced by the dual character of agglomerated industry and space, as well as the problem of unequal regional development in China [47]. In digital transformation's impact on innovation performance, there is likely a special producer services agglomeration threshold, which causes the impact of digital transformation on regional innovation performance different in varying producer services agglomeration intervals. Following that, this paper will investigate the threshold effect of producer service industry agglomeration from the standpoints of congestion and scale. On the one hand, in low-agglomeration locations, the market is immature, the digital information network is complex, and there is a lack of standardization and organization due to the congestion effect of the agglomeration of producer services. Thus, "information noise" might have an impact on the innovative effect of digital transformation [48]. On the other hand, due to the scale effect of agglomeration in productive service industries, regions with higher agglomeration levels often have relatively close industrial connections and higher technological levels. This can improve the better innovation environment and lay the ground work for digital transformation by strengthening information knowledge flow and technology accumulation, removing entry barriers, and promoting enterprise innovation performance. Furthermore, with the increasing concentration of productive service industries, the scale and efficiency of business digital development have improved.

Based on this, we propose Hypothesis 2: Producer service industry aggregation has a significant threshold effect on digital transformation's impact on innovation performance. Digital transformation has a comparatively small impact on innovation performance in locations with a low concentration of producer services. With the increasing concentration of producer services, digital transformation will have a significant "marginal increase" positive impact on innovation performance.

The frame diagram of theoretical assumptions in this paper is shown in Fig. 1 based on the above theoretical analysis and research assumptions. This paper focuses on the empirical test of two hypotheses. Theoretically, we demonstrate the positive effects of digital transformation on innovation performance from both the supply side and the demand side. At the same time, the positive moderating effect of productive services agglomeration on the relationship between the two is elaborated from the forward end, backward end and side perspective, which in turn gives the assumption of a non-linear impact. The empirical investigation of hypothesis 1 is then completed by combining variable tests, residual tests, and the benchmark regression model. Further, the threshold test and dynamic threshold model are applied to prove hypothesis 2.

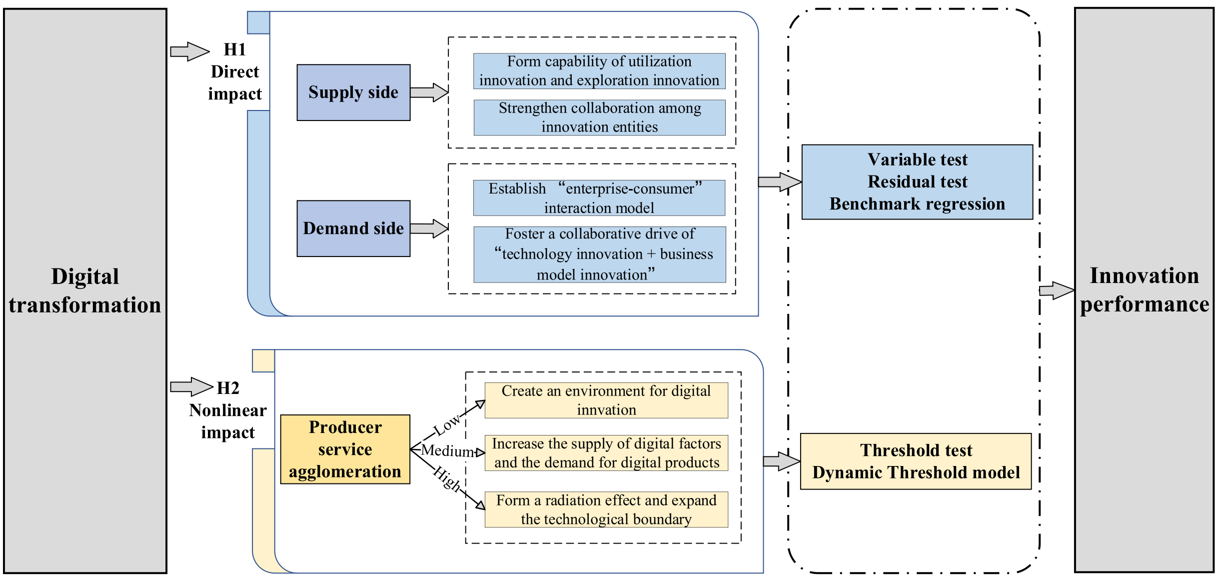


Fig. 1. Framework diagram of theoretical hypothesis.

4. Research and design

In order to answer the two research hypotheses proposed in the third part, this paper will use patent grant stock to represent innovation performance, and use machine learning and natural language processing methods to conduct word frequency statistics on regional enterprise annual reports. On this basis, the dynamic panel threshold model is used to examine the relationship between digital transformation, producer services agglomeration and innovation performance. This study will deepen the understanding of the general law of digital economy, provide a new perspective for analyzing the driving force of regional innovation performance improvement, and offer reference for promoting the construction of digital China and innovative country. Next, this paper will focus on the introduction of research design, including model construction, variable measurement and data sources.

4.1. Model setting

4.1.1. Construction of benchmark regression model

To examine how digital transformation affects innovation performance, this paper first develops the straightforward linear regression model. See formula (1).

$$Inno_{it} = \mu_i + \alpha Digi_{it} + \beta^{`} X_{it} + \varepsilon_{it} \tag{1}$$

where $Inno_{it}$ is the explained variable, representing the innovation performance level of region i in period t. $Digi_{it}$ is the explanatory variable, representing the digital transformation degree. X_{it} is the control variable, μ_i represents the unknown individual effect, and ε_{it} represents the random error term. α is the influence coefficient of $Digi_{it}$ on $Inno_{it}$, and, $\beta^{`}$ indicate the parameter vector of the influence coefficient of the control variables. The unknown coefficients can be determined by choosing appropriate samples and estimate techniques, which allows for the analyzing the relationship between innovation performance and digital transformation.

4.1.2. Construction of dynamic panel threshold model

The homogeneity assumption is implied by Model 1, which holds that the impact of digital transformation on innovation performance is constant across all locations and epochs, and every time $Digi_{it}$ that adds a unit, $Inno_{it}$ will add α units. However, this is not the case. According to the previous studies in Section 2 and theoretical analysis in Section 3, we believe that there is a complex nonlinear relationship between digital transformation and innovation performance. At present, the classical static threshold model proposed by Hansen is mostly used in the study of nonlinear relations. Nonetheless, such a model is bound to encounter endogeneity issues amongst variables, resulting in biased model estimate. Meanwhile, the fixed effects regression estimation adopted requires that the covariable is a strong exogenous variable. However, in many practical applications, the condition of strong exogeneity is restrictive. In addition, innovation performance measured by patent grant has been verified to have strong prior dependences [49]. To avoid the endogeneity problem, strong exogenous variable limitation and the early-stage dependency of patent grant, we refer to the previous studies [50,51] and combine the GMM estimation method with the threshold model to construct the dynamic threshold model, which introduced the lag terms of innovation performance $Inno_{it-1}$、$Inno_{it-2}$.

This paper proposes a dynamic threshold model using variables selected based on the concentration of producer services and the single and double threshold model of digital transformation on innovation performance:

$$Inno_{it} = \omega_{11} Inno_{it-1} + \omega_{12} Inno_{it-2} + \alpha_1 Owner_{it} + \alpha_2 City_{it} + \alpha_3 Infor_{it} + \alpha_4 Traffic_{it} + \beta_1 Digi_{it} I(Agglo_{it} \le \eta) + \beta_2 Digi_{it} I(Agglo_{it} > \eta) + u_i + \varepsilon_{it} \tag{2}$$

$$Inno_{it} = \omega_{21} Inno_{it-1} + \omega_{22} Inno_{it-1} + \alpha_5 Owner_{it} + \alpha_6 City_{it} + \alpha_7 Infor_{it} + \alpha_8 Traffic_{it} + \beta_3 Digi_{it} I(Agglo_{it} \le \eta_1) + \beta_4 Digi_{it} I(\eta_1 < Agglo_{it} \le \eta_2) + \beta_5 Digi_{it} I(Agglo_{it} > \eta_2) + u_i + \varepsilon_{it} \tag{3}$$

where i and t represent provinces and years, respectively. Of the main control variables, $Owner_{it}$ indicates ownership structure; $City_{it}$ indicates urbanization; $Infor_{it}$ indicates the level of informatization; $Traffic_{it}$ indicates the level of transportation infrastructure. Of the core variables, $Inno_{it}$ represents innovation performance; $Digi_{it}$ represents a digital transformation; $Agglo_{it}$ represents the concentration level of producer services; I(•) is an indicative function; η is the threshold value of the threshold variable $Agglo_{it}$, η_1 and η_2 are single and double thresholds; u_i is the specific effect of the individual; ε_{it} is a random interference term. Notably, β_1 indicates the influence coefficient of digital transformation index matched with the first cluster of producer service agglomeration, and β_2 indicates the influence coefficient of digital transformation index matched with the second cluster of producer service agglomeration. $\omega_{11,}\omega_{12}$ indicates the influence coefficient of the lag terms of innovation performance on $Inno_{it}$ under the condition of simple threshold effect; Similarly, t he implication of the corresponding influence coefficient in the double threshold dynamic regression shown in formula (3)is the same as that in f ormula (2).

In addition, the multi-threshold panel model is analogized and will not be described here.

4.2. Description of variables and data sources

(1) Explained variable: innovation performance. Previous studies have extensively measured and applied regional innovation performance, and the commonly used indicators include new product sales [52], innovation efficiency [53] and patent output [54]. Among them, although new product sales can reflect the economic value generated by innovation input, it ignores the complex influence of market factors in the sales process，and thus fails to represent the direct innovation performance. Further, the measurement method of innovation efficiency fully considers two aspects of innovation input and innovation output, but it is essentially a growth rate index, which cannot represent the stock performance of innovation. At the same time, this method will obtain different measurement results due to the selection of evaluation methods and input and output indicators [55]. In view of this, in this paper, we evaluate regional innovation performance based on the perspective of patent output. Referring to the studies of Li et al. (2022) [56] and Liu et al. (2021) [57], we adopted the perpetual inventory method to carry out inventory treatment on the amount of patent grants to represent the innovation performance. Its advantages are embodied in two aspects. On the one side, there is a strong correlation between the number of patent grants and innovation input such as R&D expenditure, which can further link innovation input and innovation output more closely. On the other side, technological innovation has a significant cyclical cumulative effect. The previous innovation foundation has an important impact on the current period's performance, that is, innovation is a cumulative concept [48,49]. It should be pointed out that the application of the perpetual inventory method has promoted the transformation of the time point quantity to the period quantity, and then relatively comprehensively reflects the information of innovative achievements and stock characteristics of the innovation performance in a certain year. Formula (4) shows the detailed calculation equation.

$$TI_{it} = (1 - \delta)TI_{t-1} + PAT_{t-1} \tag{4}$$

where TI_{it} is the innovation capacity stock at the start of the t period, PAT_{t-1} represents the number of patents granted in the current period, and δ is the depreciation rate.

To calculate TI_{it}, two key problems must be solved. First, the depreciation rate must be determined. In previous literature [8,25], scholars generally set the depreciation rate as 10 %. Second, initial stock TI_0 must be identified. In a perpetual inventory model, the initial innovation capacity stock is generally calculated according to formula (5).

$$TI_0 = \frac{PAT_0}{\overline{g} + \delta} \tag{5}$$

where TI_0 is the stock of innovation capacity in the first year, PAT_0 is the number of patents granted in the first year, and $\overline{g}$ is the average annual logarithmic growth rate of all patents issued during the data collection period.

(2) Explanatory variable: digital transformation. Presently, the research on digitalization covers the regional, industry, and enterprise levels, among which the research on enterprise digital transformation is relatively abundant. At the regional level, scholars have measured the digital development index, digital economy efficiency and digital economy scale respectively through the comprehensive index system method, DEA data envelopment analysis method and national economic accounting method. However, some scholars choose single indicators as proxy variables for the regional digitalization level, such as the output of the electronic information manufacturing industry, the number of Internet broadband access ports, and e-commerce sales. This paper argues that all the above methods have some defects. For the former, the digital economy and digital transformation must not be confused. The core of the digital economy is a form of economic development supported by digital technology and developed by information and data [58]. However, digital transformation is primarily the digital upgrade of the business model, production mode, value logic and organizational structure of a traditional micro subject based on digital technology and the Internet platform [59,60]. In theory, the digital economy provides a sound macro ecological environment for its active transformation of the digital transformation, while digital transformation provides micro competitiveness and a solid foundation for the vigorous development of the digital economy. In terms of the latter is concerned, digitalization can transform industrial organizations and vigorously develop the digital economy driven by the

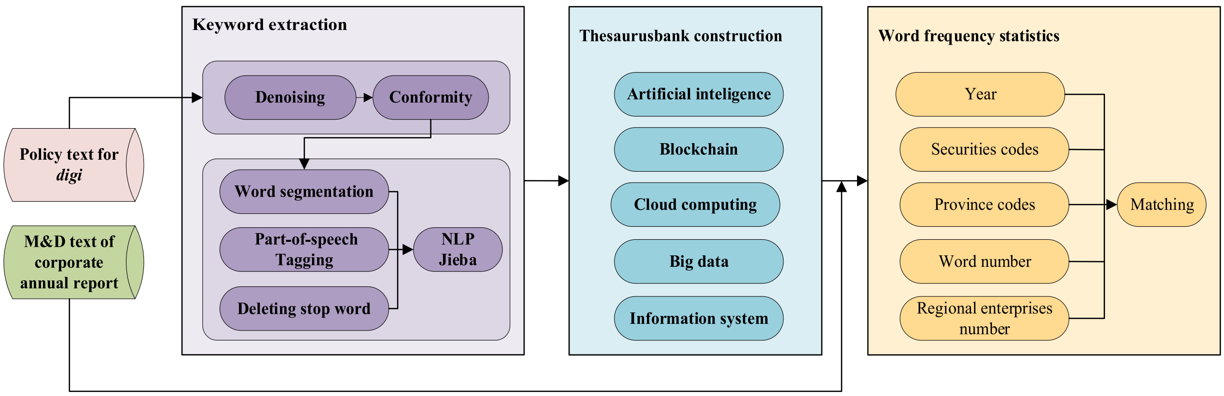


Fig. 2. Overall structure of the measurement of *digi*.

collective force of digital transformation of various micro-subjects within the region. Nevertheless, most studies measure regional digitalization from a single perspective, such as the application scale of digital technology or the output of the digital industry, which cannot scientifically explain the regional digital transformation level.

Given the above analysis, we attempt to adopt machine learning and natural language processing methods to produce statistics on the word frequency of “digital transformation” in regional enterprise annual reports from a micro perspective [61]. We obtain the digital transformation index of each province by matching the four dimensions of securities code, word frequency, province and year. This consists of the following four steps, as shown in Fig. 2. ① The classification of annual reports: In this paper, Python software is applied to collect all the annual reports of listed companies in each region. and extract text content on “management discussion and analysis” (MD&A). ② The construction of a “digital transformation” thesaurus bank: Based on enterprise digitalization, the Guide to Digital Transformation for Small and Medium-sized Enterprises, the 14th Five-Year Plan for Digital Economy Development and other policy documents related to China’s digital transformation since 2013, a thesaurus bank of digital transformation is constructed. A detailed list of policies is reported in **Appendix 1**. Meantime, we supplement the ABCD thesaurus bank of Digital Transformation constructed by Wu et al. (2021) to comprehensively describe the degree of digital transformation [27]. As can be seen from the word cloud in Fig. 3., the keywords can be divided into eight seed words: Information System, Internet, Fintech, Smart, Artificial Intelligence, Blockchain, Cloud Computing and Big Data, which suggests that the digital transformation index can be constructed from eight dimensions. Table 1 lists specific keywords for each dimension; ③ Natural language processing. To match the annual report text with diverse keywords, the Jieba lexicon library of natural language processing is employed. Thus, each enterprise’s word frequency of “digital transformation” is obtained. **Appendix 2** reports the core algorithms. ④ Matching of regional data: Through the four-dimensional matching of securities codes, word frequency, province and year, the total word frequency in each region and the number of listed companies are obtained. We calculate the logarithm of the mean word frequency within the region to represent the regional digital transformation index.

(3) Threshold variable: agglomeration of producer services. The agglomeration of producer services reflects the spatial distribution of the same kind of producer services industry [42]. Based on the study of Liu Y et al. (2017) [62], this paper uses location entropy to express the agglomeration level of producer services in terms of agglomeration density in geographic space. Formula (6) lists how to calculate the agglomeration degree of producer services.

$$agglo_{it} = LQ_{it} = \frac{E_{it}/Y_{it}}{E_t/Y_t} \tag{6}$$

Where E_{it}、 E_t indicate the economic index of regional producer services and the economic index of national producer services agglomeration, respectively; Y_{it}、 Y_t refers to the regional output value and national output value, respectively. Specifically, this paper refers to Gu (2011) for defining producer services [63]. Using the statistical calibre of inter-provincial employment by industry in China, this paper identifies the five categories of producer services as “transportation, warehousing, and postal services” “scientific research, technical services and geological surveys” “R&D research, technical services, and the geological exploration sector” “finance industry” as well as “leasing and business services”. The larger the value of LQ_{it}, the higher the level of industrial agglomeration. When $LQ_{it} > 1$, it means that the province has the advantage of specialization during the time t; when $LQ_{it} > 1.2$, the province i possesses a higher level of specialization.

(4) Control variables: Building on previous research, this work controls the effect of numerous variables on innovation

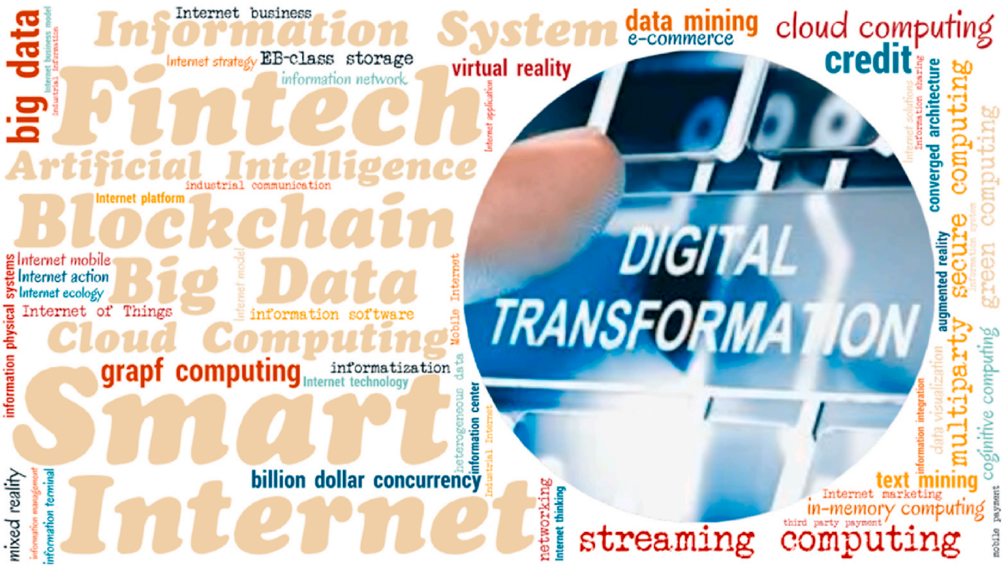


Fig. 3. Word cloud for digital transformation.

Table 1
Keywords for digital transformation.

Classification	Keywords
Information System	Information sharing, information management, information integration, information software, information system, information network, information terminal, information center, informatization, networking, industrial information, industrial communication
Internet	Mobile Internet, Industrial Internet, Internet solutions, Internet technology, Internet thinking, Internet action, Internet business, Internet mobile, Internet application, Internet marketing, Internet strategy, Internet platform, Internet model, Internet business model, Internet ecology, e-commerce
Fintech	mobile payment, third party payment, NFC payment, B2B, B2C, C2B, C2C, O2O, digital marketing, unmanned retail, Internet finance, digital finance, fintech, quantitative, finance, open banking
Smart	smart energy, smart wear, smart agriculture, smart transportation, smart healthcare, smart customer service, smart home, smart investment, smart culture and tourism, smart environmental protection, smart grid, smart marketing
Artificial Intelligence	artificial intelligence, business intelligence, image understanding, investment decision aid system, intelligent data, analytics analysis, intelligent robotics, machine learning, deep learning, semantic search, biometrics face recognition, speech recognition, identity verification, autonomous driving, natural language processing
Blockchain	blockchain, digital currencies, distributed, computing, differential, privacy technology, smart financial contracts
Cloud Computing	cloud computing, streaming computing, graphic computing, in-memory computing, multiparty secure computing, green computing, cognitive computing, converged architecture, billion dollar concurrency, EB-class storage, Internet of Things, information physical systems
Big Data	big data, data mining, text mining, data visualization, heterogeneous data, credit, augmented reality, mixed reality, virtual reality

performance. Specifically, it especially covers ownership structure (Owner), determined by the proportion of private sector employees to regional employees; Urbanization (City), as expressed by the proportion of urban residents in comparison to all other populationof the area; Information level (Infor), measured by the volume of post and telecommunications business per capita; The level of transportation infrastructure (Traffic), measured by the total mileage of roads per capita.

To sum up, Table 2 lists the variable declaration of this paper.

In this paper, 30 regions in mainland China from 2012 to 2022 are selected as research samples (Tibet was not included due to substantial missing data). All of the original data in the research were collected from the Chinese Bureau of Statistics' official public statistics. Table 3 displays the variables' descriptive statistics.

5. Empirical test and results

1. In order to verify the two research hypotheses, based on the research design, empirical tests, and results analysis will be conducted in this part. We follow the process below (see Fig. 4). First, the space-time evolution trend of the digital transformation of samples is analyzed and elaborated. Secondly, we test the multicollinearity, unit root of variables and test the normality and heteroscedasticity of residulas to ensure the reliability of the research data. Thirdly, the benchmark regression model is used to test the relationship between digital transformation and innovation performance, which proves hypothesis 1. Furthermore, a non-linear dynamic threshold model is applied to test the threshold role of producer services agglomeration in the process of digital transformation affecting innovation performance, that is, hypothesis 2. Finally, the reliability of the research results is improved by the robustness test of various methods.

5.1. Analysis of the digital transformation index

This paperdetermines the digital transformation index of the 30 inland provinces of China (except Tibet) using the calculation approach mentioned above from 2012 to 2022, selecting the three sections of 2012, 2016, 2020 and 2022, and draws a digital index map of each region, focusing on observing the spatiotemporal evolution trend of transformation, as shown in Fig. 5.

With the continuous advancement of the Digital China strategy, digital transformation in various regions of China has shown an increasing trend from 2012 to 2022. The key reasons lie in the guidance on policies and the development of digital technology. In 2011,

Table 2
Variable declaration.

Type	Variable	Measurement	Source
Dependent variable	Innovation performance (*inno*)	The number of granted patents based on perpetual inventory method	China Regional Statistical Yearbook
Key explanatory variable	Digital transformation (digi)	Word frequency statistics based on natural language processing	M&A text in annual reports of listed energy companies (Reptile technique by Python)
Threshold variables	Agglomeration of producer services *(aggllo*)	Location entropy method based on employment number	National Bureau of Statistics
Control variables	Ownership structure (owner)	private sector employees/regional employees	EPS global statistics
	Urbanization (city)	urban residents/all other residents of the area	China Regional economic Database
	Information level (infor)	post and telecommunications business/total population	China Regional economic Database
	The level of transportation infrastructure (traffic)	the total mileage of roads/total population	China Regional economic Database

Table 3
Descriptive statistical analysis of variables.

Variable	*Inno*	*Digi*	*Agglo*	*Owner*	*City*	*Infor*	*Traffic*
Obs	330	330	330	330	330	330	330
Mean	12.2283	2.7371	1.0174	0.1046	0.5898	0.3612	3.8946
Std.Dev	1.5659	0.6673	0.3761	0.0736	0.1210	0.3707	2.4070
Min	7.8490	0.8109	0.5998	0.0171	0.3496	0.0619	0.5149
Max	15.9060	4.5272	2.7413	0.2803	0.8960	1.9513	14.5037

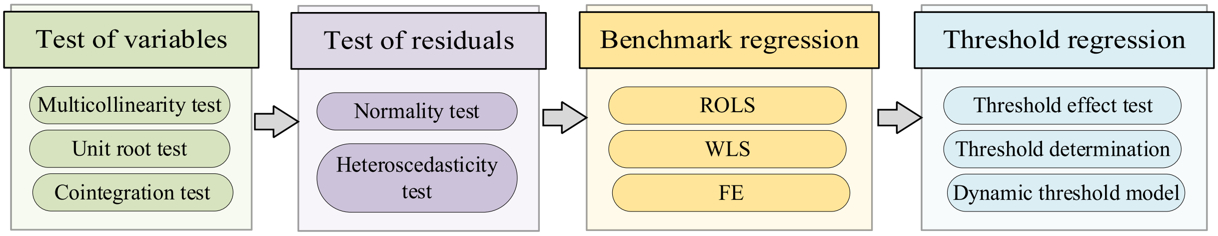


Fig. 4. Flowchart of empirical analysis.

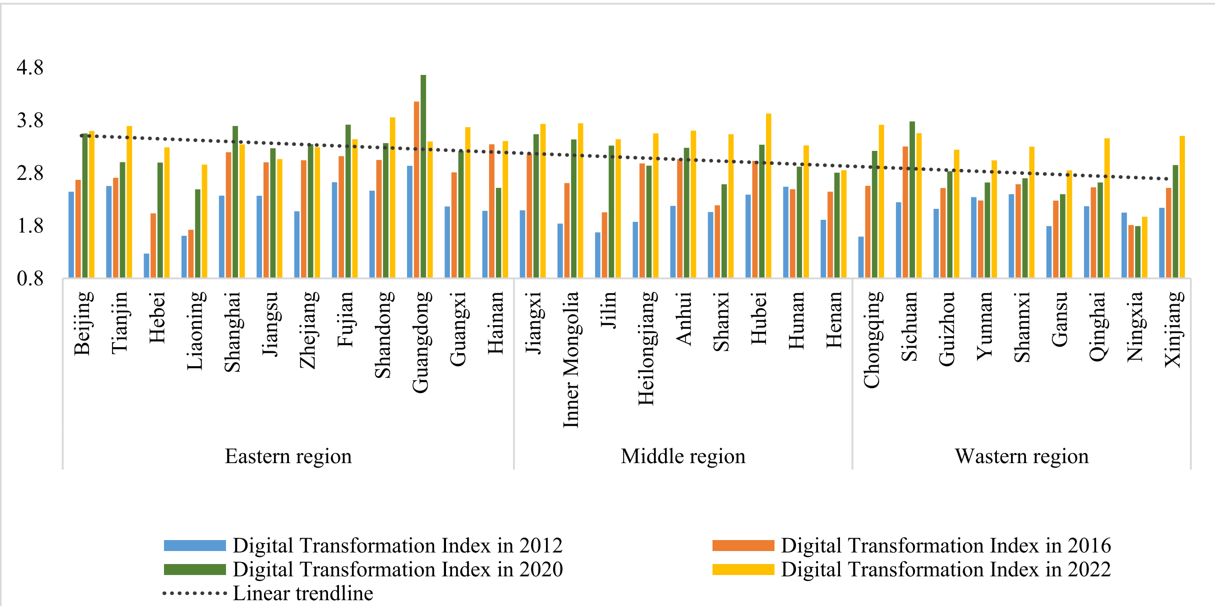


Fig. 5. Digital transformation index by region.

China proposed the deep integration of "informatization" and "industrialization", and under the boost of "broadband strategy", the "two" integration of the basic environment has obvious effects, manifested in the constant growth of fixed broadband and other information technology penetration rate, which laid the foundation for China's digital transformation in 2012. From 2012 to 2015, China's policies mainly concentrated on digital infrastructure construction, "Internet plus" and big data strategy. The policy release promoted digital technology, optimized the Internet ecology and provided technical and policy support for the improvement of digital transformation in 2016. In the following five years, the construction of network power and the digital economy strategy accelerated the process of digital China, and the digital concept penetrated production and life. Among them, large enterprises and Internet platform enterprises represented by state-owned enterprises have accelerated the pace of digital transformation. By 2020, China has built the world's largest fiber optic network and 4G network, and 96 percent of households have fixed broadband penetration. In 2022, with the full implementation of the 14th Five-Year Plan, telecommunications business revenue continues to grow rapidly, accompanied by a positive trend, optimized structure and strong momentum. Notably, the launch of the "East number and West calculation" injected digital momentum into the western region, making the degree of digital transformation in the western region surge in 2022. Overall, China's 5G network currently ranks first in terms of construction speed and scale and has made remarkable achievements in quantum computing, the Internet of things, artificial intelligence and other fields. In addition, the dynamism of the network economy continues to increase with strong digital infrastructure conditions, which has contributed to the continuous improvement of the digital transformation index.

There is a regional imbalance in the distribution of digital transformation in China. Guo et al. (2023) pointed out that the digital transformation is highly correlated with the level of regional economic development [17]. When regional per capita *lngdp* is taken as the characteristic variable of regional economic development, we find that digital transformation presents a significant positive correlation with lngdp. As shown in Fig. 6, the Pearson correlation coefficient is 0.76 with p value 0.0001, and influence coefficient in the fitting curve is 1.01, which is significant at the 10 % level. It can be argued that the digital transformation index is higher for regions with stronger economic development, with Guangdong, Fujian, Sichuan, Shanghai and Beijing ranking first to fifth, respectively. These regions all have a higher degree of informatization, marketization, and openness. In 2022, the e-commerce transaction volume of the above five provinces totaled 141367.6749 billion RMB, representing 47.1461 %, close to half of all national e-commerce sales. Guangdong, Shanghai and Beijing rank in the country's top three for e-commerce sale. They have vigorously promoted the construction of digital infrastructure and made a strong contribution to building a digital China. Using Guangdong Province as an example, the scale of Guangdong's digital economy exceeded 5 trillion yuan in 2022, ranking first in the country for five consecutive years, accounting for 47.50 % of GDP. At the same time, the Guangdong province has achieved full coverage of 5G networks in central urban areas and important regions. The last regions are Qinghai, Gansu, Ningxia, and other provinces. A multi-ethnic province in western China, Qinghai is among the areas with the least lagging economic development. Qinghai Provinces economic evolution is significantly below the national average, and it is also internally uneven. Qinghai Province has developed since implementing the "Western Development" model with the aid of policies. In 2022, Qinghai Province's GDP had reached 49,500 yuan/person, in contrast to 2000, when it was only 19,500 yuan/person. However, the province's digital transformation index has plenty of room for growth due to the general economic development environment and geographic position, which limits the development of high-tech sectors like the Internet. It is worth noting that China's "East Data and West Calculation" project has officially been launched, and digital transformation in the western regions has attracted the government's attention. The degree of digital transformation in the western region is relatively low, limited by economic development and scientific and technological level. However, such regions have advantages in terms of resource endowments and energy prices, which can mitigate the energy consumption problems of digital transformation [64]. Therefore, the western region is likely to have a high potential for digital development.

5.2. Test of variables

Before performing linear regression, it is necessary to test the applicability of the model. The implementation of linear regression needs to meet five basic conditions, namely,the correlation between independent variables and dependent variables, no multicollinearity between independent variables, stationary variables, and the residuals following with distribution and homogeneity of variance. Therefore, this paper carries out the relevant variable tests and residual tests.

5.2.1. Multicollinearity test

In linear regression, the model estimation is distorted due to the existence of precise or high correlation between explanatory variables. Therefore, a collinearity analysis of explanatory variables is required. This paper first performs a Pearson correlation test between variables, as shown in Fig. 7. It is generally believed that collinearity between variables can be considered if the correlation coefficient is greater than 0.7. The correlation coefficients between independent variables are all less than 0.7, indicating that the correlation is relatively weak. Thus, there is no collinearity between variables.

It is a common practice in academic circles to test whether a variable has multicollinearity based on the variance inflation factor (VIF). The test results are shown in Table 4. The VIF value of urbanization *(City)* is the largest at 3.0500, less than 10. The test results make it more convincing that there is no multicollinearity between variables.

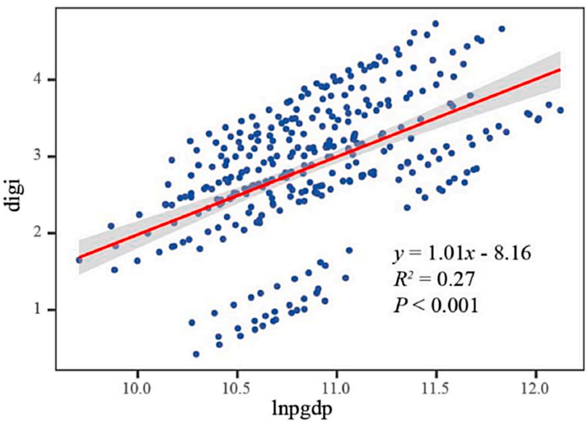


Fig. 6. Scatter fitting graph of digital transformation and economic development.

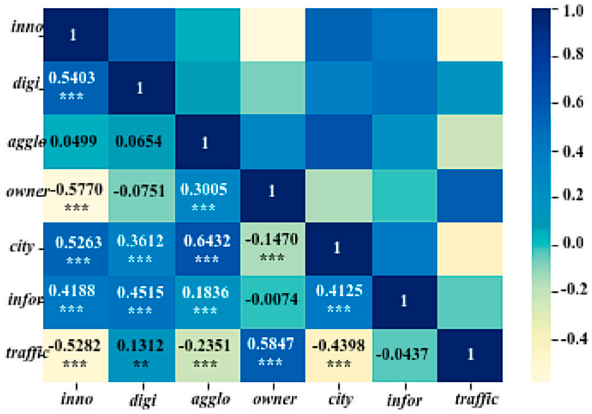


Fig. 7. Heat map of Pearson correlation test.
Note: The statistical values at 10 %, 5 %, and 1 % significant levels are indicated by *, **, and *** respectively.

5.2.2. Cointegration and unit root tests

Before panel model regression analysis, a unit root test is necessary to prevent spurious regression. This paper uses the software EViews9.0 to run the LLC test, IPS test, Fisher-ADF test, and Fisher-PP test on the key variables, avoiding the potential flaws of a single test technique. The original assumptions of these four test methods all contain unit roots. Table 5 displays the outcomes of the second difference test for each variable. According to the test results, no variable under the original value test passed all four tests with a significance level of 1 %. and all the variables have a unit root. However, all statistics pass the first-sequence difference test at a significance level of 1 %, demonstrating that all variables continue to be stationary after the first-sequence difference and behave as a single first-sequence integral.

The variables in the basic model are cointegrated by the methods of Pedroni, Kao and Westerlund. Table 6 displays the findings, where most P values are less than 1 %. This shows that the original reasoning for rejecting the cointegration test was the belief that “no cointegration relationship exists”, i.e., that the variables in the basic model have a steady, long-term relationship. The findings demonstrate that the set form of the regression equation can be accepted, allowing further investigation.

5.3. Test of residuals

5.3.1. Normality test

The residual normality test is used to check whether the residual term satisfies the normal distribution. We combine statistical test and histogram visualization to test the normal distribution of residuals. In terms of statistical test, the *S*–W test is recommended for small samples (less than 50) and the K–S test is recommended for large samples (more than 50) [65]. The sample size of the study is greater than 50, so the K–S test is selected. Specifically, the K–S test shows significant results ($p < 0.05$), which means that the null hypothesis is rejected (null hypothesis: the data is normally distributed). It is worth noting that the condition of normality test is difficult to satisfy in practice. Lilliefors (1967) pointed out that if the absolute value of kurtosis is less than 10 and the absolute value of skewness is less than 3, then the data, although not absolutely normal, is basically acceptable as a normal distribution [66]. In Table 7, the residual skewness is -0.6330 and the kurtosis is 0.4000, so the normal distribution of the residual is basically acceptable. Meantime, the histogram of the residuals in Fig. 8 (a) is approximately normal distribution, and the p-p scatter plot in Fig. 8 (b) is approximately a diagonal line, indicating that the residuals are positively distributed.

5.3.2. Heteroscedasticity test

The basic assumption of OLS is that the variance of the random disturbance term e is constant σ^2, that is $\mathrm{Var}(e_i) = \sigma^2$. When $\mathrm{Var}(e_i) \neq \mathrm{Var}(e_j)(i \neq j)$, it is thought that heteroscedasticity occurs. In the case of heteroscedasticity, the parameter estimators are not effective, and the significance test of variables is meaningless, resulting in invalid model prediction. Therefore, the heteroscedasticity test is carried out by graphical method and statistical test of residual fluctuation. On the one hand, since the residual can be regarded as the realized value of the disturbance term, the existence of heteroscedasticity can be investigated by the fluctuation of the residual. Fig. 9 describes the scatter plots of residuals and fit values (a), and residuals and digi (b), respectively. It can be considered that there is heteroscedasticity. Furthermore, according to the results of the BP (Breusch-Pagan) test and White test in Table 8, both P values are less

Table 4
The VIF of each variable.

Variable	*Digi*	*Agglo*	*Owner*	*City*	*Infor*	*Traffic*	Mean
VIF	1.6100	2.7200	2.5000	3.0500	1.4000	2.5200	2.3000
1/VIF	0.6195	0.3679	0.3996	0.3279	0.7148	0.3963	0.4348

Table 5
Unit root test results.

Variable	Original value				First difference			
	LLC	IPS	ADF-Fisher	Fisher-PP	LLC	IPS	ADF-Fisher	Fisher-PP
Inno	−0.2897	5.5970	6.9531	50.1123	−8.0928***	−3.7704***	110.4340***	187.4980***
Digi	−7.2612***	0.4482	55.9187	27.0786	−2.2657**	−2.5165***	89.6711***	229.4670***
Agglo	−6.3862***	−2.2254**	101.8560***	67.6126	−15.1231***	−7.3291***	177.3080***	324.0380***
Owner	−1.0747	1.8466	36.3755	66.8940	−6.6533***	−4.1456***	118.4320***	383.4510***
City	4.3445	10.5210	5.6656	24.2086	10.6969*	−1.7920**	90.0930***	355.505***
Infor	−19.0776***	−14.3220***	294.4220***	53.9974	7.5288**	−3.7672***	108.672***	6.6970***
Traffic	−0.4598	4.2014	37.0590	66.9612	3.3303***	−1.9018**	95.3948***	333.2170***

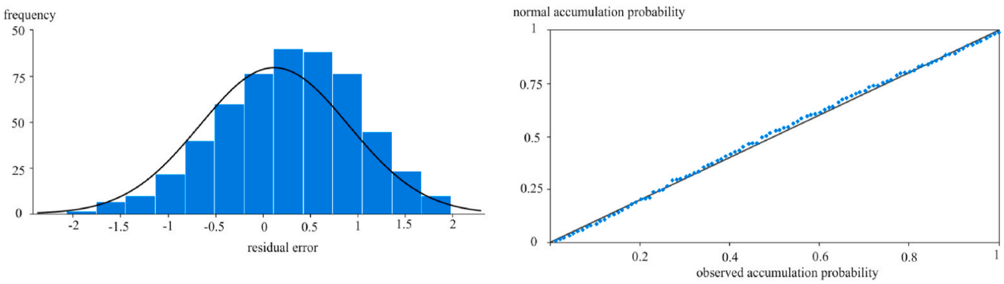
Note: The statistical values at 10 %, 5 %, and 1 % significant levels are indicated by *, **, and *** respectively.

Table 6
Cointegration test results.

Test	Statistics	t-Statistic	Prob.
Kao	Modified Dickey-Fuller	−2.4709	0.0067
	Dickey-Fuller	−3.3020	0.0005
	Augmented Dickey-Fuller	0.1248	0.4503
	Unadjusted modified Dickey	−1.5895	0.0560
	Unadjusted Dickey-Fuller	−2.8750	0.0020
Pedroni	Modified Phillips-Perron	10.3523	0.0000
	Phillips-Perron	−7.1380	0.0000
	Augmented Dickey-Fuller	−5.6869	0.0000
Westerlund	Variance ratio	10.7142	0.0000

Table 7
Residual normality test results.

Variable	Sample	Mean	Std	Skewness	Peakness	Kolmogorov-Smirnov Test		Shapiro-Wilk Test	
						Staticis D	P value	Statistics W	P value
e	330	0	0.808	−0.633	0.4	0.094	0.0000	0.972	0.0000



(a) (b)

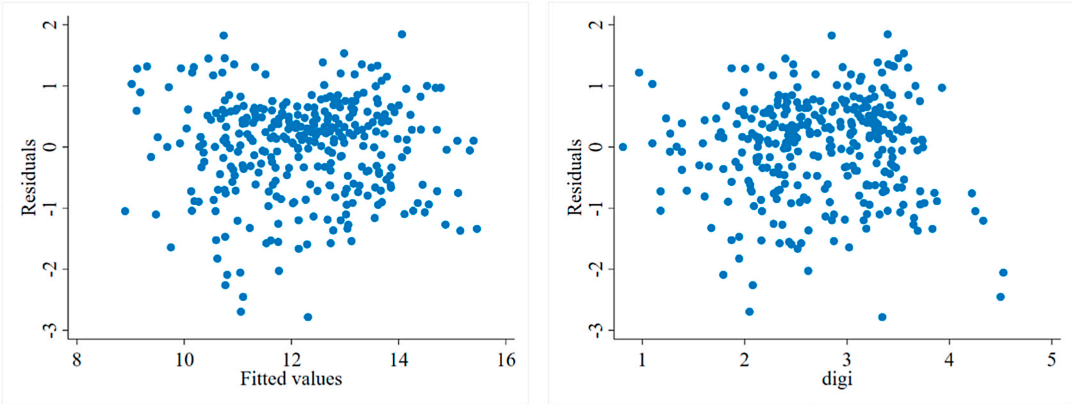
Fig. 8. Histogram (a) and p-p chart (b) of residuals.

than 0.10, rejecting the null hypothesis of homoscedasticity. On this basis, it can be determined that the model has heteroscedasticity.

5.4. Analysis of the benchmark model

Based on the above tests, it is reasonable to perform multiple linear regression. Notably, to correct for heteroskedasticity, we utilize the regression methods of heteroskedasticity-robust OLS regression (ROLS) and weighted least squares (WLS). At the same time, according to the Hausman test, we further build a fixed effect model. Table 9 shows the regression results. The results of the three models show that digital transformation has a significant positive effect on innovation performance. Because of the comparison of goodness of fit R2, we focus on the regression results of fixed effects in column 3 of Table 9.

The panel regression results show that (1) at a significance level of 1 %, the digital transformation index positively correlates with innovation performance, indicating that, digital transformation considerably boosts innovation performance throughout the sample



(a) (b)

Fig. 9. Scatter plot - Residuals and fit values (a), residuals and digi (b).

Table 8
Heteroscedasticity test results.

Breusch-Pagan test		White test	
Statistics	P value	Statistics	P value
3.7200	0.0537	87.0600	0.0000

Table 9
Panel data regression estimation results.

Variable	(1)	(2)	(3)
	ROLS	WLS	Fe
Digi	1.0745***	0.8615***	0.4706***
Owner	−6.8538***	−7.1501***	0.0124
City	1.2304**	1.3661**	12.8861***
Infor	0.6553***	0.6937***	0.1848***
Traffic	−0.2286***	−0.2634***	0.1035*
constant	9.9324***	10.6063***	2.8683***
R^2	0.7339	0.7470	0.9080
MSE	0.0066	0.0072	
RMSE	0.0814	0.0850	
Hausman Test			72.3100***
N	330	330	330

Note: The statistical values at 10 %, 5 %, and 1 % significant levels are indicated by *, **, and *** respectively.

period. Innovation performance increases by 0.4706 % for every 1 % increase in digital transformation. This conclusion is consistent with the theoretical analysis of this paper and verifies the rationality of hypothesis 1. As for control variables, As for control variables, urbanization positively affects innovation performance at a 1 % significance level. Innovation is an urban phenomenon, as high-quality talents and capital are highly concentrated in cities, which is conducive to innovation. Informatization positively impacts innovation performance at a 1 % significance level. Informatization helps reduce the cost and risk of innovation, stimulate innovation potential, and improve innovation performance by addressing the mismatch of production factors and restructuring innovation business processes. Transportation infrastructure construction favorably affects innovation performance at a 10 % significance level. According to New Economic Geography, transportation infrastructure optimization can effectively reduce the flow cost of innovation elements between regions, improve the innovation network and promote innovation.

5.5. *Dynamic threshold model analysis*

5.5.1. *Threshold effect test*

Based on Equations (2) and (3), this paper examines the validity and existence of the methods mentioned above to create a dynamic panel threshold model with producer services agglomeration as the threshold variable.

First, three sets of respective hypothesis tests are conducted ① H_0^{I}: No doorstep value exists; H_1^{I} : there is one doorstep value; ② H_0^{II}:

there is only one doorstep value; H_1^{II}: there are two doorstep values; ③ H_0^{III}: there are only two doorsteps value; H_1^{III}: there are three doorsteps. Table 10 displays the test results. There is a double-threshold effect of producer services agglomeration between digital transformation and the innovation performance, with the double-threshold model passing at 1 % level while the triple-threshold model fails. Regional innovation performance, has double thresholds of 1.1591 and 1.5892 aboveboard (see Table 11).

Secondly, the likelihood ratio function chart shows the estimation results of the concentration threshold of producer services and the corresponding 95 % confidence interval structure. In Fig. 10, when the concentration of producer services is 1.1591 and 1.5892, respectively, the likelihood ratio statistical test has an LR value of zero. The 95 % confidence interval is within the original hypothesis $H_0 : \gamma = \gamma_0$ acceptance domain of the model, and the threshold estimate equals its true value. Thus, it is classified into three categories based on the threshold heterogeneity interval: low producer services agglomeration ($Agglo \leq 1.066$), medium producer services agglomeration ($1.1591 < Agglo \leq 1.5892$), and high producer services agglomeration ($Agglo > 1.5892$).

5.5.2. Dynamic threshold regression

Table 12 displays the results of the dynamic panel threshold regression. The agglomeration level of producer services changes from low to high under the dual threshold effect of digital transformation. This is led by the aggregation of producer services to boost innovation performance, and the effect coefficient increases continuously, which verifies Hypothesis 2. When the agglomeration level of producer services is lower than 1.1591, the effect of digital transformation on innovation performance is weak and significant at a level of 0.01. With the level of producer service concentration continuously rising, the impact of digital transformation on innovation performance gradually increases. When the concentration level of producer services is higher than the first threshold ($1.1591 < Agglo \leq 1.5892$), digital transformation's effects on innovation performance pass the 1 % significance test and the elasticity coefficient increases to 0.1166. With the further improvement of the concentration level of producer services, the elastic coefficient increases nearly 4 times and is still significant at the 0.01 level after crossing the second threshold. Each 1 % increase in digital transformation leads to a corresponding 0.5265 % increase in innovation performance. This indicates that a higher concentration level of producer services will more favorably influence the innovation-driven effect of digital transformation. At the 1 % level in the model, the lag term of the explanatory variable innovation performance is significantly positive, suggesting that this paper is necessary to control the dynamic lag of innovation performance. In the Hansen Test of Overid, the significance level of the statistical value is 0.4820, greater than 0.1, which proves the rationality of the model tool variable setting. The P values of AR (1) and AR (2) for the autocorrelation test of the perturbation term once again prove the correctness of the selection of the first-order difference GMM method.

Derived from the above findings, this study concludes that there is a complicated nonlinear dynamic link between innovation performance and digital transformation, verifying the existence of Metcalfe's Law of digital transformation in the Chinese context.

Specifically, as shown in Fig. 11, the high range of producer services agglomeration is the optimal range in which digital transformation exerts a positive impact on innovation performance. With the deepening concentration of producer services, the influence of digital transformation on innovation performance generally has a promoting effect, but the transition degree differs. As a new technology-intensive format, digital transformation has a higher demand for intermediate services and technical support. The promotion of the virtual accumulation of factors and the use of digital technology to enable traditional manufacturing enterprises in the region can stimulate their endogenous innovation vitality and promote the improvement of innovation performance.

The aggregation of producer services can provide a better innovation environment and digital industry foundation for the digital transformation of enterprises, strengthen knowledge flow and technology accumulation, remove digital transformation barriers, and promote the further improvement of innovation performance. When the concentration level of producer services is at a low threshold, the innovation conditions required for digital transformation are insufficient to innovatively drive new models brought about by this transformation, such as intelligent manufacturing and service digitalization; therefore, the innovation-driving effect of digital transformation cannot be fully manifested. With the continuous improvement of the concentration level of producer services, the nonlinear positive effect of digital transformation on innovation performance shows a trend of weakening first and then strengthening. The innovation-driven effect of digital transformation is greatest when producer services cluster in the high threshold range.

5.6. Robustness test

To verify the robustness of the estimation results, this paper uses three methods of transforming the estimation method, replacing the core explanatory variable, reducing the sample based on the dynamic threshold model and transforming the estimation method. Table 13 shows the robustness test results. ① Replacing the core explanatory variable: Based on Han et al. (2023), this paper constructs a regional digital economy index from the digital environment, digital industrialization and industrial digitalization, to characterize the regional digitalization degree from the macro level [67]. We also use DIFF-GMM to re-estimate, as shown in column (1); ②

Table 10
Test results of the significance of the threshold effect of producer services agglomeration.

Model	Variance ratio	P value	BS	Critical value		
				10 %	5 %	1 %
Single threshold	17.3686***	0.0000	300	24.3889	28.5589	51.1836
Double threshold	15.5921***	0.0067	300	21.6406	25.0806	31.8769
Triple threshold	15.1629	0.5067	300	21.0024	27.3075	40.0024

Note: The statistical values at 10 %, 5 % and 1 % significant levels are indicated by *, ** and *** respectively.

Table 11
The threshold value and confidence interval.

Model	Threshold estimators	95 % CI
Single threshold	1.1591	[1.1461, 1.4522]
Double threshold	1.5892	[1.4522, 1.9046]

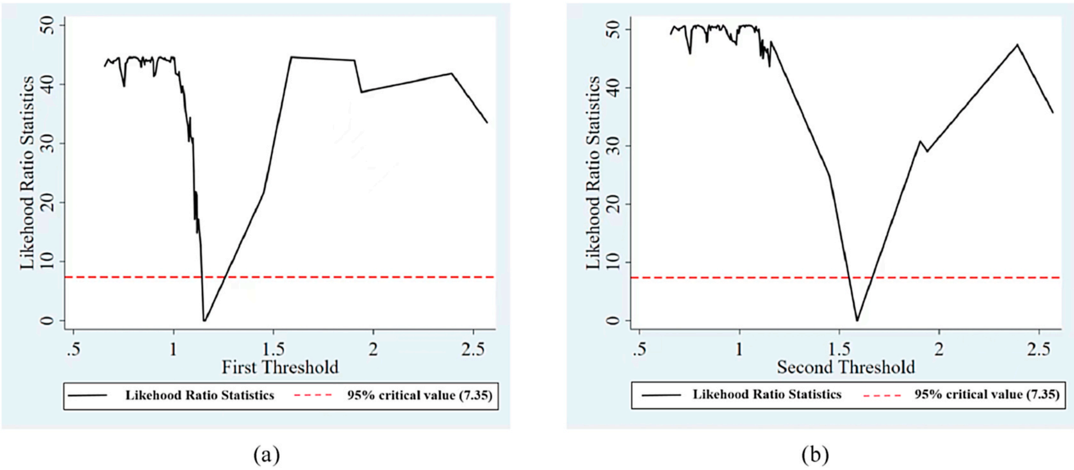


Fig. 10. Estimates and confidence intervals for the level of producer services agglomeration at the first threshold (a) and the second threshold (b).

Table 12
Results of model parameter estimates.

Variable	Coef.	Std. Err.	t	P>|z|	95 % Conf. Interval	
L1.Inno	0.8908 ***	0.0300	29.6900	0.0000	0.8296	0.9521
L2.Inno	−0.2736 ***	0.0331	−8.2700	0.0000	−0.3411	−0.2060
Owner	−0.1673	0.1991	−0.8400	0.4070	−0.5739	0.2393
City	5.7707 ***	0.2756	20.9400	0.0000	5.2079	6.3335
Infor	0.0550 ***	0.0050	11.0400	0.0000	0.0448	0.0651
Traffic	0.0438 **	0.0202	2.1700	0.0380	0.0025	0.0851
$Digi(Agglo \leq 1.1591)$	0.0576 ***	0.0111	5.1700	0.0000	0.0348	0.0803
$Digi(1.1591 < Agglo \leq 1.5892)$	0.1166 ***	0.0165	7.0600	0.0000	0.0829	0.1504
$Digi(Agglo > 1.5892)$	0.5265 ***	0.0207	25.4900	0.0000	0.4843	0.5687
AR (1)	z = −2.8800 p = 0.0040					
AR (2)	z = 1.0500 p = 0.2940					
Hansen Test of Overid	p = 0.4820					
N	240					

Note: The statistical values at 10 %, 5 %, and 1 % significant levels are indicated by *, **, and *** respectively.

Reducing the sample: According to the ranking of the mean value of the digital transformation, we removed 1 %, 5 % and 10 % of the sample, and re-estimated 28, 26 and 24 regions using DIFF-GMM [51]. Due to space constraints, this paper only reports the estimated results of 26 regional samples, see column (2). It is not difficult to find that the changing trend and significance levels of the influence coefficients in each column are similar to the above results, indicating that the empirical results in this paper are robust; ③Transforming the estimation method. When the traditional static threshold regression method is applied, under the adjustment of producer services agglomeration, digital transformation also presents a positive impact on innovation performance. Based on this, hypothesis 2 in this paper can be considered robust.

6. Discussion

Unlike research on the digital transformation of enterprises, this paper explores the relationship between digital transformation and innovation performance from a regional level. Based on the interpretation of the regional digital transformation index, it is found that the degree of regional digitalization is increasing yearly, and there is a certain unbalanced distribution among regions. Regions with a high level of economic development such as Guangdong Province have a relatively high degree of digital transformation. However, regions with backward economic development such as Gansu rank lower. This conclusion is similar to the previous research on the regional digital economy [67], which proves the inherent relationship between regional digital transformation and digital economy to

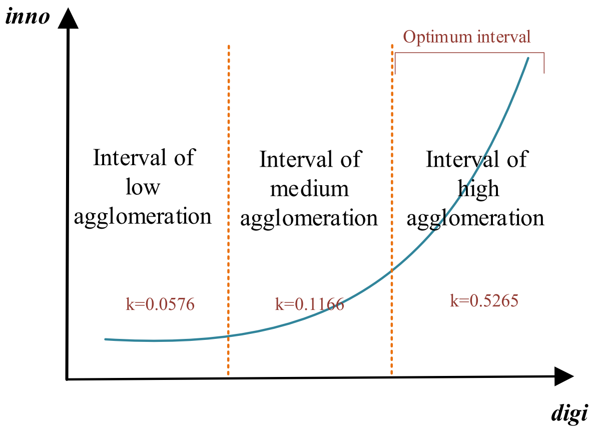


Fig. 11. Schematic diagram of the nonlinear relationship between digital transformation and innovation performance.

Table 13
Robustness test.

Variable	(1)	(2)	(3)
	Variable replace	Sample cut	Method replace
L1.Inno	0.7515***	0.7612***	
L2.Inno	−0.1993***	−0.1665***	
$Digir(Agglo \leq 1.1067)$	0.2285***		
$Digir(1.1067 < Agglo \leq 1.4522)$	1.0020***		
$Digi(Agglo > 1.4522)$	1.3755***		
$Digi(Agglo \leq 1.2461)$		0.0322**	
$Digi(1.2461 < Agglo \leq 1.5892)$		0.2007***	
$Digi(Agglo > 1.5892)$		0.4552***	
$Digi(Agglo \leq 1.1514)$			0.3536***
$Digi(1.1514 < Agglo \leq 1.5892)$			0.5321**
$Digi(Agglo > 1.5892)$			0.9110***
constant			2.0542***
Control variables	Control	Control	Control
AR (1)	z = −1.9700 p = 0.0490	z = −2.3100 p = 0.0210	
AR (2)	z = 0.8500 p = 0.3940	z = −0.4900 p = 0.6230	
Hansen Test of Overid	p = 0.6220	p = 0.999	
N	240	208	330

Note: The statistical values at 10 %, 5 %, and 1 % significant levels are indicated by *, **, and *** respectively.

some extent. The digital economy creates a sound macroeconomic environment for digital transformation, and digital transformation lays a solid micro-foundation for digital economy. Therefore, the development trends of the two are similar.

After passing the Pearson correlation test of variables (Fig. 7), multicollinearity VIF test (Table 4), unit root test (Table 5), and cointegration test (Table 6), we tested the normality of the residuals (Table 7 and Fig. 8) and the model heteroscedasticity (Figs. 9 and 8), and found that the residuals approximately followed the positive distribution, but the model had heteroscedasticity. Therefore, we applied heteroscedasticity robust regression (ROLS) and weighted least squares regression (WLS) to modify the heteroscedasticity and reported the fixed-effect model based on the Hausman test (Table 9). The estimated results in Table 9 demonstrate the innovation-driven role of digital transformation. In previous studies, Lin and Mao (2023), Kastelli et al. (2022) and Usai et al. (2021) respectively obtained a positive relationship between digital transformation and innovation performance by taking Chinese agricultural enterprises, Greek manufacturing industry, and the European Union as samples, respectively [19,68,69]. Our research complements the innovation-driven effect of digital transformation at China's provincial level, which provides a sufficient micro-foundation for the construction of a digital-driven innovation power. However, different from the analysis from the perspective of innovation supply [70], this paper demonstrates the promoting effect of digital transformation on innovation performance from both demand and supply aspects, which further enriches the theoretical research on digital transformation.

In addition, some scholars have focused on a more complex non-linear relationship between digital transformation and innovation. Ma and Guo (2022) introduced the second term of digital transformation and found a U-shaped relationship between digital transformation and innovation performance [71]. Zhang et al. (2023) set the threshold variables as digital transformation, innovation output, and R&D capital investment, and used the threshold model to obtain the non-linear characteristics of the positive relationship between digital transformation and high-tech industry innovation [72]. Similarly, the paper also pays attention to the non-linear relationship between the two, and the results in Table 10 indicate that there is a double threshold effect between the two. Several studies have noted the impact of agglomeration on the relationship between the two, such as urban agglomeration and manufacturing agglomeration [73,74]. However, existing studies have paid less attention to the producer service industry, an emerging service industry that supports the development of the manufacturing industry. This study is the first to take the producer service industry as the threshold variable, and according to the results in Table 11 and Fig. 10, the two threshold values are 1.1591 and 1.5892 respectively. In terms of the model, we introduce the lag term of innovation performance and combine the GMM estimation method with the traditional threshold model to construct a dynamic threshold model. On the one hand, the application of this method can make up for the limitation of the quadratic entry method in setting the regulatory variables, on the other hand, it can relax the assumption of strong exogeneity of the variables explained by the traditional static threshold model, and fully consider the pre-accumulation of patent authorization and the endogeneity problems caused by missing variables and reverse causality. From Table 12 and Fig. 11, as the agglomeration degree of producer services successively crosses the first and the second threshold, the positive impact of digital transformation on innovation performance continues to increase, and both are significant at the 0.01 level. The relevant conclusions also passed the robustness test of the three methods in Table 13. With the degree of agglomeration increases, producer services will form the causal accumulation of a "self-reinforcing" effect, and continue to strengthen the innovation effect of digital transformation through industry correlation and technological support. In this regard, we believe that the industrial layout of producer services is an effective way to promote digital transformation and improve innovation performance. The finding provides new evidence for the non-linear relationship between digital transformation and innovation performance, offers a new perspective for deepening the innovation-driven effect of digital transformation, and forms new inspiration for the empirical study of industrial agglomeration in different segments.

7. Conclusions

7.1. Research conclusions

The digital economy is a crucial foundation for regions to cultivate new economic growth points, form new driving forces, and achieve high-quality development. Based on Chinese provincial data from 2012 to 2022 as research samples, we use baseline regression model and dynamic threshold model to analyze the innovation-driven effect of digital transformation and its complex nonlinear relationship under the agglomeration heterogeneity of producer services. The research conclusions are as follows.

(1) In order to test the two hypotheses of the paper, we first measure the core variables. It is found that, during the study period, the national-level digital transformation index showed an increasing trend year by year. This indicates that the vigorous development of China's digital economy has led regional governments and business operators to have high expectations of digital transformation and actively promote the digital transformation process. At the regional level, the significant imbalance of digital transformation between regions significant, and the digital divide is constantly increasing, showing a gradient distribution similar to economic development that decreases from "east-central-west". With the rapid development of the digital economy, the eastern region has experienced a high level of digital transformation and growth due to the relatively robust new digital infrastructure and the agglomeration of digital talents.

(2) The benchmark regression test shows that digital transformation plays a significant role in supporting innovation performance, which can be regarded as a new driving force to promote the construction of an innovative China. This conclusion confirms the first hypothesis of this paper, that is, innovation performance is improved by digital transformation. On the supply side, digital transformation is conducive to fostering organizational dual innovation capability. On the demand side, digital transformation has promoted the formation of the "enterprise-consumer" interaction model, showing a strong driving role in the collaborative innovation of technology and business models.

(3) Taking producer service aggregation as a threshold variable, digital transformation has a significant double threshold effect on enterprise innovation performance. The dynamic threshold model and various robustness tests provide sufficient evidence for the research hypothesis 2, that is, digital transformation has a comparatively small impact on innovation performance in locations with a low concentration of producer services. With the continuous improvement of the producer service aggregation level, the promoting effect of digital transformation on enterprise innovation performance gradually enhances. Compared to regions with low producer service aggregation, regions with high producer service aggregation can provide the necessary intermediate services and technical support for digital transformation and innovation development, improve factor allocation efficiency, and strengthen the innovation effect of digital transformation.

7.2. Management inspiration

Based on the above conclusions, this paper recommends the following managerial tactics.

(1) Managers should focus on the overall planning of digital transformation and encourage the close coupling of digitalization with actual businesses. They should consolidate the digital foundation of businesses by bolstering the "hard" conditions like creating digital platforms and the "soft" conditions like digital talent teams. The action plan accelerates the integration of digital transformation and the profitable service sector and creates a prototype for a "digital integration" firm.

(2) Managers should provide the best possible distribution of digital resources throughout regions and sectors, build new digital infrastructure, bridge the digital divide, and form a benign regional digital economic competition system. For the central and western Chinese regions such as Inner Mongolia, Jilin, and Qinghai, where the pace of digital development is slow, the

government and the market must improve the top-level design capability of digital construction at the institutional level. They should create a good digital ecological environment and strengthen the digital economy regulatory system. Furthermore, the government and the market must strengthen the market allocation of data elements, reduce transaction costs, and encourage enterprises to improve innovation through digital transformation. This will help balance the development of the digital economy among regions.

(3) Managers must strengthen policies to guide the accumulation of productive service industries. On the one hand, they should establish an effective institutional environment and policies for the productive service industry, and accelerate breaking down of administrative barriers between cities. Cities should remove the closed and single industrial development mode, establish across-city industrial networks, improve the contact pattern of economic space, and move toward a diversified and open economy. On the other hand, they must also eliminate institutional barriers to support the flow of market-oriented and benefit-compensation mechanisms; thus, the economies of scale of aggregation can be fully exploited.

7.3. Limitations of the study

(1) This research uses panel macroeconomic data from 30 provinces in China for empirical analyses, which is limited. To strengthen the credibility of the research findings, we will attempt to increase the sample size, use more microdata for the analysis, and compare macro data with micro data.
(2) This paper discusses the dynamic threshold effect of agglomerating productive services. However, in the digital transformation process affecting enterprises' innovation performance, there may be other external or internal factors, and follow-up studies should focus on the testing mechanism to fully open the "black box" of digital-driven innovation development.
(3) It should be pointed out that this paper focuses on the regulatory impact of specialization agglomeration, but there is still a lack of discussion on industrial diversification agglomeration and the collaborative development of other industries related to digital transformation, which will be explored in detail in future studies.

Ethics approval statement

Not relevant.

Patient consent statement

Not relevant.

Permission to reproduce material from other sources

Not relevant.

Clinical trial registration

Not relevant.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Yingying Ding: Conceptualization. **Ziyi Shi:** Writing – original draft, Data curation, Methodology, Resources, Software, Validation, Visualization, Writing – review & editing. **Ruichao Xi:** Methodology. **Yanxia Diao:** Writing – review & editing. **Yu Hu:** Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supply Chain Resilience by the Digital Economy and Research on Enhancement Paths (2023RKX080)" and Shandong Province Cultural and Tourism Research Project (23WL(Y)38).

Appendix

Table 14
The title of policy texts.

No.	Policy Title	Rank	Policy Title
1	Guide to Digital Transformation for Small and Medium-sized Enterprises	16	Opinions on promoting the development of "Internet + Medical health"
2	The 14th Five-Year Plan for Digital Economy Development	17	Guiding Opinions on promoting the standardized and healthy development of platform economy
3	Implementation plan for promoting the action of "Using data to empower wisdom on Cloud" to cultivate new economic development	18	Opinions on Further implementation of the "Internet + Circulation" action Plan
4	Digital Agriculture Rural Development Plan (2019–2025)	19	Opinions on promoting the innovative development of cloud computing and Cultivating new business forms of information industry
5	Notice to accelerate the development of the industrial Internet	20	Guiding Opinions on actively promoting the "Internet Plus" action
6	Special action plan for digital Empowerment of small and medium-sized enterprises	21	Guiding Opinions on accelerating the work of "Internet plus government Services"
7	Guidelines on accelerating the development of virtual reality industry	22	Opinions on Accelerating the development of digital and intelligent energy
8	Special action plan for deep integration	23	Guiding opinions on promoting the digital transformation and upgrading of the living service industry
9	Industrial Internet Development Action Plan	24	Guidance on the digital transformation of the banking and insurance industries
10	Guiding opinions on promoting the development of sharing economy	25	Planning for the development of a new generation of artificial intelligence
11	Guiding Opinions on developing a stable digital economy and expanding employment	26	Made in China 2025
12	Opinions on building a more complete system and mechanism for market-based allocation of factors	27	"14th Five-Year Plan" big data industry development plan
13	Guiding Opinions on promoting the development of "Internet Plus" smart energy	28	Notice on accelerating the digital transformation of State-owned Enterprises
14	Opinions on supporting the healthy development of new business forms and models	29	Opinions on Promoting highway digital Transformation and Accelerating the construction and development of smart highways
15	Opinions on Innovating Management and Optimizing Services to Foster and Strengthen new drivers of economic Development and Accelerate the replacement of old drivers with new ones	30	Notice on pilot work on digital transformation of small and medium-sized enterprises in cities

Note: The eighth item comes from https://www.miit.gov.cn/. Others are all from https://www.gov.cn/

Algorithm 1
Pseudocode of keyword matching based on natural language processing

```
import jieba
import os
import csv
def read_dict (file):
  text = open (file, encoding = 'utf-8').read (.)
  text = text.split ('\n')
  words = [w for w in text if w]
  return words
digis = read_dict (r'digis.txt')
def senti_count (text):
  wordlist = jieba.lcut (text)
  digi_count = 0
  for digi in digis:
  digi_count = digi_count + wordlist.count (digi)
  return {'wordnum': len (wordlist), 'digi': digi_count}
csvf = open (r'keyword.csv', 'w', encoding = 'utf-8', newline = '')
writer = csv.writer (csvf)
writer.writerow (('security code','region code', 'year', 'wordnum', 'digi'))
file_list = os.listdir (r'annual_report-TXT-UTF8')
for f in file_list:
  file = 'annual_report-TXT-UTF8\\' + f
  text = open (file, encoding = 'utf-8').read (.)
  senti_score = senti_count (text)
```

(continued on next page)

Algorithm 1 (*continued*)

```
    wordnum = senti_score ['wordnum']
    digi = senti_score ['digi']
    security code = f [:6]
    regional code = f [7:10]
    year = f [7:11]
    writer.writerow ((security code, regional code, year, wordnum, digi))
csvf.close (.)
```

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