

Article

Spatiotemporal Evolution, Regional Correlation, and Sustainable Innovation Entity Quality Structure of Digital Technology Patents in China

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Abstract

Against the backdrop of China's rapid digital economy growth and the pursuit of the Sustainable Development Goals, this study investigates the spatiotemporal evolution, regional correlation, and innovation entity quality structure of digital technology patents in China. Using patent data (1994–2025) from the incoPat database, this study employs descriptive statistics, correlation analysis, and multiple linear regression to examine patent application trends, provincial distribution patterns, and the characteristics of major patent assignees. The results reveal that China's digital technology patent applications have experienced explosive growth since 2016, establishing global leadership in quantity, yet exhibit a structural pattern of “quantity leading, quality lagging” with limited high-value patents. Spatially, patents are highly concentrated in eastern coastal provinces, forming a “strong east, weak west” pattern. Correlation and regression analyses show a robust positive association between patent counts and provincial GDP, while population size also exhibits a significant positive effect, albeit with slightly lower explanatory power. Among the top ten global patent holders, six are Chinese enterprises concentrated in Guangdong, Zhejiang, and Beijing, but their share of high-value patents remains limited compared to international counterparts. These findings indicate a dual agglomeration effect, which may pose challenges to achieving balanced regional development.

Keywords: digital technology patents; spatiotemporal evolution; patent quality structure; sustainable development goals



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1. Introduction

In the current era, the digital economy has emerged as a primary engine of global economic growth, evolving with unprecedented speed, scale, and impact [1]. From the perspective of sustainable development, however, the contribution of digital technologies to economic growth must be evaluated not only by their scale but also by their capacity to promote balanced regional development, industrial upgrading, and inclusive access to innovation benefits—core concerns of the United Nations Sustainable Development Goals (SDGs). China has placed a strong emphasis on advancing digital technologies and the digital economy. The country's 14th Five-Year Plan identifies “accelerating digital development and building a Digital China” as a key strategic priority, while policy documents

such as the 14th Five-Year Plan for the Development of the Digital Economy further outline the direction for its growth [2,3]. In the period of digital economy, digital technologies are characterized by high technological sophistication and demanding standards. As a result, independent intellectual property rights in digital technologies have become a central focus of market competition, and the alignment of patents with standards serves as a critical driver of high-quality development in the digital industry [4]. The international deployment of standard-essential patents (SEPs) by major economies in the digital economy sector will shape the future landscape of competition for market dominance in the global digital economy [5,6].

Meanwhile, the SDGs provide a systematic action framework for global development. Digital technologies are widely seen as a key force in advancing the SDGs and accelerating the sustainable transformation of various industries. Emerging technologies such as artificial intelligence, blockchain, and digital twins have demonstrated considerable potential for achieving specific SDG targets [7,8]. As the world's second-largest economy and the largest developing country, China faces a dual mission in driving digital technology innovation and implementing the SDGs. On the one hand, it must seize opportunities for digital technology development to build technological competitive advantages; on the other hand, it needs to respond to the principle of balanced development advocated by the SDGs, address the regional misallocation of innovation resources, and ensure that the benefits of digital technologies reach underdeveloped areas more equitably [9–11].

The vigorous growth of the digital economy is inseparable from technological innovation. As a key output of innovation, patents contain rich information on technologies, innovation entities, and market dynamics. Patents not only provide legal protection for enterprises' innovation outcomes but also serve as important indicators of corporate competitiveness and market value [12]. Moreover, they facilitate industry-university-research collaboration between enterprises, universities, and research institutions, promoting knowledge transfer and sharing. Through patentometric analysis, researchers can gain deep insights into the evolutionary paths of digital technologies and accurately map the competitive landscape, thereby providing strong support for governments in formulating sound industrial policies and for enterprises in devising forward-looking R&D strategies [13–15].

Regarding digital technology innovation, existing research has accumulated substantial achievements. In the study of patent metrology for digital technology innovation, academia has developed two major technological identification pathways: the IPC mapping method and the keyword identification method. These approaches systematically delineate the development patterns of digital technology from dimensions such as global competition patterns, regional spatial distribution, and innovation subject networks [14,16–18]. In terms of research on the regional distribution and influencing factors of digital technology patents in China, studies indicate that although the scale of digital technology patents in China has achieved rapid growth, the regional distribution exhibits significant imbalance: the eastern coastal region holds an absolute advantage in patent applications, followed by the central region, while the western region generally lags behind [19]. This regional disparity is driven by multiple factors, including economic development levels, research resources, policy environments, and market demand. Institutional factors such as fair competition reviews and digital infrastructure play a significant moderating role in incentivizing corporate digital innovation [13,20,21]. In research on technological innovation and balanced development from the perspective of sustainable development goals, studies have revealed the enabling role of digital technology in pollution reduction, carbon emission mitigation, and industrial upgrading. For instance, research shows that digital technology innovation, measured by digital patents, significantly promotes the synergy between urban pollution control and

carbon emission reduction, with more pronounced effects in central and western regions, lower-tier cities, and resource-based cities [14].

However, there remain areas where existing research can be deepened. First, patent metrology studies have largely focused on the static stock distribution of patents, paying insufficient attention to dynamic flow processes such as patent transactions, transfers, and licensing. This makes it difficult to uncover the actual pathways and obstacles to technology diffusion, even though patent transactions have been identified as a core dimension for evaluating digital technology performance [22]. Second, although regional distribution studies have revealed the imbalanced pattern of digital technology patents in China, there is a lack of systematic theoretical explanation and empirical testing regarding how this imbalance affects regional sustainable development capabilities and how to understand the tension between efficiency and equity in the allocation of innovation resources within the framework of the SDGs. Third, research on digital technology from the SDGs perspective has largely remained at the level of describing global macro trends or assessing the potential of specific technologies. There has been insufficient exploration of the localized mechanisms in the complex context where China, as a major developing country, faces the overlapping challenges of digital transformation and sustainable development goals.

To address these research gaps, this study takes patents in the field of digital technology in China, sourced from the incoPat database, as the research sample. It employs a combination of descriptive statistics, correlation analysis, and multiple linear regression to systematically investigate the evolutionary trends, regional distribution characteristics, and innovation subject patterns of digital technology innovation in China. At the theoretical level, this study attempts to construct a full-chain analytical framework of “patent layout–transaction–diffusion,” integrating technology life cycle theory, regional innovation theory, and sustainable development theory to reveal the role and mechanisms of digital technology innovation in regional balanced development. At the practical level, the findings can provide decision-making support for governments to formulate differentiated digital technology innovation policies and guide the high-quality development of the digital economy industry, as well as offer guidance for enterprises to optimize patent portfolio and operation strategies and respond to international competition in key technological fields.

Based on the above research objectives, this study proposes the following three core research questions:

RQ1: What characteristics do the spatiotemporal evolution of digital technology patents in China exhibit?

RQ2: What statistical relationships exist between the number of digital technology patents in Chinese provinces and their economic development and population size?

RQ3: What characteristics are exhibited by the geographical distribution and patent quality structure of major patent assignees in China?

Unlike causal inference studies grounded in experimental or quasi-experimental designs, patentometric analysis—as a well-established methodology for measuring technological innovation—is primarily tasked with systematically characterising, quantifying, and comparing the distribution and evolution of innovative activities. To this end, this study follows a “description–explanation–implication” framework: it describes the spatiotemporal patterns of digital technology innovation through patent data, explains the statistical relationships between patent counts and regional economic factors using correlation and regression analyses, and draws policy implications within the context of the Sustainable Development Goals. While this approach does not aim for precise causal identification, it furnishes a systematic empirical basis and testable propositions for future theoretical and causal inquiries.

2. Literature Review

This paper presents a literature review encompassing three thematic areas: patentometrics of digital technology innovation, the regional distribution of digital patents and its influencing factors, and the perspective of the Sustainable Development Goals.

2.1. Patent Metrology Research on Digital Technology Innovation

Patent data, with its multi-dimensional structured information encompassing technology, law, spatiotemporal context, and innovation entities, has become a core quantitative tool for empirical research in digital technology innovation.

Existing research on digital technology patents primarily forms two parallel and complementary approaches. The first is the mapping method based on official industrial statistics classifications and the International Patent Classification (IPC), which offers the advantages of standardization and reproducibility. For example, Zhou and Li established a detailed mapping to IPC categories. This allowed them to systematically identify “digital patents” from commercial databases such as IncoPat, providing a reliable framework for subsequent macro-level aggregate and industrial distribution analyses [23]. The second approach is the keyword identification method based on text analysis, which involves constructing a lexicon of digital technology features and searching through full texts including patent titles, abstracts, and claims [24,25]. This method is more flexible but its effectiveness heavily depends on the quality and completeness of the constructed keyword lexicon, introducing a certain degree of subjectivity.

At the macro level, using patent data for cross-country comparisons and competitiveness assessments is a well-established paradigm for characterizing the global digital technology innovation landscape. For example, Bielig found that although Germany is the largest source of patents in Europe, it ranks as a “second-tier innovation player” in global competition with the United States and China [25]. Liu et al., by proposing a novel AI patent search strategy, overcame the narrow scope of earlier studies. Using network analysis and a main path algorithm, they mapped the spatiotemporal trends, collaboration networks, and technological evolution paths of global AI patents, revealing characteristics such as concentrated innovation and limited collaboration in this field [26]. Saheb et al. conducted a comprehensive analysis of big data technology patents, not only showing the distribution of major innovative countries and institutions but also revealing, through the analysis of scientific literature cited by patents, a relatively weak connection between technology and scientific research in this domain [27].

In China, patentometrics is widely used to uncover the spatial distribution patterns and geographic agglomeration effects of innovation activities. Ren et al. identified urban digital patents and innovatively introduced the quality dimension of “patent knowledge breadth.” They found that patent scale exhibits significant “economic dependence” and spatial agglomeration, while knowledge breadth shows “anti-economic dependence” and weak spatial agglomeration [24]. Chen and Cai, from the perspective of industrial penetration heterogeneity, matched digital technology patents with application fields and detailed manufacturing subsectors, revealing that the promotion effect of digital technology on manufacturing growth is highly concentrated in the machinery and equipment manufacturing industry, while its penetration impact on light textile manufacturing and resource processing industries is relatively limited [28].

With the development of data analysis and natural language processing, patentometrics research is shifting from quantitative statistics to in-depth mining and frontier detection of technological content. For example, Yuan et al. used the Latent Dirichlet Allocation (LDA) topic model to conduct machine learning analysis on patent texts in the field of digital elderly care, automatically identifying five technological hotspot themes and accordingly

dividing the development stages of this technological field [29]. Kwon et al., by combining Word2Vec semantic analysis with LDA clustering, proposed a patent analysis framework for predicting logistics technology changes, identifying technological gaps, and ultimately supporting technology roadmap development [30]. Additionally, Li et al. comprehensively applied bibliometrics and patent analysis to conduct a panoramic assessment and prediction of academic research trends, technological development hotspots, and competitive landscapes of various countries in the field of digital twins, demonstrating the comprehensive application value of this method in technology competitive intelligence (TCI) analysis [31].

Network analysis is a useful method for exploring digital technology innovation. The global inventor network reveals the internationalization trend of R&D by Chinese enterprises, indicating that city-level network centrality is closely related to the attractiveness of R&D collaboration [32]. The global innovation network can also be used to explore changes in China's position within the global innovation system. In terms of influencing factors, economic factors and technological information factors show the strongest correlation with the innovation network [33].

In summary, existing literature on the patentometrics of digital technology innovation has established a cutting-edge analytical framework encompassing methodological foundations, global and national macro-level trend analyses, regional spatial distribution characterizations, innovation entity networks, technological content mining, and strategic applications. However, several directions remain for further exploration: at the global comparative level, there is a need to dynamically examine the trajectories and driving mechanisms of changes in the relative positions of major innovative countries (especially China) based on longer-term and more comprehensive global patent data; at the regional analysis level, further research is required on the deep formation mechanisms of inter-provincial differences, spatial spillover effects, and their dynamic correlations with regional high-quality development indicators; at the innovation ecosystem level, the analysis of the dynamic evolution of the roles, functions, collaboration models, and network structures of various innovative entities, along with their policy implications, still needs to be deepened.

2.2. *The Regional Distribution and Influencing Factors of Digital Technology Patents in China*

Digital technologies (DTs) constitute an integrated system of information, computing, communication, and connectivity technologies. Mastering cutting-edge digital technologies is a core lever for seizing development opportunities and building technological competitive advantages in the digital era [34]. With the accelerated advancement of global industrial digital transformation, the volume of digital technology patents in China has grown rapidly, yet their regional distribution exhibits significant imbalance [24]. The total number of granted digital technology patents in China continues to rise, but the layout of patent families remains limited, and patent coverage in developed countries is insufficient. The technological focus is primarily on artificial intelligence, patent classification and natural language processing have become the most influential applications [35].

The regional differentiation of digital technology patents in China is driven by multiple factors. For example, Sun believes that exports and technological infrastructure explain the differences in patents among provinces. In addition, foreign-funded enterprises seem to be less important in China's innovation system, while state-owned and collective enterprises contribute significantly to the creation of new products in China [36].

Many studies suggest that the spatial distribution of patents is closely related to factors such as markets and population. Research indicates that the intensity of technological, design, and market innovation in Chinese cities is positively correlated with population size and per capita GDP, and that peripheral cities exhibit strong market innovation but

relatively weak technological innovation [37]. Technological innovation can also influence markets; for instance, regional lead markets are determined by regulatory advantages, demand advantages, and technological advantages [38]. Therefore, technological innovation and market factors can interact with each other.

In summary, existing research has achieved substantial progress in understanding the regional distribution characteristics, microeconomic consequences, and mechanisms of digital technologies, forming an analytical framework of “institutional environment–technology adoption–economic performance.” However, given the current situation of China’s digital patents being “large in quantity but not strong in quality” (few patent families and weak overseas layout), future research urgently needs to shift from static stock analysis to dynamic flow analysis, delving deeper into the operational logic of patent transaction markets, the barriers to technology diffusion, and how to effectively convert technological advantages into genuine industrial competitive advantages through strategic patent operations.

2.3. Technological Innovation and Balanced Development from the Perspective of the Sustainable Development Goals

Digital technologies play a critical supporting role in the sustainable development transition as they assist various industries in advancing the SDGs. Among the 17 SDGs, “building resilient infrastructure, promote inclusive and sustainable industrialization” and “fostering innovation and reducing inequality within and among countries” are most directly relevant to the analysis of digital technology patents—the former connecting innovation quantity and quality to industrial upgrading, and the latter linking the spatial distribution of innovation to regional equity. To fully unleash the positive value of digital technologies, it is necessary not only to promote their systematic integration but also to precisely grasp the direction of policy changes that align digitalization with the SDGs, while deeply understanding the core connotations of the sustainable development goals. Achieving deep integration between digital technologies and the SDGs requires a comprehensive implementation pathway that coordinates three major dimensions: technological innovation, the construction of supporting governance frameworks, and the development of core capacities [7].

A large-scale bibliometric analysis based on Elsevier’s SDG research mapping technology indicates that artificial intelligence and robotics are the digital technologies most broadly associated with the SDGs, while technologies such as 3D printing, cloud computing, drones, and extended reality demonstrate application potential for specific SDGs. Emerging technologies such as digital twins and blockchain are rapidly gaining research attention [8]. At the level of strategic planning and operational practice, deeply aligning corporate business objectives with the SDGs represents the core pathway to achieving long-term sustainable development [39]. Enterprises can fully tap into the inherent potential of digital transformation by synergizing business goals with sustainable development objectives, thereby enhancing both operational efficiency and development sustainability in strategic decision-making and day-to-day operations [40]. Currently, digital transformation has triggered systemic changes across many industries globally, with efficiency improvement and sustainable development at its core [41].

In fact, examining digital technologies within the context of the Sustainable Development Goals significantly broadens the research perspective and value connotations of this field. Current research has successfully shifted from a unilinear “technology–economy” logic to a composite “technology–society–ecology” systems thinking, demonstrating profound real-world insights, particularly in the identification of risks associated with technology application and the exploration of governance pathways. However, future research still needs to deepen its efforts in the following areas: quantifying the actual net effects of

digital technology patents in bridging the digital divide in specific SDG domains (such as poverty eradication and quality education) requires more refined causal inference incorporating regional differences in patent density and quality structure; within the “tripartite coordination” system, designing specific incentive mechanisms to resolve the tension between enterprises’ short-term cost pressures and long-term sustainable benefits necessitates exploring differentiated combinations of policy tools based on the regional innovation heterogeneity uncovered in this study; against the backdrop of lagging international patent portfolios, securing greater voice in global sustainable development governance through standard-setting and intellectual property operations in the digital technology field requires proposing pathways for transitioning from scale expansion to quality improvement, building on the “quantitative lead, qualitative lag” characteristics revealed in this research.

3. Materials and Methods

3.1. Data Sources

incoPat is a global patent intelligence service platform that collects over 100 million patent documents from 170 countries, regions, and organizations [42]. The data is sourced from official and legitimate commercial channels and is updated four times per week. The platform provides bilingual (Chinese–English) titles and abstracts for global patents [43], along with Chinese translations of the full texts of patents from major countries such as the United States, Germany, and Russia. It supports more than 240 searchable fields, integrates legal status information such as patent litigation, assignment, and licensing, and systematically processes patent family and citation relationships. The built-in patent value evaluation model generates a “Patent Value Degree” indicator, which has been shown to have a high correlation with actual patent transaction prices [44]. In terms of search and analysis, incoPat supports multiple search modes, including advanced search, batch search, semantic search, and graphic search. It also provides visualization tools such as statistical analysis, cluster analysis, and 3D patent sandbox, making it widely applicable in patent bibliometric analysis, technology trend identification, competitor monitoring, and patent value assessment.

This study uses incoPat as the data source, primarily based on three considerations. First, the breadth and standardization of data coverage. The database offers relatively comprehensive coverage of patent documents from major countries and regions worldwide, with a unified field structure that facilitates cross-country and cross-regional comparative analyses. Second, the depth of value-added data processing. incoPat integrates legal status information such as patent litigation, assignment, licensing, reexamination, invalidation, and customs recordation, and organizes patent family and citation relationships, providing structured data support for patent quality assessment, technology diffusion path tracking, and innovation network analysis [45]. Third, the operability of patent value assessment. The platform’s built-in value evaluation model comprehensively scores patents across technical, legal, and market dimensions. Empirical studies have shown a significant positive correlation between this indicator and the natural logarithm of actual patent transaction prices, making it an important reference for measuring patent quality and economic value. Overall, the data quality and analytical capabilities of incoPat support this study’s patent analysis efforts in the digital technology field.

In terms of technical scope, this paper focuses on the digital technology field, covering areas such as artificial intelligence, blockchain, cloud computing, and big data. These technologies are not only key drivers of industrial innovation in the digital economy era but also persistent hot topics in recent patent bibliometric research. For data acquisition, the incoPat patent database was selected, and a search strategy combining keywords and International Patent Classification (IPC) codes was adopted. The keyword library

was constructed in a bilingual (Chinese–English) manner to cover the core concepts and common synonymous expressions of each technical direction. Meanwhile, the classification codes of relevant technical branches were determined by referring to the International Patent Classification system to compensate for potential omissions in keyword-based searches. After merging the two sets of search results using Boolean logic, multiple rounds of pre-searches were conducted for iterative adjustments until an optimal balance of recall and precision was achieved.

3.2. Search Strategy

3.2.1. The Dynamic Characteristics and Handling Principles of the incoPat Patent Database

Patent databases are subject to changes over time due to the legal status of patent applications (e.g., active, lapsed, withdrawn), and database updates are subject to a certain lag. Consequently, executing the same search strategy at different time points may produce varying statistical results. To ensure data reproducibility, the retrieval update date for this study is set as 7 April 2026, and all patent data statistical analyses were completed before this date.

3.2.2. Iterative Determination of Search Keywords

This study adopted an iterative trial-and-error method to define the search keywords. Initial keywords were first compiled by consulting relevant literature and industry reports on digital technology. Multiple rounds of combined-keyword pre-searches were performed in the incoPat patent database. Following each round, 100–200 randomly selected patents were reviewed by title and abstract to identify irrelevant or missing patents. Based on the pre-search results, noisy and unrelated terms were progressively removed, while frequently omitted terms were added. After several iterations, the final search terms and strategy were determined, as presented in Table 1.

Table 1. Search keywords and search strategy.

Search Dimension	Search Field	Limiting Condition	Search Expression(s)
Subject Search	Title & Abstract (TIAB)	Core technical keywords	(TIAB = (blockchain OR Blockchain OR big data OR Big Data OR computing power OR Computing Power OR distributed computing OR Distributed Computing OR cloud computing OR Cloud Computing OR data mining OR Data Mining OR Hadoop OR open-source distributed system framework OR high-performance computing OR High-Performance Computing OR HPC OR data-intensive computing OR Data-Intensive Computing OR cloud computing platform OR Cloud Computing Platform OR edge computing OR Edge Computing OR parallel processing OR Parallel Processing OR containerization OR Containerization OR Docker Kubernetes OR heterogeneous computing OR Heterogeneous Computing OR AI training OR AI Training OR real-time data processing OR Real-time Data Processing OR data lake OR Data Lake OR stream computing engine OR Stream Computing Engine OR Apache Flink OR in-memory computing OR In-Memory Computing))
Field Limitation	International Patent Classification (IPC-LOW)	a. Electric digital data processing b. Systems based on computational models c. Special applications of data processing	(G06F OR G06N OR G06Q)

Table 1. Cont.

Search Dimension	Search Field	Limiting Condition	Search Expression(s)
Time Range	Publication Date	Complete technological development cycle	[1994-01-01 TO 2025-12-31]
Patent Validity	Legal Status/Patent Validity	Includes 6 statuses: Valid, Pending, Invalid/Lapsed, PCT-Expired, PCT-Active, Unconfirmed	status = (Valid)
Logical Combination	Full-Text Search Expression	Comprehensive logic of subject, field, and time	((TIAB = (. . .)) AND (IPC-LOW = (G06F OR G06N OR G06Q))) AND (PD = [17820101 TO 20251231]) AND (status = (Valid))

Table 1 presents the patent search strategy used in this study, covering five dimensions: subject search, field limitation, time range, patent validity, and logical combination. The subject search relies on core technical keywords in titles and abstracts. The field limitation uses International Patent Classification codes (IPC-LOW) to focus on electric digital data processing, systems based on computational models, and special applications of data processing. The time range covers the complete technological development cycle from 1994 to 2025. The patent validity condition includes only patents with a valid status. The logical combination integrates the above conditions into a full-text search expression to form the final search query.

It should be noted that although the IPCs G06F, G06N, and G06Q are core classifications for digital technology patents, their scope is relatively broad and includes a small number of patents not directly related to digital technology (such as basic hardware patents, traditional business methods, etc.). To reduce noise, this study restricted the keywords to the title and abstract fields. To evaluate the accuracy of the search strategy, 200 randomly selected patents were manually reviewed after the formal search in the incoPat database. The results showed that approximately 80% of the patents were relevant, indicating that the precision rate was within an acceptable range and sufficient to meet the analytical needs of this study.

3.3. Statistical Methods

This study employs descriptive statistics and visualization, correlation analysis, and univariate fitting combined with multiple linear regression.

3.3.1. Descriptive Statistics and Visualization

Descriptive statistics and visualization aim to reveal the basic characteristics and evolution patterns of technological innovation activities in the digital technology field through quantitative summarization and graphical presentation of patent data. Specifically, this study conducts the analysis from the following five dimensions:

First, application trend analysis. By examining the annual distribution of patent applications, this study characterizes the activity level and phased evolution features of core technology research and development, identifying the budding, growth, and mature stages of technological development. To further quantify the long-term evolution trend of patent applications, this study performs polynomial trend fitting with linear, quadratic and cubic specifications on the annual patent count series, and selects the optimal specification according to the principle of parsimony (Occam's razor) by comparing the goodness of fit (R^2) and F -statistic of each model.

Second, geographical distribution analysis. Based on patent priority countries/regions and patent family information, this study maps the geographical distribution pattern of technological innovation outcomes and identifies major innovative countries/regions and

their technological competitiveness. For provincial-level distribution in China, basic descriptive indicators including mean and standard deviation of patent counts are calculated to characterize the degree of inter-provincial innovation disparity.

Third, patent quality assessment. Using indicators such as the incoPat patent value score, citation frequency, and patent family size, this study comprehensively evaluates the technological influence, legal stability, and economic value of patents. Specifically, GDP-based patent density is defined as the number of digital technology patents generated per 100 million yuan of GDP, and population-based patent density is defined as the number of digital technology patents per million permanent residents. The two indicators eliminate the interference of economic scale and population base on cross-regional innovation comparison, and their specific calculation formulas are presented in the Section 4.

Fourth, patent density analysis. Taking Chinese provinces as basic units, this study correlates the number of patents with regional gross domestic product (GDP) and population size. Using two indicators—patent density per unit GDP and patent density per capita—this study measures the innovation output efficiency and agglomeration intensity of each province in the digital technology field, revealing the synergistic relationship between technological innovation and regional economic development. On this basis, this study constructs a three-dimensional patent quality measurement framework covering the number of invention applications, the number of invention grants, and the number of high-value patents. High-value patents are uniformly de-fined as patents with an incoPat Patent Value Degree score of 10, which represents the highest comprehensive value level integrating technical advancement, legal stability and market potential. This three-dimensional framework is applied to analyze the patent quality structure of major innovation entities.

Fifth, innovation entity analysis. By statistically ranking the number of patents held by applicants/patentees, this study identifies core R&D institutions and their innovation collaboration patterns.

Based on the above analysis, this study comprehensively employs visualization tools such as line charts, bubble charts, and bar charts to present the analytical results intuitively, systematically characterizing the macro-level trends and micro-level features of technological innovation in the digital technology field.

3.3.2. Correlation Analysis

Correlation analysis aims to measure the degree and direction of the linear association between two variables. This study employs the Pearson product-moment correlation coefficient to measure the correlation between the number of patents and GDP, as well as between the number of patents and population size. For two continuous variables X and Y , based on observations from n samples, the Pearson correlation coefficient r is shown in Equation (1).

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (1)$$

In Equation (1), $\bar{X}$ and $\bar{Y}$ are the sample means of variables X and Y , respectively. The correlation coefficient r ranges from $[-1, 1]$, with $r > 0$ indicating a positive correlation, $r < 0$ indicating a negative correlation, and the closer $|r|$ is to 1, the stronger the linear correlation. A significance test (two-tailed test) is also performed on the correlation coefficient to determine whether the observed correlation in the sample exists in the population. If $p < 0.05$, the correlation coefficient is considered statistically significant.

3.3.3. Multiple Linear Regression

Building upon the correlation analysis, this study further constructs a multiple linear regression model to quantify the impact of economic development level and population

size on the number of patents. First, univariate regression fitting is carried out to explore the potential nonlinear relationship between a single influencing factor and patent count. Five fitting specifications are set simultaneously, including linear, quadratic polynomial, cubic polynomial, power function and exponential function. The optimal fitting model is selected by comparing the coefficient of determination R^2 of each specification, so as to more accurately capture the change law of patent count with the influencing factor. Among them, the power function model takes the form of $Y = \alpha \times X^\beta$, where α is the scale parameter and β is the elasticity coefficient, which reflects the percentage change in the dependent variable when the independent variable changes by 1%. Second, a multiple linear regression model is constructed to examine the combined effect of multiple factors. The basic form of multiple linear regression is shown in Equation (2):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (2)$$

In Equation (2), y is the dependent variable, $x_1, x_2, \dots, x_k$ are the independent variables, β_0 is the regression constant (intercept), $\beta_1, \beta_2, \dots, \beta_k$ are the partial regression coefficients, and ε is the random error term. The partial regression coefficient β_j represents the average change in the dependent variable y for each unit change in the independent variable x_j , holding all other independent variables constant.

3.4. Patent Quality Determination

This study evaluates patent quality from multiple dimensions to enhance the robustness of the research conclusions.

(1) Core Indicator: Patent Cooperation Value Degree. The Patent Cooperation Value Degree is a comprehensive assessment indicator that integrates multiple dimensions, including legal stability, technological advancement, market potential, R&D investment, industry influence, and citation frequency. It ranges from 1 to 10, with higher scores indicating greater core value of the patent. In this study, a score of 10 is defined as a “high-value patent,” while scores of 1–9 are classified as “ordinary-value patents.”

(2) Auxiliary Validation Indicators: To test the robustness of the conclusions, two publicly available indicators are introduced: (a) Patent family size (simple family size ≥ 3 is considered high-value), reflecting the breadth of market coverage; and (b) Forward citation count (cited ≥ 10 times is considered high-impact), reflecting technological influence.

3.5. Data Preprocessing

To ensure the reliability, accuracy, and reproducibility of the patent analysis results, this study performed systematic data cleaning and preprocessing on the retrieved results. The specific operational procedures are as follows:

Step 1: Removal of duplicate records. For patent families resulting from the same patent being filed in different countries or regions, as well as data redundancy caused by database updates, this study performed batch merging and deduplication based on patent application numbers. The patent record corresponding to the earliest priority date was retained as the analysis unit to ensure that the sample contained no duplicate counts.

Step 2: Noise data filtering. Based on the retrieval results, a combination of manual judgment and machine assistance was used to screen and remove noise data. First, keyword exclusion rules were constructed to filter out noise documents that clearly deviated from the research topic. Second, cross-validation was performed on the semantic consistency between IPC codes and titles/abstracts to eliminate patent records with classification errors or topic deviations, ensuring that the sample data was highly relevant to the digital technology field.

Step 3: Outlier identification and correction. For anomalies in the data, such as formatting errors, missing fields, and date logic contradictions (e.g., application date later than publication date), this study performed item-by-item verification and correction with reference to official registration information from national intellectual property offices. Records that could not be verified or had missing critical fields were excluded to ensure data completeness and standardization.

Step 4: Data standardization. To facilitate subsequent econometric analysis, this study standardized the format of multi-source heterogeneous data. Specifically, this included: unifying the date format to “YYYY-MM-DD”; converting patent classification codes from various countries into the International Patent Classification (IPC) standard format; and normalizing applicant names by consolidating different variants of the same institution (e.g., full names, abbreviations, Chinese and English translations) to ensure the accuracy of innovation entity analysis.

Through the above cleaning and preprocessing procedures, this study ultimately obtained a total of 111,762 valid granted invention patents worldwide, including 31,716 high-value patents with an incoPat patent value score of 10, accounting for 28.4%, patents with a simple family size of ≥ 3 totaled 23,590, accounting for 21%, and patents with a forward citation count of ≥ 10 totaled 16,317, accounting for 14.6%.

The time span of the research data is from 1994 to 2025, fully covering the evolution of digital technology from its embryonic stage to its rapid development stage, forming a patent analysis sample set with time-series characteristics and laying a solid data foundation for subsequent empirical research.

4. Results

This section systematically presents the empirical research results of China’s digital technology innovation from three dimensions based on patentometric analysis. Section 4.1 compares global and Chinese patent application trends (1994–2025) to reveal China’s growth characteristics and key inflection points at different stages, assessing its role and contribution to the global landscape. Section 4.2 focuses on the provincial level, analyzing the statistical relationships between patent volume, economic development, and population size, introducing patent density indicators to measure regional innovation efficiency, and quantifying the influence of each factor through correlation analysis and multiple linear regression. Section 4.3 further explores the level of innovation entities, examining the geographical distribution and patent quality structure of China’s leading enterprises among the global top ten patentees, revealing China’s advantages in patent scale and the structural characteristic of a relatively low proportion of high-value patents.

4.1. Global and Chinese Patent Application Trends in Digital Technology

The evolution trajectory of digital technology innovation activities can be systematically revealed through patent application trends. This section compares and analyzes global and Chinese patent application trends, identifies growth characteristics and key inflection points at different stages, and, in conjunction with a comparison of trends among major innovative countries, evaluates China’s position and contribution in the global digital technology patent landscape.

4.1.1. Overall Trends in Global and Chinese Patent Applications

The annual trends in the number of granted invention patent applications in the global and Chinese digital technology fields from 1994 to 2025 are shown in Figure 1.

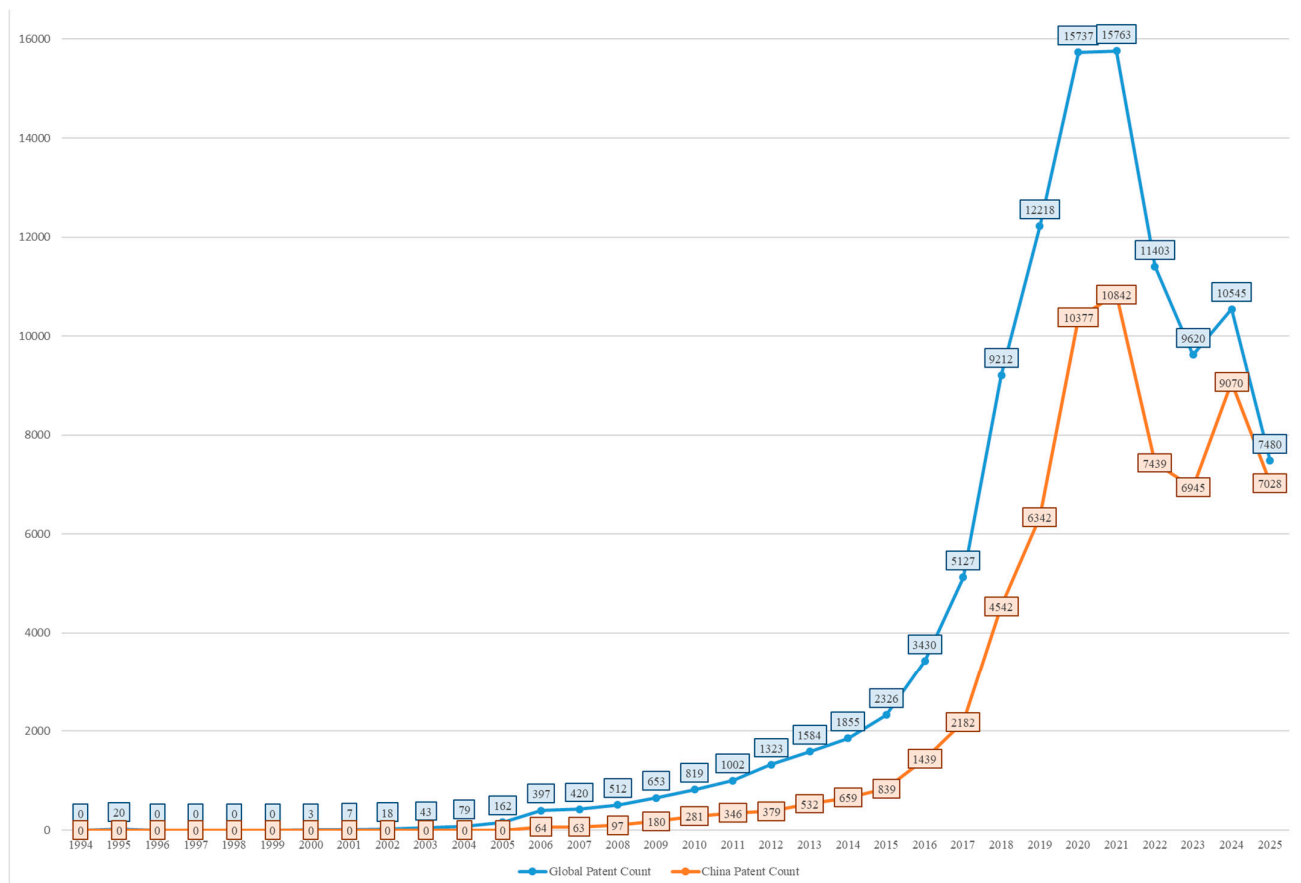


Figure 1. Trends of granted digital tech patents in the global and Chinese digital technology fields.

According to Figure 1, generally, the global digital technology patent applications have gone through four distinct phases: an early budding period (1994–2005), a steady development period (2006–2015), a rapid growth period (2016–2020), and an adjustment and decline period (2021–2025). China’s patent application trajectory is generally consistent with the global trend in terms of overall direction, but exhibits unique phase-specific characteristics in terms of growth magnitude, inflection point timing, and contribution share.

(1) Early Budding Period (1994–2005). During this stage, global digital technology was in its initial exploratory phase. Patent application volumes remained at a relatively low level with no significant annual fluctuations. The world’s first digital technology-related patent was filed in 1995 by American inventors John Christopher Harvey and James William Cuddihy, relating to a signal processing device and method (Publication No.: S8914825B1). China’s participation during this stage was extremely low, with very few patent applications, reflecting that the China’s digital technology innovation system had not yet been established and research and development activities were primarily concentrated in a small number of research institutions.

(2) Steady Development Period (2006–2015). Starting in 2006, global digital technology patent applications began to show steady growth. Cumulative applications over this decade reached 10,891, including 7344 high-value patents with a score of 10, accounting for 23.16%; Patents with a simple family size of ≥ 3 totaled 4346, accounting for 39.9%; and patents with a forward citation count of ≥ 10 totaled 4011, accounting for 36.8%. laying a technological foundation for subsequent international competition and cooperation. During this period, China gradually integrated into the global wave of innovation. From 2005 to 2010, patent applications slowly increased from 0 to 281, while policies began to lay out digital infrastructure and data resource development. From 2011 to 2015, with the introduction

of policies such as the “Big Data Development Action Plan”, patent applications rapidly jumped from 346 to 839, indicating an initial release of innovation vitality from enterprises and research institutions under policy incentives. Nevertheless, China’s share of the global total remained relatively small, positioning it as a technology follower.

(3) Rapid Growth Period (2016–2020). During this stage, global digital technology patent applications experienced explosive growth, with cumulative applications over five years reaching 45,724, more than triple the volume of the previous stage. China became the core engine of this growth, with cumulative applications of 24,882, accounting for 54.4% of the global total. China’s annual applications surged from just over 1439 in 2016 to a peak of 10,377 in 2020, an unprecedented rate and scale of growth. This explosive growth benefited from intensive strategic planning at the national level: the “Cyberpower Strategy Implementation Plan” and the “Digital Economy Development Strategy Outline” served as top-level guidance, while the National Digital Economy Innovation and Development Pilot Zones acted as regional testing grounds. Specific initiatives such as the “Cloud Adoption, Data Utilization, and Intelligence Empowerment” action and the three-year artificial intelligence action plan promoted deep integration of industrial digitalization and digital industrialization, while laws such as the Cybersecurity Law and the Data Security Law provided institutional safeguards. This series of policy measures effectively stimulated innovation vitality across society, rapidly establishing China as a core force in the global digital technology patent landscape.

(4) Adjustment and Decline Period (2021–2025). After 2021, the number of global digital technology patent applications declined, with a total of 54,811 applications filed over five years, which is 9087 more than the total during the rapid growth period. During the same period, China’s application volume also showed a downward trend, dropping to 6945 in 2023, but still significantly higher than the levels before 2019. This decline may be attributed to multiple factors, including technological evolution entering a “deep zone” with increasing innovation difficulty, corporate research and development strategies shifting from quantity expansion to quality improvement, and adjustments brought about by changes in the international technology competition environment.

4.1.2. Regression Analysis of Global and Chinese Patent Applications

Next, regression models are performed on global and Chinese patent application counts. Here, three regression equations—linear, quadratic, and cubic—are established simultaneously. The curves of the three regression equations are shown in Figure 2.

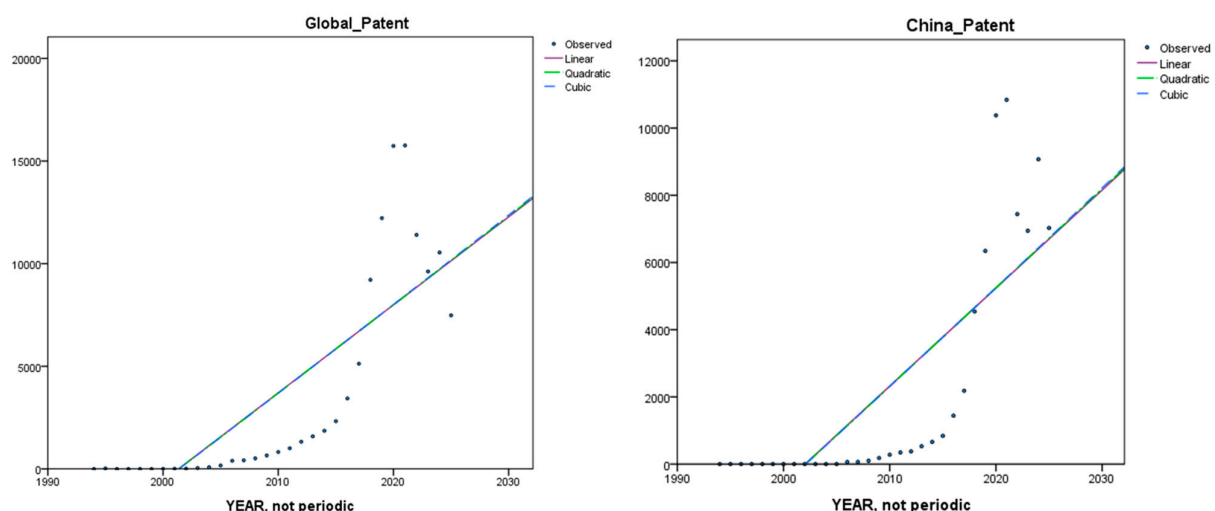


Figure 2. Three regression curves for global and Chinese patent application counts.

According to Figure 2, whether for global or Chinese patent counts, the linear, quadratic, and cubic regression curves almost coincide, indicating that the increase in information provided by the quadratic and cubic equations over the linear equation is not significant. This is also reflected in the F-statistics and R^2 values of the regression equations. For the regression of global patent counts, the F-statistics for the linear, quadratic, and cubic regression equations are 53.247, 53.512, and 53.777, respectively, and the R^2 values are 0.640, 0.641, and 0.642, respectively, showing little difference. For the regression of Chinese patent counts, the F-statistics for the linear, quadratic, and cubic regression equations are 47.640, 47.933, and 48.228, respectively, and the R^2 values are 0.614, 0.615, and 0.617, respectively, showing little difference again. According to the principle of parsimony (Occam's razor), it is more reasonable to use the linear equation for description in this case, which are shown in Equation (3):

$$\begin{cases} Patent_{global} = -857836.13 + 428.63t \\ Patent_{China} = -584056.88 + 291.73t \end{cases} \quad (3)$$

In Equation (3), the number of global patent applications and the independent variable, year, exhibit a positive regression relationship, with a regression coefficient of 428.63, indicating that the number of global patents shows a certain upward trend over time, increasing by an average of approximately 428 applications per year. A significance test of the regression equation shows that the regression equation is significant at the 0.001 level ($p = 0.000$, $F = 53.247$, $R^2 = 0.640$), indicating a moderately good fit. This demonstrates a significant linear relationship between the number of global patent applications and the year, and the overall model is reliable. Similarly, the number of patent applications in China also shows a positive regression relationship with the independent variable, year, with a regression coefficient of 291.73. A significance test of the regression equation shows that the regression equation is significant at the 0.001 level ($p = 0.000$, $F = 47.640$, $R^2 = 0.614$), indicating a significant linear relationship between the number of patent applications in China and the year, and the overall model is reliable. To some extent, both linear equations suggest that, despite fluctuations in the actual data, the overall trend in patent applications in recent years is relatively clear, remaining steadily at a relatively high level.

4.2. Correlation Analysis of Digital Technology Patent Counts with Economic Development and Population Size Across Chinese Provinces

The innovation output of digital technology is highly dependent on regional economic foundations and human resource endowments. As a core indicator of technological innovation output, understanding the statistical relationship between the distribution of patent counts and regional economic scale as well as population structure is a key issue for comprehending China's regional innovation landscape in digital technology. To this end, this section first characterizes the distribution of patent counts across provinces and provides a formula for calculating patent density. Subsequently, correlation analysis and multiple linear regression methods are employed to examine the quantitative relationships between patent counts, GDP, and population.

4.2.1. Distribution Characteristics of Digital Technology Patent Counts Across Chinese Provinces

In China, digital technology patent applications have been recorded since 2006; therefore, the subsequent analysis uses 2006 as the starting point. Additionally, due to some patents being classified, having undisclosed addresses, or missing address information, the total number of patents in the country may not necessarily equal the sum of patents across all provinces [42].

Between 2006 and 2025, the mean number of patent applications across Chinese provinces was 1970.32, with a standard deviation of 3589.896, indicating significant disparities in patent application volumes among provinces. The distribution of patent application numbers by province is shown in Figure 3.

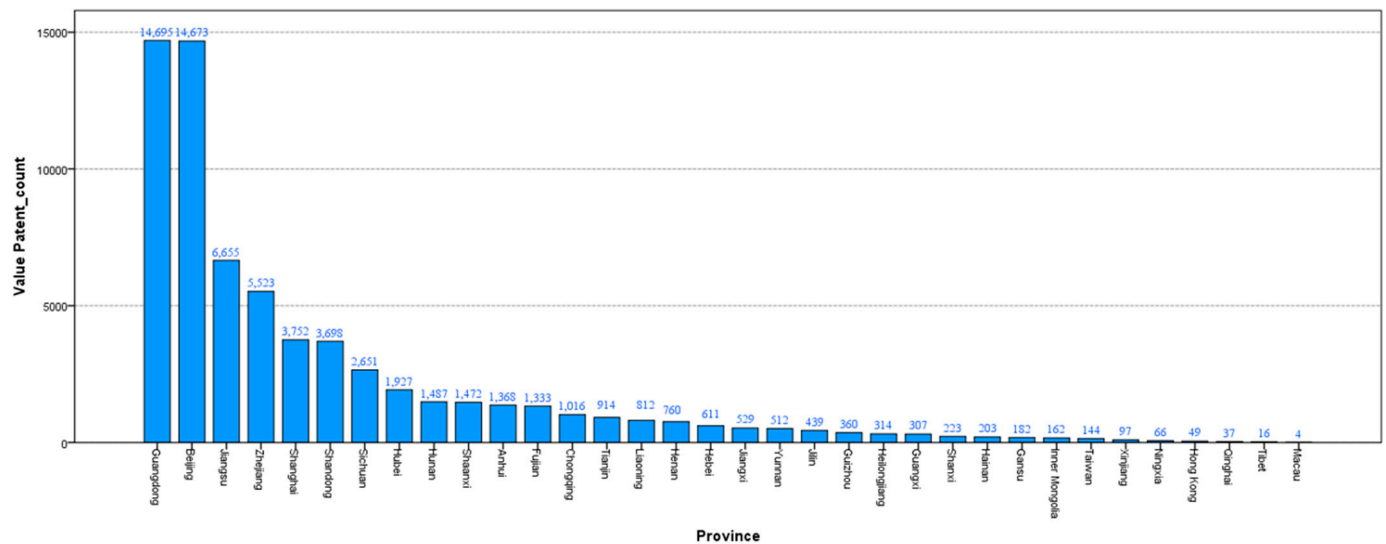


Figure 3. Provincial distribution of digital technology patents in China.

According to Figure 3, the interprovincial distribution of digital technology patents in China exhibits a notable pattern of “core agglomeration, strong in the east and weak in the west.” Specifically, Guangdong and Beijing, as hubs of digital technology innovation, have a patent volume far exceeding that of other provinces, forming an absolute leading position in the first tier. Eastern coastal provinces and municipalities such as Jiangsu, Zhejiang, and Shanghai follow closely, constituting a stable support in the second tier. Central region provinces including Hubei, Hunan, and Anhui have a mid-level number of patents, demonstrating a certain degree of innovation capability. In contrast, western region provinces such as Tibet, Qinghai, and Ningxia have extremely limited patent numbers, showing a significant gap compared with the eastern region. This distribution pattern intuitively reflects the regional imbalance in China’s digital technology innovation capabilities—the eastern coastal region, with its strong economic foundation, well-established innovation ecosystem, and abundant talent resources, has become the core agglomeration area for digital technology innovation; whereas the central and western regions, constrained by their level of economic development and endowment of innovation resources, lag behind in overall innovation output.

4.2.2. Patent Density

The absolute number of patents is significantly influenced by regional economic scale and population size, making it difficult to directly reflect innovation efficiency. To more accurately measure the innovation performance of each province relative to its economic output and population size, this study introduces the concept of patent density. Patent density is defined as the number of patents per unit of economic output or per unit of population. By linking patent volume to regional fundamental endowments, this indicator effectively removes the effects of scale and population base, revealing the true level of innovation efficiency across provinces.

First, patent density is measured from the dimension of economic output, and its calculation is shown in Equation (4):

$$\text{Patent Density}_{GDP} = \frac{\text{Number of Patents}}{\text{Average GDP}} \quad (4)$$

In Equation (4), the number of patents refers to the total number of granted invention patents in the digital technology field obtained by each province between 2014 and 2025. The average GDP refers to the mean value of the gross domestic product of each province over the corresponding years, expressed in units of 100 million yuan. This indicator measures the number of patents generated per 100 million yuan of GDP, reflecting the technological innovation content per unit of economic output. A higher value indicates that the province is more efficient in utilizing its economic resources for technological innovation.

Here, the patent density based on average GDP for each Chinese province is calculated according to Equation (4). It should be noted that in the calculation of patent density based on economic output, due to the difference in currency units between Hong Kong, Macao, Taiwan, and mainland China (namely the Hong Kong dollar, Macanese pataca, and New Taiwan dollar, respectively), direct inclusion in a GDP comparison using the unified unit of “100 million yuan” is not feasible. Therefore, the analysis sample for this part includes only the 31 provinces, autonomous regions, and municipalities in mainland China, excluding Taiwan, Hong Kong and Macao. A comparison of economy-based patent density across Chinese provinces (excluding Hong Kong, Macao, and Taiwan) is shown in Figure 4.

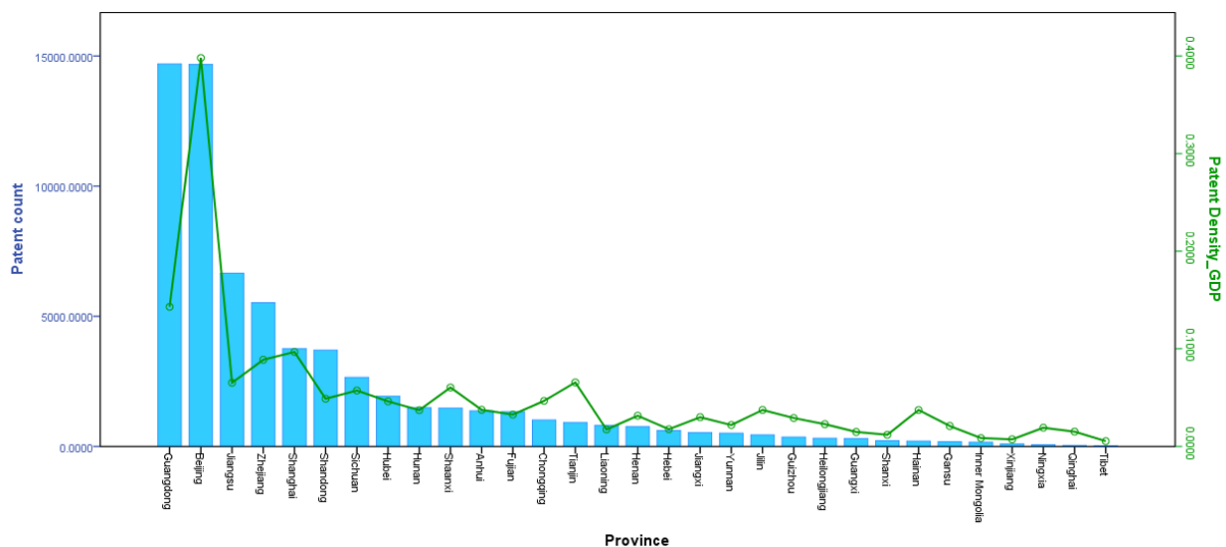


Figure 4. Comparison of economy-based patent density across Chinese provinces (Excluding Taiwan, Hong Kong, and Macao due to currency differences).

Figure 4 presents the distribution of economic output-based patent density across provinces. Considering the economy-based patent density of each province, Beijing leads by a substantial margin with 0.398 patents per 100 million yuan, indicating that its digital technology innovation content per unit of economic output is the highest, and the efficiency of transforming economic resources into innovation outcomes is extremely prominent. Guangdong ranks second with 0.143 patents per 100 million yuan, followed closely by eastern coastal provinces and municipalities such as Shanghai, Zhejiang, Tianjin, and Jiangsu, whose economy-based patent densities all fall within the range of 0.06 to 0.10, forming a high-innovation-efficiency cluster along the eastern coastal region. It is worth noting that some key central and western provinces, such as Shaanxi (0.06 patents per

100 million yuan) and Sichuan (0.057 patents per 100 million yuan), also demonstrate respectable economic innovation efficiency, with a relatively small gap from their eastern counterparts. In contrast, provinces such as Tibet (0.005), Xinjiang (0.007), Inner Mongolia (0.009), and Shanxi (0.012) record the lowest levels of economy-based patent density in the country, reflecting that the contribution of technological innovation per unit of economic output in these regions remains limited, and the synergistic effect between economic development and technological innovation needs to be strengthened.

Second, patent density is measured from the dimension of economic output, and its calculation is shown in Equation (5):

$$\text{Patent Density}_{\text{Population}} = \frac{\text{Number of Patents}}{\text{Population}} \quad (5)$$

In Equation (5), the population data are sourced from the main data of the Seventh National Population Census [46], with the unit being million people. This indicator measures the number of patents per million people, reflecting the level of technological innovation output on a per capita basis. A higher value indicates that the population resources of the province have been more fully utilized in digital technology innovation activities.

Next, a comparison figure of population-based patent density across Chinese provinces is presented. Since the measurement method for population is the same across mainland China, Hong Kong, Macao, and Taiwan—all based on headcount—those three regions are also included when comparing Chinese provinces, as shown in Figure 5.

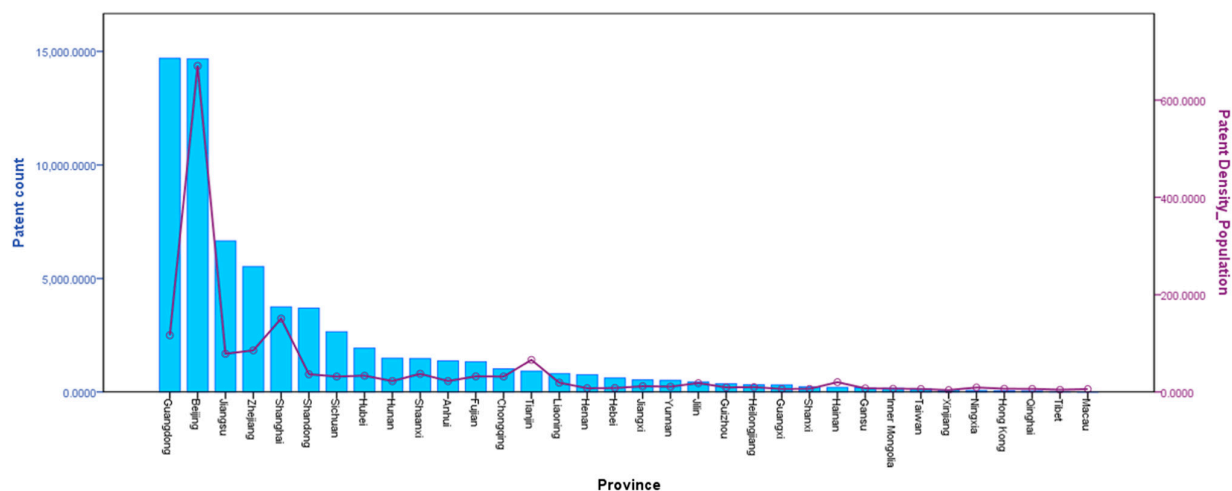


Figure 5. Comparison of population-based patent density across Chinese provinces.

Figure 5 presents the distribution of population-based patent density across provinces. As clearly shown in the figure, Beijing ranks first by a large margin with 670.21 patents per million people, with its per capita innovation output far exceeding that of other provinces, highlighting its core position as a hub for digital technology innovation. Shanghai ranks second with 150.86 patents per million people, followed closely by Guangdong with 116.62 patents per million people, together forming the first tier of population-based patent density. Eastern provinces and municipalities such as Zhejiang (85.54 patents/million) and Jiangsu (78.53 patents/million) also perform prominently, constituting the second tier. The central and western regions show a differentiated pattern: provinces such as Shaanxi (37.24 patents/million), Hubei (33.37 patents/million), Chongqing (31.70 patents/million), and Sichuan (31.68 patents/million) perform at a moderate level, demonstrating a certain capacity for localized innovation agglomeration. In contrast, populous provinces such as Henan (7.65 patents/million), Hebei

(8.19 patents/million), and Guangxi (6.12 patents/million) have significantly lower population-based patent density, reflecting that their population size advantages have not been effectively translated into innovation output advantages, and per capita innovation efficiency urgently needs improvement. Meanwhile, the population-based patent density of Hong Kong, Macao, and Taiwan ranges from approximately 6.56 to 5.85 patents per million people, comparable to levels observed in Shanxi, Qinghai, and Guangxi. Western regions such as Tibet (4.39 patents/million) and Xinjiang (3.75 patents/million) record the lowest levels, reflecting the limited effectiveness of converting population resources into patent output in these areas.

4.2.3. The Impact of Economic and Population Factors on the Number of Patent Applications

In this section, the impact of economic development and population factors on the number of patent applications across Chinese provinces is examined. To preliminarily reveal the direction and strength of the relationships among digital technology patent counts, economic development levels, and population size, the Pearson correlation analysis was conducted. The results show that the correlation between patent count and economic development is very strong ($r = 0.853$, $p = 0.000$), and the correlation between patent count and population size is also relatively strong ($r = 0.457$, $p = 0.007$).

To further clarify the relationship between economic and population factors and patent counts, a scatter plot is first drawn, as shown in Figure 6.

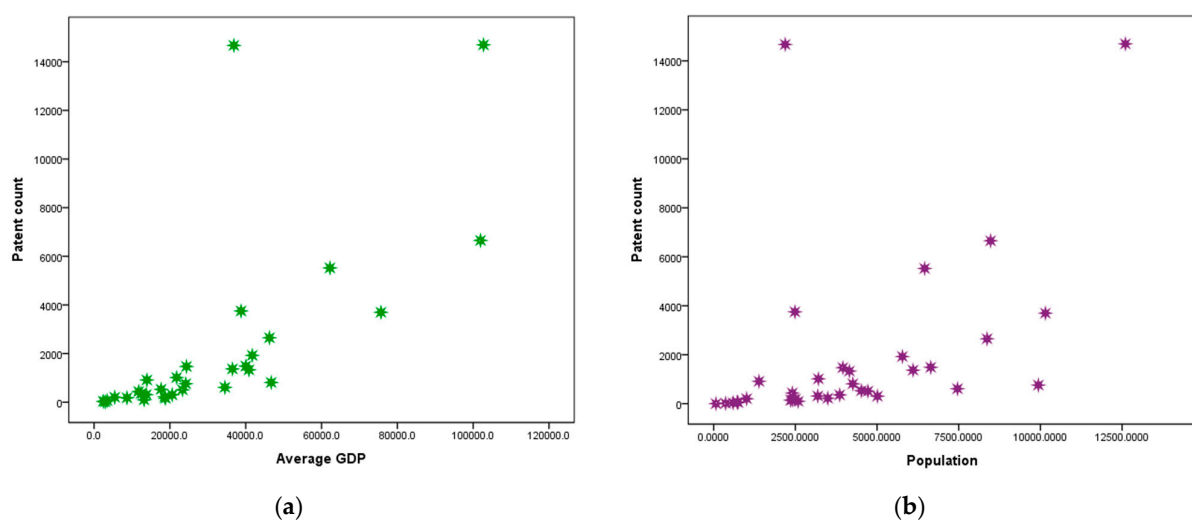


Figure 6. (a) Scatter plot of economic factors and patent count. (b) Scatter plot of population factors and patent count.

Based on the scatter plots shown in Figure 6 and the Pearson correlation coefficients, both economic development and population size exhibit a positive correlation with patent count. To further clarify the causal relationships among them, regression analysis is employed here, with regression equations established using economic development and population size as independent variables, respectively, and patent count as the dependent variable.

First, the impact of economic factors on patent count is considered, and five regression models—Linear, Quadratic, Cubic, Power, and Exponential—are employed for the regression, as shown in Figure 7.

Figure 7 presents the fitting results of economic factors and patent count under linear, quadratic, cubic, power, and exponential regression models. It can be observed that all

fitted equations exhibit positive growth, and the fit to the data points is generally good. Significance tests were conducted for all equations, and the results are shown in Table 2.

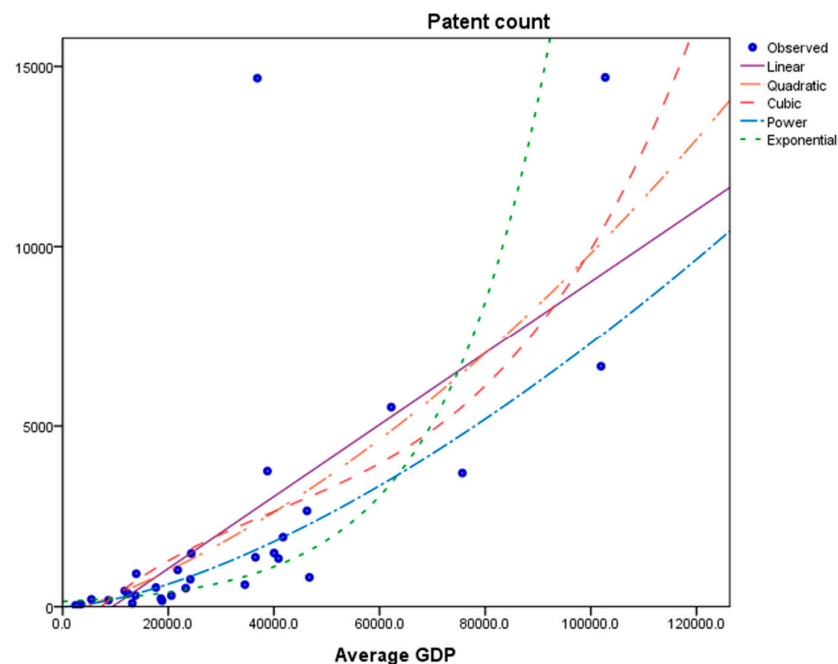


Figure 7. Fitted curves of the relationship between economic factors and patent count based on different regression models.

Table 2. Significance tests for various regression models of economic factors on patent count.

Equation	<i>p</i> -Value	<i>R</i> ²
Linear	0.000	0.480
Quadratic	0.000	0.492
Cubic	0.000	0.500
Power	0.000	0.798
Exponential	0.000	0.648

According to Table 2, all regression models are statistically significant ($p < 0.001$), indicating that the influence of economic factors on patent count is not due to chance. In terms of goodness of fit, the power model has the highest ($R^2 = 0.798$), substantially outperforming other models, suggesting that the power function better captures the nonlinear, accelerating growth relationship between economic scale and patent output. Although the R^2 values of the linear, quadratic, and cubic models are relatively lower (0.480–0.500), they also pass the significance test, further supporting the robustness of the positive driving effect of economic development on innovation. Since the power model is the optimal model for describing the relationship between economic factors and patent count, here, a power function regression equation is established, and its general form of the equation is presented in Equation (6).

$$Y = \alpha \cdot X^\beta \quad (6)$$

In Equation (6), Y represents the dependent variable, X represents the independent variable, α is a constant term called the scale parameter, and β is the power exponent called the elasticity coefficient. Substituting the numerical values, the power function

regression equation for the effect of economic factors on patent count is obtained as shown in Equation (7):

$$\text{Patent Count} = 1.703 \times 10^{-4} \times (\text{Average GDP})^{1.526} \quad (7)$$

In Equation (7), since $\beta = 1.526 > 1$, it indicates that patent count grows at an accelerating rate with GDP growth. That is, for every 1% increase in GDP, the patent count increases by approximately 1.526%. To some extent, this indicates that the larger the economic scale, the higher the innovation efficiency.

Second, to examine the impact of population size on patent count, the same five regression models—Linear, Quadratic, Cubic, Power, and Exponential—are employed, as shown in Figure 8.

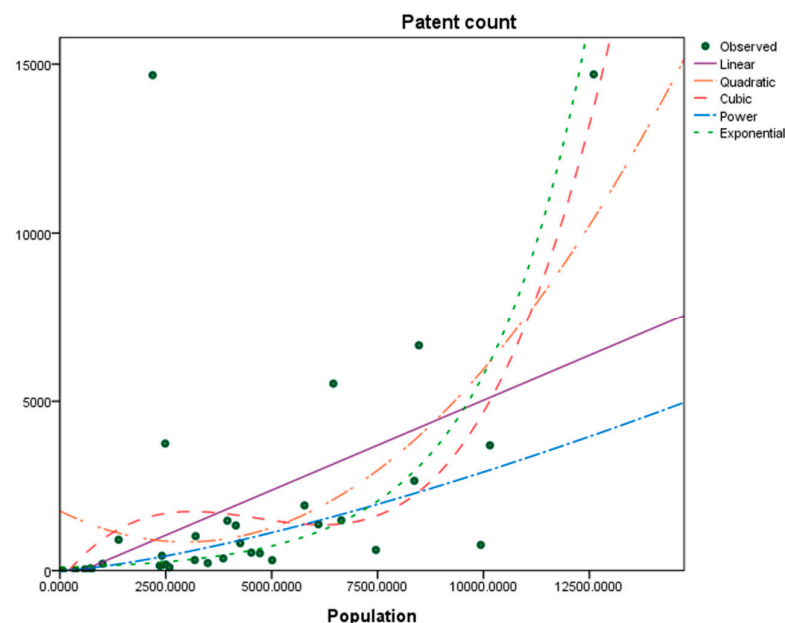


Figure 8. Fitted curves of the relationship between population factors and patent count based on different regression models.

Figure 8 presents the fitting results of population factors and patent count under linear, quadratic, cubic, power, and exponential regression models. All fitted equations exhibit positive growth, and most of them are generally good. Significance tests were conducted for all equations, and the results are shown in Table 3.

Table 3. Significance tests for various regression models of population factors on patent count.

Equation	<i>p</i> -Value	<i>R</i> ²
Linear	0.007	0.209
Quadratic	0.003	0.314
Cubic	0.001	0.405
Power	0.000	0.643
Exponential	0.000	0.477

According to Table 3, all regression models are statistically significant ($p < 0.01$), indicating that the impact of population size on patent count is also significant. In terms of goodness of fit, the Power model has the highest ($R^2 = 0.643$), substantially outperforming other models. Compared with economic factors (Power model $R^2 = 0.798$ in Table 2), population size has a weaker explanatory power for patent count, suggesting that economic

development level is a more critical driver of digital technology innovation than population size. However, due to the significance of population factors in the Power model, a power equation with population factors as the independent variable is further constructed, as shown in Equation (8).

$$\text{Patent Count} = 0.009 \times (\text{Population})^{1.376} \quad (8)$$

In Equation (8), since $\beta = 1.376 > 1$, it indicates that patent count grows at an accelerating rate with population size. For every 1% increase in population, the patent count increases by approximately 1.376%. However, compared with the economic factors model ($\beta = 1.526$ in Equation (7)), the accelerating effect of population size is slightly weaker, suggesting that while population agglomeration contributes to innovation output, its driving force is less potent than that of economic scale.

In summary, both economic development and population size have a significant positive impact on patent count. Both factors are closely associated with digital technology innovation output and together constitute important determinants of regional patent performance.

4.3. Geographical Distribution and Patent Quality Structure of Major Patentees

Digital technology innovation activities are ultimately undertaken by specific innovation entities. The distribution pattern of patentees and the structure of patent quality directly reflect the innovation ecosystem characteristics and core competitiveness of a country or region. This section focuses on the top ten core patentees by patent applications in the global digital technology field, systematically examines the geographical agglomeration characteristics and patent quality structure of major Chinese innovation entities, and makes appropriate comparisons with leading international enterprises to reveal the characteristics of China's digital technology innovation.

4.3.1. Regional Distribution and Quality Structure of Enterprises Among the Global Patent Holders

To better understand the geographical landscape of technological innovation leadership, it is essential to examine not only where the world's leading patent-holding enterprises are originally registered but also the quality of their patent portfolios. Table 4 presents the regional distribution and quality structure of enterprises among the top ten global digital technology patent holders.

According to Table 4, among the top ten global patent holders, eight are Chinese enterprises based on their actual R&D locations, concentrated in Guangdong (2 enterprises, 3233 patents), Zhejiang (2 enterprises, 2707 patents), and Beijing (3 enterprises, 2278 patents). Notably, Alibaba Group Holding Limited, though registered in the Cayman Islands, is counted under Zhejiang as its core R&D activities are located in Hangzhou. Guangdong features an innovation cluster led by Tencent and Ping An, Zhejiang features a platform-led ecosystem driven by Alibaba and Alipay, and Beijing demonstrates diversified strengths through Baidu, ICBC, and State Grid. This distribution aligns closely with the earlier regional patent density analysis, further reinforcing Guangdong, Beijing, and Zhejiang as China's leading digital technology innovation hubs.

In the above table, among the top 10 global patent holders in the digital technology field, Chinese enterprises occupy 8 seats, indicating that China has established a clear advantage in patent volume. However, from the perspective of patent quality dimensions (Patent Cooperation Value Degree = 10, simple family size ≥ 3 , forward citation count ≥ 10), Chinese and foreign enterprises exhibit significant structural differences: IBM leads in technological stability, overseas expansion, and technological influence; Alibaba and Ant

Group achieve coordinated development in both quantity and quality; Tencent and Ping An show “quantity leadership with quality divergence”; Baidu, ICBC, and State Grid show “quantity without quality”; and Switzerland-based nChain demonstrates “quality prioritized over quantity.”

Table 4. Regional distribution and quality structure of patent holders among the top ten global digital technology patent holders.

ID	Patent Holder	Country (by Registration)	Actual R&D Location	Classification	Total Patents	Patent Cooperation Value Degree = 10	Simple Family Size ≥ 3	Forward Citation Count ≥ 10
1	Tencent Technology (Shenzhen) Co., Ltd. (Shenzhen, China)	China	China	China	1739	—	—	405
2	Alibaba Group Holding Limited (Hangzhou, China)	Cayman Islands	China	China	1671	849	821	173
3	Ping An Technology (Shenzhen) Co., Ltd. (Shenzhen, China)	China	China	China	1494	—	572	317
4	International Business Machines Corporation (Armonk, NY, USA)	United States	United States	Non-China	1217	1094	419	379
5	Beijing Baidu Netcom Science Technology Co., Ltd. (Beijing, China)	China	China	China	1053	—	—	110
6	Alipay (Hangzhou) Information Technology Co., Ltd. (Hangzhou, China)	China	China	China	1036	353	362	85
7	Industrial and Commercial Bank of China Co., Ltd. (Beijing, China)	China	China	China	759	—	—	—
8	Microsoft Technology Licensing, LLC (Redmond, WA, USA)	United States	United States	Non-China	636	494	382	107
9	Advanced New Technologies Co., Ltd. (Grand Cayman, Cayman Islands)	Cayman Islands	China	China	595	437	435	—
10	State Grid Corporation of China (Beijing, China)	China	China	China	466	—	—	—

Note: A dash “—” indicates that the patent holder did not rank in the top 15 for that indicator, not that the value is zero. Alibaba Group Holding Limited and Advanced New Technologies Co., Ltd. are registered in the Cayman Islands but conduct their core R&D activities in Mainland China and are therefore classified as Chinese innovation entities.

4.3.2. Patent Quality Structure of Major Chinese Patent Holders

Number of Patents reflects the breadth of innovation activities, while patent quality indicates the depth of innovation capacity. To further reveal the innovation quality of major Chinese patent holders, this study analyzes the patent quality structure of the eight Chinese enterprises mentioned above based on the Patent Cooperation Value Degree evaluation system. The Number of Invention Applications, Number of Invention Grants, and Number of Patents with Patent Cooperation Value Degree 10 are used as key indicators to measure innovation quality. Figure 9 presents the three-dimensional distribution of these eight Chinese enterprises across the three patent quality indicators.

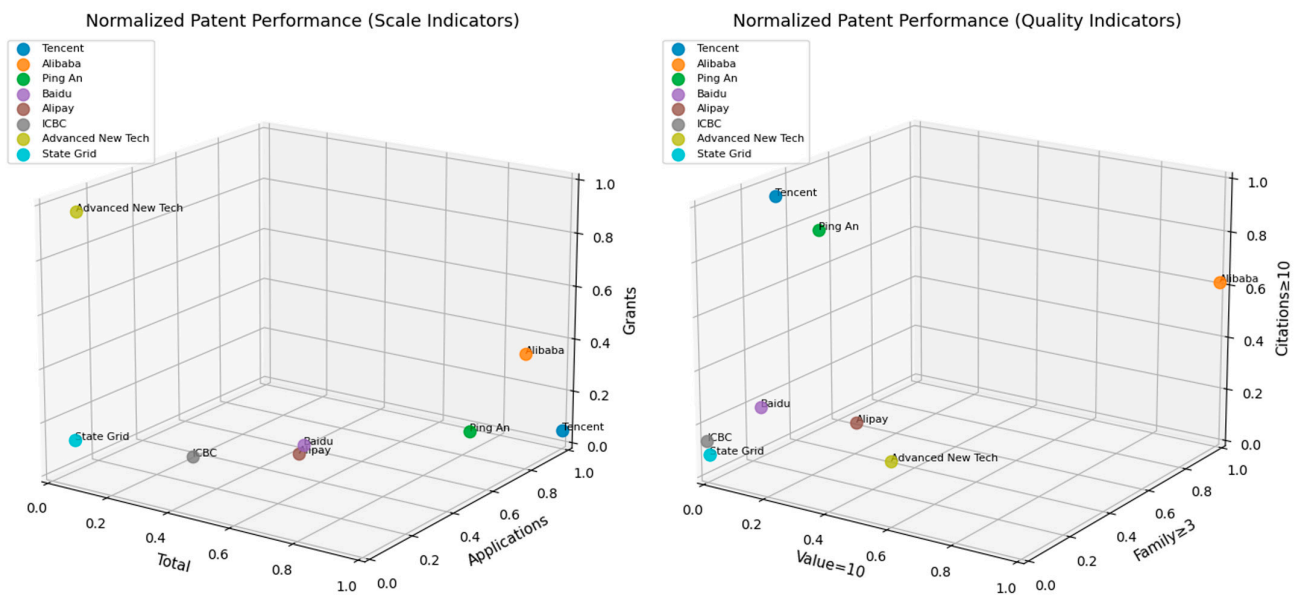


Figure 9. 3D Scatter Plot of Patent Quality Indicators for Chinese Enterprises.

As shown in Figure 9, Chinese enterprises have achieved global competitiveness in patent scale, yet their performance varies across the three quality indicators: Number of Invention Applications, Number of Invention Grants, and Number of Patents with Patent Cooperation Value Degree 10. Tencent and Ping An have formed notable advantages in invention applications and grants, but their number of patents with patent cooperation value degree 10 remains relatively limited. Alipay has accumulated considerable achievements in high-value patents. Meanwhile, the performance of ICBC and State Grid across the three indicators exhibits divergent development patterns. From a regional perspective, Beijing-based enterprises have established a certain accumulation in invention grants and high-value patents; Guangdong-based enterprises possess the largest scale of invention applications, yet their share of high-value patents requires improvement; Zhejiang-based enterprises, leveraging e-commerce and fintech scenarios, have formed distinctive advantages in high-value patents, but their number of invention grants remains relatively weak.

An analysis of the regional distribution and patent quality structure of Chinese enterprises among the top ten global patent holders reveals the following: Chinese enterprises have established a significant scale advantage in the number of invention applications. However, a notable gap persists between Chinese enterprises and globally advanced counterparts in terms of the number of invention-grants and the number of patents with patent cooperation value degree 10, exhibiting a structural characteristic of “leading in applications, catching up in grants and high-value patents.”

5. Discussion

5.1. Addressing the Research Questions

Regarding the first research question, the analysis of global and Chinese digital technology patent application trends, as well as the comparison of patent application trends among major countries, shows that China’s digital technology patent applications have experienced explosive growth since 2016, with its share of global patent applications continuously increasing. China has now firmly secured the top position in the world. However, in quality dimensions such as patent family layout and overseas market coverage, China still lags significantly behind the United States and Japan, exhibiting a pronounced asymmetric characteristic of “quantity leading, quality lagging.” Validated by alternative indicators such as patent family size and patent citation frequency, the above conclusions remain

consistent, indicating that this feature is not attributable to the choice of a single quality indicator and demonstrates good robustness.

Regarding the second research question, the analysis of the provincial distribution of digital technology patent counts and patent density reveals that China's digital technology patents are highly concentrated in the eastern coastal regions. Five provinces/municipalities—Guangdong, Beijing, Jiangsu, Zhejiang, and Shanghai—together account for over 60 percent of the total, while patent output from western provinces is extremely limited, presenting a significant “strong east, weak west” spatial pattern. Correlation analysis and multiple linear regression results indicate that the number of digital technology patents across Chinese provinces has a robust and significantly positive correlation with GDP. However, after controlling for GDP, population size shows a negative association with patent counts, suggesting that provinces with large populations but comparable economic output may have lower innovation efficiency. Simply relying on population size does not necessarily lead to increased innovation output; the key lies in the alignment of economic structure and innovation investment. Validated by alternative quality indicators such as patent family size and citation frequency, the above conclusions regarding regional distribution remain consistent, indicating that this spatial pattern demonstrates good robustness.

Regarding the third research question, Chinese enterprises among the top ten global patent holders are highly concentrated in Guangdong, Zhejiang, and Beijing, exhibiting a typical “head agglomeration” characteristic. From the perspective of patent quality structure and based on a comprehensive analysis of the three dimensions—Patent Cooperation Value Degree, patent family size, and citation frequency, the patent quality of the aforementioned leading enterprises is significantly better than that of universities and research institutes, while the patent quality of a large number of small and medium-sized enterprises and patent holders in western regions is generally low. This “quality gap,” when combined with the regional agglomeration effect, may further exacerbate the uneven distribution of digital technology dividends. It is worth noting that there is a structural discrepancy between quantity ranking and quality ranking: international enterprises represented by IBM exhibit a clear advantage in the proportion of high-value patents, while some Chinese enterprises display a pattern where quantity outpaces quality. Examined through the lens of SDG 9 and SDG 10, the regional agglomeration and quality differentiation of digital technology innovation may exacerbate rather than alleviate regional development imbalances. How to ensure that the benefits of innovation reach underdeveloped regions more equitably has thus become a critical issue for achieving the Sustainable Development Goals.

Collectively, these findings suggest that China's digital technology patent landscape presents a mixed picture from a sustainability perspective. While the scale of innovation output aligns with SDG 9's emphasis on enhancing technological capabilities, the pronounced regional concentration and quality differentiation raise concerns about SDG 10's commitment to reducing inequality. The “dual agglomeration effect”—whereby both patent quantity and high-quality patents cluster in economically advanced regions and among leading enterprises—implies that the benefits of digital innovation may not be diffusing to underdeveloped areas as SDG 10 would require. This tension between efficiency-driven agglomeration and equity-oriented diffusion constitutes a central sustainability challenge that requires deliberate policy intervention.

5.2. Relationship with Existing Research

This study introduces multi-dimensional quality indicators, including the number of invention applications, the number of invention grants, and the number of patents with a patent cooperation value degree of 10, to systematically reveal the structural tension

between the “quantity” and “quality” of China’s digital technology patents. This finding not only corroborates the macro-level description of China’s digital patent scale by Zhou and Li, which was based on IPC mapping, but also deepens the understanding of the true level of China’s digital technology innovation from a quality perspective [23]. Furthermore, this study identifies a significant quality differentiation between leading enterprises and universities/research institutes, providing complementary evidence from the Chinese context for the research by Ren et al. on “patent knowledge breadth,” and demonstrating that regional differentiation and actor differentiation in patent quality are equally important research dimensions [24]. Zhou et al. conducted patent analyses in four frontier fields in China—artificial intelligence, blockchain, cloud computing, and big data—and found that enterprises (especially technology-oriented firms) occupy an absolutely dominant position in digital patent creation, while cross-enterprise and cross-industry patent transactions remain inactive [19]. This study further reveals that behind this pattern of enterprise dominance lies a significant quality differentiation—leading enterprises possess markedly higher patent quality, while a large number of small and medium-sized enterprises (SMEs) exhibit relatively low patent quality. This “quality gap” may serve as an important factor constraining the vitality of technology transactions, thereby offering a new explanatory perspective for understanding the inactive patent transaction phenomenon identified in their study.

With respect to the progressive dialogue with research on the mechanisms influencing regional digital innovation, existing studies have confirmed that factors such as economic development level, scientific research resources, policy environment, and digital infrastructure play a significant driving role in regional digital innovation [17,20,21]. Furthermore, research has found that the fair competition review system can incentivize corporate digital technology innovation by optimizing the market competition environment and the allocation of credit resources, an effect that is more pronounced in regions with stronger intellectual property protection and more developed digital infrastructure [16]. The results of the multiple linear regression analysis in this study are generally consistent with these findings, and further reveal that R&D investment intensity and high-tech industry agglomeration are the core factors driving regional digital innovation, while the incentive effect of the policy environment is more significant in regions with relatively weaker innovation foundations.

With respect to the dialogue with research on the Sustainable Development Goals (SDGs), existing studies have revealed the enabling role of digital technology in pollution reduction, carbon emission mitigation, and industrial upgrading [14], while also identifying practical challenges such as digital divides, cost barriers, and privacy concerns [10]. Zhu & Shangguan pointed out that the integration of digital and real economies achieves synergistic evolution through pathways such as patent innovation diffusion and optimal allocation of production factors, aligning with the orientation toward technological innovation and balanced development advocated by the SDGs [11]. This study finds that leading enterprises play a pioneering role in industrial innovation and upgrading (SDG 9) by virtue of their high-quality patents. However, the regional concentration of high-quality patents may exacerbate the uneven distribution of innovation resources, posing a challenge to narrowing regional development gaps (SDG 10). This finding echoes the concerns raised by Koch & Panwar regarding the “digital divide” [10], and further reveals that, while attention has been paid to the access gap to digital technology (the first-level digital divide), greater vigilance is needed regarding the “capability gap” (the second-level digital divide) at the level of technological innovation quality, which may become a deep-seated obstacle to inclusive and sustainable development.

5.3. Policy Implications for the Sustainable Development Goals

The findings of this study have multiple implications for advancing the implementation of the United Nations Sustainable Development Goals (SDGs), particularly SDG 9 (Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation) and SDG 10 (Reduce inequality within and among countries).

The study finds that China's digital technology patents are characterized by being "large but not strong," with a significantly differentiated patent quality structure, indicating a gap relative to the specific targets of SDG 9.5 (Enhance scientific research and upgrade industrial technological capabilities). High-quality patents are core assets for industrial innovation and upgrading, as well as a key benchmark for measuring the achievement of SDG 9. It is recommended that innovation policy design shift from a "quantity incentive" to a "quality orientation." This includes incorporating quality indicators such as the share of invention patents, patent family layout, patent maintenance duration, and patent transaction activity into innovation evaluation systems. To address the issue of low patent quality at universities and research institutes, a full-chain service system encompassing "patent quality pre-examination, high-value patent cultivation, and specialized operation" should be established. Leading enterprises should be encouraged to enhance their international competitiveness through mechanisms such as patent pool construction and standard-essential patent portfolio development, thereby supporting high-quality development with high-quality innovation.

The study finds that China's digital technology patents are highly concentrated in the eastern coastal regions, and that high-quality patents further agglomerate toward leading enterprises and developed areas. This dual agglomeration effect may exacerbate rather than alleviate regional development imbalances, creating tension with the goal of reducing inequality advocated by SDG 10. The spatial agglomeration of technological innovation has its own inherent economic logic; however, policy intervention can promote inclusive development without sacrificing efficiency. Differentiated regional innovation policies are recommended. Eastern regions should focus on establishing an integrated pathway connecting "technology, industry, and standards," cultivating globally competitive digital industry clusters, and driving development in the central and western regions through industrial transfer and technology spillovers. Central and western regions, in turn, need to increase investment in digital infrastructure, establish digital technology innovation programs with distinctive regional characteristics, and leverage models such as "enclave economies" and R&D enclaves to absorb technology spillovers from the east. Efforts should also be made to explore cross-regional patent technology transfer and benefit-sharing mechanisms, lowering the threshold for central and western regions to access high-quality patent technologies, and ensuring that innovation dividends reach underdeveloped regions more equitably.

5.4. Contributions and Research Significance

Theoretically, this study makes three interconnected contributions. First, at the empirical fact-finding level, drawing on systematic patent data covering 31 provinces over a 30-year period, it provides the first comprehensive characterisation of the spatiotemporal differentiation pattern of China's digital technology patents along the dual dimensions of quantity and quality, thereby filling the gap left by previous studies that have largely focused on a single dimension or a single temporal snapshot. Second, at the conceptual framework level, it proposes the notion of a "Dual Agglomeration Effect" that integrates quantity agglomeration at the regional level with quality differentiation at the actor level into a unified analytical framework, extending regional innovation theory's understanding of agglomeration from a mere concentration of volume to a polarisation of quality. Third, at

the theoretical dialogue level, by introducing technological catch-up theory into the digital patent context, it identifies China as being in a transitional phase from quantity-driven expansion to quality-oriented upgrading, offering an operational empirical basis for future research to investigate when and how policy incentives generate quality differentiation in innovation outcomes.

At the practical level, this study has multiple implications for policy making and corporate strategy. First, the “dual agglomeration effect” of China’s digital technology patents identified in this study—regional agglomeration of patent quantity and actor differentiation of patent quality—provides a quantitative basis for governments to formulate differentiated regional innovation policies. Second, the problem of relatively low patent quality in universities and research institutes revealed by this study suggests the need to establish a full-chain service system of “patent quality pre-examination, high-value patent cultivation, and specialized operation” to promote industry-university-research collaborative innovation. Finally, the leading role of leading enterprises in industrial innovation and upgrading by virtue of their high-quality patents suggests that enterprises should strengthen patent pool construction and standard essential patent layout to strive for greater voice in global digital economy governance, supporting high-quality development with high-quality innovation.

5.5. Limitations and Future Directions

This study has the following limitations. First, at the data level, the study is based on patent data collected in the incoPat database. Although this can reasonably reflect the overall pattern of digital technology innovation, patent data themselves have a certain time lag, and it is difficult to fully cover technological innovation activities that are not patented (such as trade secrets, open source technologies, and algorithmic innovation). In addition, due to the granularity of the IPC system, the three major classes G06F, G06N, and G06Q may include a small number of patents that are not related to digital technology. Second, at the methodological level, this study mainly employs correlation analysis and multiple linear regression methods. Although some influencing factors are controlled, it remains difficult to completely avoid endogeneity issues, and the research findings should be interpreted primarily as correlations rather than causal relationships. In terms of patent quality measurement, although three indicators—Patent Cooperation Value Degree, patent family size, and citation frequency—were employed for cross-validation, it remains difficult to comprehensively cover the legal stability and commercial value of patents. Third, at the analytical dimension level, although this study emphasizes in the discussion the importance of moving from “static stock” to “dynamic flow,” due to limitations in data availability, it does not incorporate dynamic flow data such as patent transactions, transfers, licensing, and pledge financing into the empirical analysis.

In response to the above limitations, future research can be expanded and deepened in the following directions: integrate multi-source data such as scientific papers, technical standards, open source community contributions, and corporate annual reports to construct a more comprehensive measurement system for digital technology innovation, thereby addressing the coverage bias that may exist when relying solely on patent data; incorporate textual semantic analysis to optimize the search strategy and improve precision; leverage policy shocks (e.g., National Big Data Comprehensive Pilot Zones, Intellectual Property Demonstration Cities, and New Industrialization Industry Demonstration Bases) to construct quasi-natural experiments, and employing causal inference methods such as difference-in-differences, instrumental variable methods, and regression discontinuity designs to more accurately identify the driving mechanisms of digital technology innovation and its regional differentiation; introduce indicators such as patent maintenance duration,

licensing fees, and litigation to assess patent quality from a more multifaceted perspective; and incorporate patent operation data from the China National Intellectual Property Administration or patent legal status change information from incoPat to further explore the market operation characteristics of digital technology patents, technology diffusion pathways, and their impact on regional balanced development, thereby deepening the understanding of the value realization process of digital technology innovation.

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