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Digital Sharing of Social Public Resources and Its Influencing Factors: Insight from China

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ABSTRACT

Digital sharing of social public resources (SPRs) is an approach of resource-allocation that can effectively compensate for the limitations of time, space and communication modes in accessing SPRs and achieve the balanced allocation of them. The purpose of this paper is to study the development level of digital sharing of SPRs and its influencing factors. The panel data of 31 Chinese provinces from 2015 to 2020 are collected. A comprehensive evaluation index system for digital sharing of SPRs is constructed to evaluate its development level using the Global Entropy Weight Method (GEWM). And the influencing factors of the sharing level are systematically identified based on the stepwise regression model. The results show that: the development level of digital sharing of SPRs varies significantly among Chinese provinces and cities, but the overall development level is gradually increasing. The government fiscal expenditure capacity, industrial structure, regional economic development level, scientific and technological innovation capacity, and urbanization level can promote the digital sharing of SPRs. The degree of external openness and regional population size have negative effects on the digital sharing of SPRs.

KEYWORDS

Social public resources; Digital sharing; Influencing factors; Stepwise regression; Panel data

1. INTRODUCTION

The digital age is coming, information and communication technologies (ICTs) are transforming the supply and consumption of social public resources (SPRs) [1]. Strengthening the construction of digital society and enhancing the digitization and intelligence of public resources and social services have also become inevitable requirements of this era. Relying on digital media and integrating public resources such as medical care, education, and public services, the government can use public service platforms such as telemedicine, online education, and e-government to effectively solve the public's problems [2].

For example, medical consortia in China improve the efficiency of information sharing among hospitals and solve the social and livelihood problems of "expensive and difficult access to medical care" [3]. ICTs-based public resource sharing can improve the supply of public resources, which can promote the equalization of basic public services and sustainable socioeconomic development [4], [5]. People in different spatially distributed groups can easily and quickly access SPRs through digital sharing [6]. Therefore, to meet people's expectation and demand for higher quality SPRs, ICTs should be used to accelerate the process of digitization and networking of SPRs, expand and enrich their supply capacity and service categories, enhance the relevance and utilization efficiency of them to make them deeply integrated into the public's production and life. However, how about the development level of digital sharing of SPRs? What are the factors hindering (promoting) the development of digital resource sharing? These are the key concerns of this research.

Digital sharing of SPRs involves multiple participants and elements. Sharing participants mainly include e-government and enterprises that can provide (receive) digital sharing services. Shared resources are tangible and intangible resources that can be shared digitally, including facilities and equipment, information and data, knowledge and staff in sectors and fields such as education, science and technology, culture, healthcare, and community services, etc. [7]. As for the measurement of the digital sharing level of public resources, scholars have studied from different perspectives with different methods. Cheng et al. analyzed the comprehensive level of basic rural public services and found that their service levels were influenced by regional economic development level as well as policies and other factors [8]. Li and Zhao used the entropy-TOPSIS model to measure the digital sharing level of SPRs (SPRDS) and found it decreases from the east to the west in the spatial dimension and increases in the temporal dimension [9]. Wu and Xiao empirically verified the unbalance of public service equalization in the temporal dimension based on quantitative and comparative analysis. And they constructed an IoT-managed public service equalization model and determined its impact on equalization [1]. Zhang and Yang evaluated the equalized supply of public resources in four dimensions: public education, social security, healthcare, and infrastructure, and found that increasing fiscal input can promote equalization of SPRs in urban and rural areas [10]. However, public resources consist of many resource categories, and it is difficult for a relatively single measurement indicator to reflect the true and accurate status of resource-sharing.

The digital sharing of public resources is impacted by the benefits, costs, and risks of sharing [11], [12]. Government expenditure, playing an important role in promoting public resource services, can effectively address the issue of balanced allocation of public resources [13]. In general, countries with high economic levels have more fiscal expenditures on social security and healthcare [14]. But there are some scholars holding different opinions about the effect of government expenditures. For example, Sanogo analyzes whether, and how, the devolution of revenue raising responsibilities to Côte d'Ivoire' municipalities enhances the access to public services. The result suggests that devolving municipality revenue mobilization positively affects the access to public services and poverty reduction. However, by exploring the link between fiscal arrangements and the quality of public services [15], Cheng et al. suggests that shared amenities like public parks may not benefit from more dispersed fiscal arrangements and that public services such as public education can benefit from fiscal decentralization [16]. Moreover, advances in science and technology can also facilitate the achievement of public resource sharing. The utilization rate of ICTs is significantly correlated with the level of public services in society [17]. The application of new technology can increase the feasibility of cross-organizational resource sharing and enable remote areas to enjoy the same quality of public resources [18]. And there are several scholars proposing that cross-jurisdictional resource sharing service models can provide at least as many mandated services as more non-mandated services, and with higher quality [19], [20]. However, there are researchers who dispute this. Mohd Rasdi and Tangaraja argued that ICT support and external motivational factors are not enablers of knowledge sharing behavior (KSB) in public sector organizations [21]. Hence, it is clear that there is still a debate about the effect of certain factors on the level of public resource-sharing, which needs to be verified based on more data and in multiple dimensions.

In addition, some studies have been conducted and they proposed countermeasure suggestions and implementation approaches to promote balanced resource-sharing such as achieving matching supply and demand of public resources [22] and promoting digital sharing of public resources [23], [24]. However, in general, there is a lack of studies that measure SPRDS from a comprehensive and multi-dimensional perspective, focusing on the digital era. Therefore, this paper proposes to measure SPRDS among 31 provinces and municipalities in China by the global entropy weight method (GEWM). And, a panel data model is constructed to identify the factors influencing the digital sharing of SPRs based on panel data from 2015 to 2020. This study is of great practical significance for using digital technology to solve public problems, exploring innovative paths to enhance the level of equalization and universality of SPRs, and promoting high-quality and stable socio-economic development.

This study is organized into four sections. This introduction is followed by the literature review (Section 1). Then, a comprehensive index system for digital sharing of SPRs is described and the GEWM is introduced. Meanwhile, the raw data sources in the evaluation process of SPRDS are presented (Section 2). The results are analyzed and discussed in terms of both sharing level measures and its influencing factors (Section 3). Finally, the main conclusions and recommendations for improving SPRDS are presented (Section 4).

2. DATA AND METHODS

2.1. Index System Setting

There are still shortcomings in compulsory education, healthcare, culture and sports, and social services in China. Using new technologies such as big data and the Internet of Things to promote the development of public services and the balanced allocation of public resources is intensely needed. According to the "the 14th Five-Year Plan for Public Services", public resource services mainly include compulsory education, medical and health care, employment and pension, culture and entertainment, and social services [41]. In addition, many scholars have constructed indicators that mainly include the above-mentioned aspects to measure basic public services (see Table 1). Therefore, this paper constructs an index system from the perspective of digitization, networking, and intelligence, following the basic principles of index system establishment and considering data availability. The index system includes six dimensions, including infrastructure, science and technology (S&T), education, culture, healthcare, and community services. It is designed to evaluate SPRDS comprehensively (see Table 2).

Table 1. Dimensions of the evaluation system for digital sharing of SPRs

	Infrastructures	S & T	Education	Culture	Healthcare	Community services
Zhang et al 2013 [25]; Li et al 2017 [26]; Lu et al 2019 [27]; Li and Zhao 2020 [9]	√	√	√	√	√	√
Liu and He 2019 [28]; Cheng and Yin 2019 [29]	√		√	√	√	√
Qi and Qin 2020 [30]; Guo et al 2021 [31]; Li and Tan 2022 [32]	√	√	√	√	√	
Wu and Xiao 2021 [1]		√	√		√	√

2.2. Data Sources

A panel data set involving 31 provinces (excluding Hong Kong, Macao and Taiwan) from 2015 to 2020.in China is selected to keep data continuity and consistency. The research data are mainly obtained from the 2016-2021 China Statistical Yearbook (CSY), China Science and Technology Statistical Yearbook (CSTCY), China Education Statistical Yearbook (CESY), China Information Yearbook (CIY), China Culture and Heritage and Tourism Statistical Yearbook (CCHTSY). Some data are also from Development Reports of China's Internet (DRCI), China Information Society Development Report (CISDR) and China National Bureau of Statistics (CNBS). Some of the missing data were complemented by interpolation and linear regression to finally obtain 3,348 sample values.

Table 2. Comprehensive evaluation index system of SPRDS

Target Layer	System Layer	Indicator Layer	Description	Attribute	Source
Comprehensive index of SPRDS	Infrastructures	Internet penetration rate	Internet penetration rate	+	CSY
		Smartphone penetration rate	Number of cell phones per 100 people	+	CNBS
		Internet broadband coverage rate	Ratio of Internet broadband access users to total households	+	CNBS
		Communication fiber optic cable construction rate	Ratio of fiber optic cable length to area	+	CNBS
	S & T	S&T information network penetration rate	Number of science popularization activities per 100 people	+	CSTSY
		S&T digital resources sharing rate	Number of retrieved papers in S&T	+	CNBS
		S&T network platform construction rate	Number of various regional S&T websites	+	CSTSY
	Education	Smart classroom construction rate	Ratio of the number of network multimedia classrooms to the total number of classrooms	+	CESY
		Smart teaching equipment sharing rate	Informatization facilities value per school	+	CESY
		Education digital resource sharing rate	Number of electronic books and audiovisual documents per capita	+	CESY
	Culture	Digital broadcasting coverage rate	Ratio of digital TV subscribers to total households	+	CHTSY
		Electronic reading room construction rate	Number of electronic reading room terminals per capita	+	CNBS
		Amount of digital cultural resources	Number of Internet products per capita	+	CIY
	Healthcare	Online medical services	Number of outpatient appointments online	+	CHTSY
		Healthcare network platform construction rate	Number of regional healthcare information statistics centers	+	CISDR
		Amount of healthcare and nursing personnel resources	Number of health technicians per 10,000 people	+	CNBS
	Community services	Online government services	Online government index	+	DRCI
		Digital life penetration rate	Mobile Internet traffic use per capita	+	CNBS

Note: "+" refers to that the indicator is positive, "-" refers to that the indicator is negative.

2.3. Global Entropy Weight Method

There are mainly subjective and objective methods to determine the indicators' weights. The subjective weight methods, such AHP and Delphi, are influenced by subjective factors and the accuracy of their results is questionable. The global entropy weight method (GEWM) is an objective weighting method. It makes full use of the objective characteristics of data, which can be used to analyze the evaluation indexes vertically and horizontally from a global perspective and assign weights to the evaluation indexes [33]. It is to sort the cross-sectional data of different years by year, organize them into a two-dimensional table of panel data, and then calculate them according to the traditional entropy weight method [34]. More scientific and objective results can be obtained by GEWM. The specific operation steps are as follows.

(1) If there exist t copies of cross-sectional data X^t for n indicators of m regions, t represents the evaluation year. These tables are arranged in chronological order to form a global entropy weight evaluation matrix of order $mt \times n$.

$$X = X^1, X^2 \ldots X^t, X^t = x_{ij}(t) \tag{1}$$

(2) To avoid the difference in data dimension among the indicators, we have to normalize the data with the below method.

$$\begin{cases} X_{ij} = \frac{x_{ij} - \min\limits_i\{x_{ij}\}}{\max\limits_i\{x_{ij}\} - \min\limits_i\{x_{ij}\}}, if\ x_{ij}\ is\ a\ positive\ indicator \\ X_{ij} = \frac{\max\limits_i\{x_{ij}\} - x_{ij}}{\max\limits_i\{x_{ij}\} - \min\limits_i\{x_{ij}\}}, if\ x_{ij}\ is\ negative\ indicator \end{cases} \tag{2}$$

Where X_{ij} and x_{ij} refer to the normalized and original values of the j-th variable for the i-th object, respectively. And $\max\limits_i\{x_{ij}\}$ and $\min\limits_i\{x_{ij}\}$ refer to the maximum and minimum values of the j-th variable among the i-th objects, respectively.

(3) Calculate the information entropy of the j-th indicator

$$E_j = -k \sum_{i=1}^{mt} P_{ij} \ln\left(P_{ij}\right) \tag{3}$$

Where $P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{mt} X_{ij}}, k = \frac{1}{\ln(mt)}$, and $E_j > 0$.

(4) Calculate the weight of the j-th indicator.

$$w_j = \frac{1 - E_j}{n - \sum_{j=1}^{n} E_j} \tag{4}$$

The weight of each indicator of SPRDS is shown in Table 3.

(5) Calculate the comprehensive evaluation value of SPRDS.

$$SPRDS_i = \sum_{j=1}^{n} w_j X_{ij} \tag{5}$$

After assigning weights to each indicator by the GEWM, the comprehensive evaluation value of SPRDS is finally calculated by using the weight of each indicator w_j and the processed data index X_{ij}. The weighted summation is shown in Table 4.

Table 3. Weight of each indicator of SPRDS

System Layer	Weight	Indicator Layer	Weight
Infrastructures	0.198	Internet penetration rate	0.030
		Smartphone penetration rate	0.026
		Internet broadband coverage rate	0.031
		Communication fiber optic cable construction rate	0.111
S & T	0.211	S&T information network penetration rate	0.048
		S&T digital resources sharing rate	0.090
		S&T network platform construction rate	0.073
Education	0.114	Smart classroom construction rate	0.024
		Smart teaching equipment sharing rate	0.051
		Education digital resource sharing rate	0.039
Culture	0.149	Digital broadcasting coverage rate	0.040
		Electronic reading room construction rate	0.028
		Amount of digital cultural resources	0.081
Healthcare	0.217	Online medical services	0.030
		Healthcare network platform construction rate	0.163
		Amount of healthcare and nursing personnel resources	0.025
Community services	0.112	Online government services	0.020
		Digital life penetration rate	0.092

3. RESULTS AND DISCUSSIONS

3.1. The Digital Sharing Level of SPRs

The GEWM is used to evaluate SPRDS in 31 provinces in China from 2015 to 2020, and the results are shown in Table 4. In general, from 2015 to 2020, the average value of SPRDS in China gradually rises from 0.1458 to 0.2907, with an average annual growth rate of 14.84%. It indicates that the digital sharing of public resources in China is showing vigorous development. However, only about 26% of provinces reached the mean in 2020. It suggested that SPRDS in China is not high and there is still much room for improvement.

From the provincial perspective, there are significant differences of the digital sharing status of SPRs among provinces. In terms of sharing level, three provinces and cities, including Beijing, Shanghai and Jiangsu, are at the top among 31 provinces, with a sharing level index of 0.5 or more in 2020. Sharing level indices of Four provinces and cities are between 0.3 and 0.5, such as Tianjin, Zhejiang, Guangdong and Sichuan. The rest of the provinces have a sharing level index between 0.1 and 0.3. In terms of the magnitude of changes in the sharing level index, the sharing level indices of all provinces show different degrees of growth from 2015 to 2020. the sharing level index of Guizhou has the fastest growth rate with annual growth rate of 28.34%. In addition, provinces located in central region (CR) and western region (WR), such as Qinghai, Tibet, Ningxia and Anhui, show more obvious growth. In general, the sharing levels in CR and WR have increased faster than in the east region (ER). There may be two reasons for this phenomenon. One is that the government has made greater efforts to supply SPRs and support their digital sharing in CR and WR, and the other is that the development of CR and WR lags significantly behind that of ER. And they have more room for growth. Combined with Figure 1, the provinces and cities with high SPRDS in China from 2015 to 2020 are mainly concentrated in the eastern coastal region. In CR and WR, the digital sharing levels of Sichuan, Hubei and Anhui are relatively high, while those in the rest of the provinces and cities are generally low. In addition, the internal differences of the sharing level indices are greater in ER than in WR and greater in WR than in CR.

Table 4. Comprehensive value of SPRDS

Province	2015	2016	2017	2018	2019	2020	Province	2015	2016	2017	2018	2019	2020
Beijing	0.460	0.483	0.489	0.562	0.603	0.652	Guangdong	0.259	0.317	0.344	0.390	0.439	0.478
Tianjin	0.220	0.240	0.229	0.267	0.313	0.365	Guangxi	0.097	0.108	0.130	0.183	0.221	0.259
Hebei	0.100	0.110	0.134	0.172	0.198	0.248	Hainan	0.098	0.106	0.1300	0.162	0.188	0.216
Shanxi	0.118	0.133	0.182	0.171	0.202	0.234	Chongqing	0.143	0.182	0.199	0.238	0.272	0.2957
Inner Mongolia	0.126	0.127	0.131	0.166	0.201	0.236	Sichuan	0.165	0.197	0.205	0.285	0.364	0.423
Liaoning	0.161	0.176	0.191	0.200	0.206	0.235	Guizhou	0.061	0.074	0.098	0.135	0.178	0.211
Jilin	0.106	0.119	0.133	0.165	0.200	0.248	Yunnan	0.113	0.077	0.098	0.131	0.178	0.215
Heilongjiang	0.134	0.150	0.161	0.176	0.195	0.210	Tibet	0.063	0.060	0.078	0.119	0.154	0.200
Shanghai	0.342	0.358	0.401	0.452	0.502	0.548	Shaanxi	0.126	0.207	0.173	0.220	0.270	0.287
Jiangsu	0.249	0.297	0.358	0.427	0.500	0.552	Gansu	0.076	0.078	0.111	0.152	0.180	0.194
Zhejiang	0.296	0.302	0.343	0.371	0.418	0.436	Qinghai	0.077	0.085	0.100	0.165	0.204	0.252
Anhui	0.093	0.122	0.144	0.189	0.227	0.259	Ningxia	0.077	0.094	0.112	0.154	0.188	0.219
Fujian	0.154	0.161	0.211	0.222	0.243	0.264	Xinjiang	0.081	0.087	0.098	0.125	0.174	0.208
Jiangxi	0.076	0.088	0.115	0.163	0.176	0.205	ER	0.229	0.250	0.277	0.316	0.351	0.388
Shandong	0.176	0.196	0.218	0.252	0.246	0.276	CR	0.109	0.124	0.145	0.177	0.201	0.234
Henan	0.089	0.103	0.122	0.156	0.180	0.204	WR	0.100	0.115	0.128	0.173	0.215	0.250
Hubei	0.145	0.157	0.162	0.200	0.235	0.286	Mean	0.146	0.163	0.183	0.222	0.256	0.291
Hunan	0.109	0.120	0.138	0.194	0.193	0.226	—	—	—	—	—	—	—

Note: The eastern region (ER) in China includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan. The central region (CR) in China includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi Hunan, Hubei, Henan. The western region (WR) in China includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

From the regional perspective, the disparity in SPRDS among the three regions is significant. The digital sharing index of ER is the highest, which is much higher than the national mean and the indices of CR and WR. The index of CR was slightly higher than that of WR until 2018. But it was overtaken by WR after 2018. Specifically, the index of ER showed a linear evolutionary trend with a relatively stable growth speed. The index of CR showed a steady upward trend. And it was characterized by synchronization with the national development trend. The index of WR grew slowly until 2017 and then transformed into a rapid growth phase to catch up to CR. It successfully overtook that of CR after 2018. (See Figure 2). One possible reason is that the digital sharing level is closely related to internal and external factors such as regional economic development, digital sharing environment, and individuals' awareness and willingness to share [34]. Moreover, the government has formulated a series of policies and initiatives to achieve balanced development and equitable sharing of public resources and services. These policies including rural revitalization and digital China, have enabled the rapid development of the backward rural areas in CR and WR, which enhanced the construction and development of regional digitalization, networking and intelligence, and promoted the development of digital sharing of SPRs.

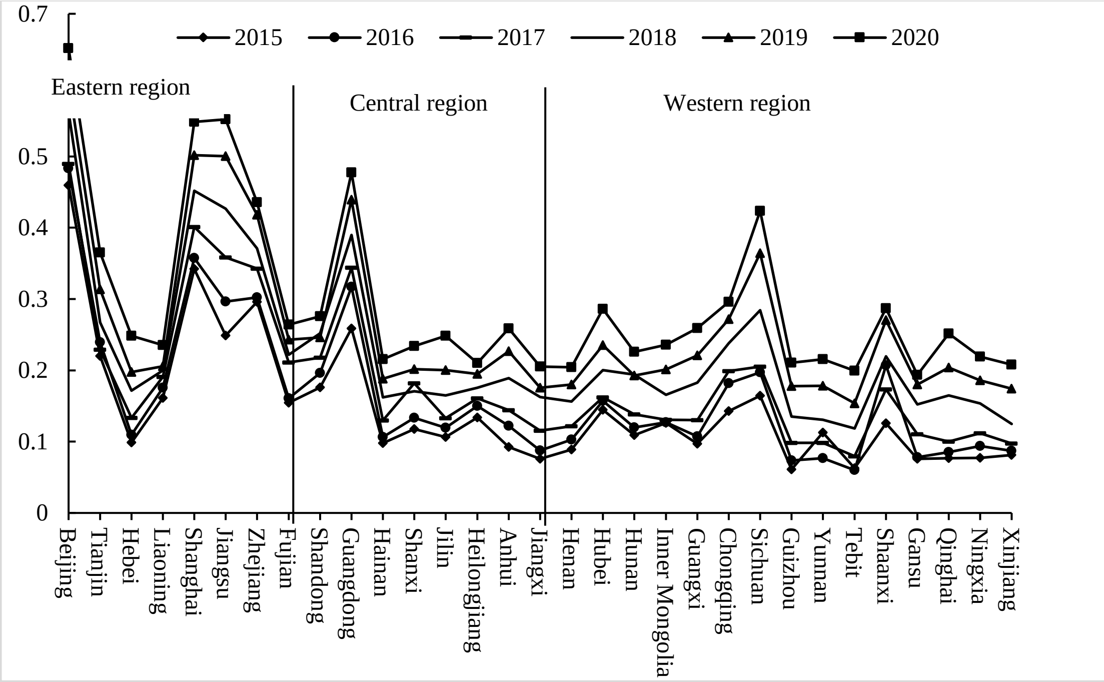

Figure 1. Distribution of the comprehensive index of SPRDS in China

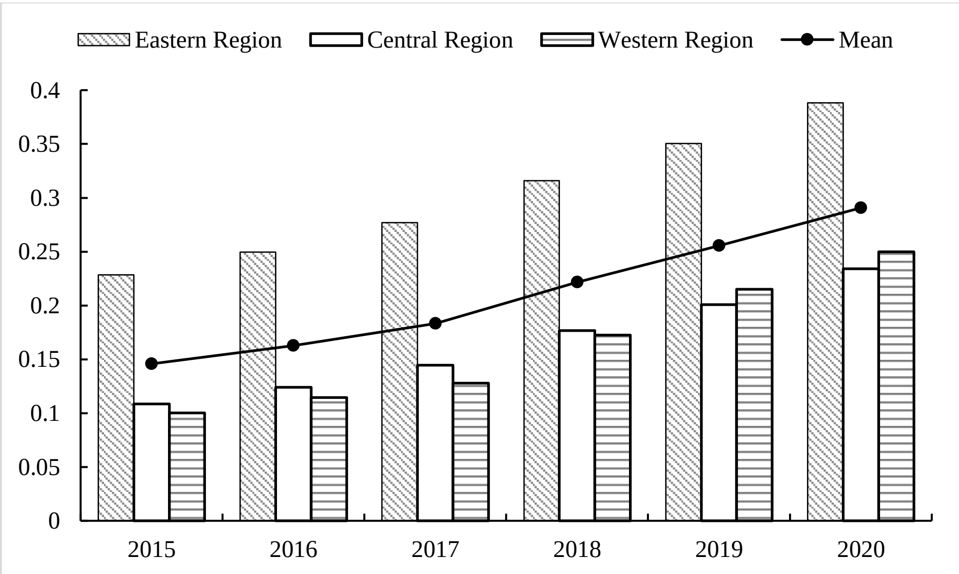

Figure 2. Trends in the of SPRDS nationwide and in the three regions

3.2. Influencing Factors

The sharing level of SPRs reflects the efficiency and fairness of resource allocation. It also directly reflects the quality of the people’s life. In addition, the balanced development and fair sharing of SPRs is important to build a moderately prosperous society and implement the rural revitalization strategy in China. Intuitively, SPRDS is not only directly influenced by the intensity of continuous government financial investment, but also has a significant correlation with the local socio-economic development [35]. In addition, factors such as urbanization, technological innovation, and population density also affect the supply and consumption of SPRs such as health, education, and employment [32], [36]. Therefore, internal and external factors are considered to deeply analyze the driving factors affecting SPRDS in this paper.

Referring to previous researches [37], [38], [39], we select eight indicators as explanatory variables considering the research design and the availability of data. These factors include government fiscal expenditure (GFE), economic development level (EDL), industrial structure (IS), degree of external openness (DEO), S&T innovation capacity (STI), urbanization level (UL), regional population size (RPS) and educational level of residents (ELR). Among them, GFE, EDL, IS, DEO, STI, UL, RPS, ELR are expressed by government general public service expenditures, regional GDP per capita, proportion of added value of tertiary industries to GDP, imports and exports of foreign-invested enterprises, R&D investment, the urbanization rate, regional resident population, and years of education per capita, respectively. In order to eliminate the influence of the dimensions, all data are normalized and analyzed. The relevant data were mainly calculated and obtained from the 2016-2021 CSTCY and CNBS.

3.2.1. Correlation Test.

A correlation test is provided in this paper. The results show that most of the variables are closely related, and their coefficients are significant at the 1% level. There is a positive correlation between them. It means that these variables can promote and enhance each other. However, their correlation coefficients between the variables are large, which implies that there may be multicollinearity between the variables (see Table 5).

Table 5. The correlation results of each variable

Variables	SPRDS	GFE	EDL	IS	DEO	STI	UL	RPS	ELR
SPRDS	1.000								
GFE	0.423***	1.000							
EDL	0.863***	0.227***	1.000						
IS	0.682***	-0.082	0.674***	1.000					
DEO	0.613***	0.586***	0.582***	0.266***	1.000				
STI	0.803***	0.770***	0.710***	0.375***	0.808***	1.000			
UL	0.768***	0.090	0.858***	0.616***	0.514***	0.563***	1.000		
RPS	0.213***	0.904***	0.051	-0.279***	0.495***	0.624***	-0.003	1.000	
ELR	0.670***	0.080***	0.685***	0.594***	0.306***	0.440***	0.870***	0.021	1.000

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$, and same below.

3.2.2. Unit-Root Test and Cointegration Test.

To avoid erroneous results of the regression model, we used IPS test to test the stationarity property of the variables. Table 6 present the results of the panel unit root tests. The results show that the null hypothesis of the existence of unit root cannot be rejected at the selected levels for IS, DEO, STI, UL, and RPS. However, all variables at the first difference are stationary at the 10% level.

Because the results of the panel unit root test indicated that the variables contained panel unit roots, the Kao cointegration test was used to investigate the long-run relationship between the variables in this paper. The test result, p-value < 0.001, indicates the null hypothesis should be rejected, i.e., there is cointegration relationship.

Table 6. The results of panel unit-root tests

Variables I(0)	GFE	EDL	IS	DEO	STI	UL	RPS	ELR
IPS	-9.264 ***	-5.581 ***	-5.306 ***	58.220	14.106	-8.077 ***	-1.534	-56.956 ***
p-value	0.000	0.000	0.000	1.0000	1.000	0.000	0.063	0.000
Variables I(1)	d_GFE	d_EDL	d_IS	d_DEO	d_STI	d_UL	d_RPS	d_ELR
IPS	-4.943 ***	-6.783 ***	-2.191 **	-2.313 *	-3.061 ***	-1.815 **	-2.9334 ***	-2.116 **
p-value	0.000	0.000	0.014	0.010	0.001	0.035	0.002	0.017

Note: I(0) refers to the level values of the variables and I(1) refers to the first difference values of the variables.

3.2.3. Analysis of the Regression Results.

According to the results of the correlation test, there may be multicollinearity between the selected indicators and SPRDS. Therefore, the regression model of the variables was conducted using the stepwise regression method to explore the influencing factors of SPRDS in this paper. The regression results are shown in Table 7. During the construction of the explanatory model using stepwise regression, the effect of ELR on SPRDS was tested to be insignificant at the 5% level. Therefore, ELR was excluded from the final regression explanatory model.

Table 7. The stepwise regression results of the explanatory model

Variables	Symbol	Coefficient	Standard error	t test	p-value
Government fiscal expenditure	GFE	0.394***	0.099	3.99	0.000
Economic development level	EDL	0.207***	0.070	2.97	0.003
Industrial structure	IS	0.254***	0.047	5.42	0.000
Degree of external openness	DEO	-0.090**	0.044	-2.03	0.044
S&T innovation capacity	STI	0.392***	0.097	4.03	0.000
Urbanization level	UL	0.238***	0.056	4.25	0.000
Regional population size	RPS	-0.200***	0.062	-3.25	0.001
Constant	_cons	-0.076***	0.028	-2.76	0.006
R^2	0.876				
R^2_a	0.871				
N	186				

According to the stepwise regression explanatory model, GFE, EDL, IS, STI and UL have a significant positive effect on SPRDS at the 1% level. Among them, the regression coefficient of GFE is largest, 0.394. It indicates that government fiscal expenditure can most significantly promote SPRDS. Each 1% increase in GFE improves SPRDS by 0.394%. The development of SPRDS requires government policy planning and financial support. The higher the government fiscal expenditure capacity, the stronger its ability to effectively supply public resources and services [40]. The regression coefficient of STI is 0.392, indicating that R&D investment can significantly promote SPRDS. In the process of digitization of SPRs, STI plays a crucial role, such as the construction of smart elderly platform, smart community transformation, and "Internet+" medical and health care. STI provides many opportunities for the full utilization of various public resources. In addition, intelligent interactive devices play an important role in the process of resource sharing. The rapid upgrade and improvement of intelligent interactive devices cannot be achieved without technological innovation. The better S&T innovation capacity, the more beneficial to SPRDS. The regression coefficients of IS, EDL and UL are similar, indicating that they have similar effects on SPRDS. A larger proportion of added value of tertiary industries to GDP tends to imply a higher EDL. Better urbanization and higher EDL will prompt people to aspire for a higher quality of life, which may increase the demand for SPRs [37]. High demand drives SPRs. The regression coefficients of DEO and RPS are less than 0, which are significant at the 1% level. It indicates that DEO and RPS have a significant negative effect on SPRDS. In general, the larger the population in a region, the lower the quantity and quality of SPRs supply per capita [39], which in turn affects the level and quality of SPRDS in society.

3.2.4. Regional Heterogeneity.

Stepwise regression models were constructed for ER, CR and WR to analyze the main influencing factors of SPRDS in different regions. The specific results are shown in Table 8.

Table 8. The regression stepwise results of three regions

	GFE	EDL	IS	DEO	STI	UL	RPS	_cons	R^2	R^2_a	N
ER	0.396***	0.328***	0.274***		0.415***		-0.299***	0.022	0.939	0.934	66
	(0.142)	(0.074)	(0.054)		(0.137)		(0.085)	(0.042)			
CR			0.268***	0.727***	0.500***	0.882***		-0.373***	0.837	0.822	48
			(0.084)	(0.247)	(0.077)	(0.104)		(0.048)			
WR	0.255**	0.369***	0.518***		0.890***	0.235***		-0.193***	0.750	0.731	72
	(0.113)	(0.135)	(0.121)		(0.218)	(0.084)		(0.049)			

Note: Standard errors in parentheses.

In Table 8, IS and STI have a positive influence on SPRDS in the three regions, which is significant at the 1% level. This indicates that the improvement of SPRDS depends on the upgrading of industrial structure and the development of S&T innovation. In addition, GFE and EDL significantly affect the development of SPRDS in ER and WR. However, their influence degrees are different. EDL in ER is higher, and its GFE promotes SPRDS more significantly than WR; economic development in WR is more backward, and its EDL promotes SPRDS more significantly. This shows that underdeveloped economic regions need to promote the development of digital sharing of SPRs by improving their economic level. In the developed economic regions, a reasonable fiscal expenditure structure can enhance SPRDS. What is more, UL has a significant contribution to SPRDS in CR and WR. It implies that the central and western regions with lower urbanization levels can promote the development of digital sharing of SPRs by narrowing the urban-rural gap and stimulating the demand for public resources. By region, in ER, SPRDS is mainly influenced by GFE, EDL, IS, STI, and RPS. In the CR, SPRDS is mainly influenced by IS, DEO, STI, and UL. In WR, SPRDS is mainly influenced by GFE, EDL, IS, STI and UL.

4. CONCLUSIONS

In this paper, Comprehensive evaluation index system of SPRDS is constructed. The panel data of 31 Chinese provinces from 2015 to 2020 are collected to measure SPRDS in China. Its evolutionary characteristics are illustrated according to the results. The influence factors of the public resource sharing are verified based on the stepwise regression model. The results show that the overall development level of digital sharing of SPRs in China is low, but its mean is gradually increasing. The gap between the eastern region and the central and western regions is obvious. Moreover, the government fiscal expenditure capacity, industrial structure, regional economic development level, S&T innovation capacity, and urbanization level can promote the digital sharing of SPRs. The degree of external openness and regional population size have negative effects on the digital sharing of SPRs.

Accordingly, we provide some recommendations for long-term and sustainable digital sharing of SPRs. The government should establish a modern fiscal system, enhance the fiscal expenditure capacity and public resource supply capacity. This could provide strong financial guarantees for the development of public resource sharing. In addition, ICTs could be used to establish a unified, coordinated and perfect public service information platform, integrate cross-sectoral and cross-regional public data resources in order to promote the digitization, networking and intelligence of SPRs. Meanwhile, the construction and application of intelligent and convenient service terminals such as digital TVs, self-media platforms and site screens could be promoted to enhance residents' enthusiasm for sharing SPRs. What's more, it will strengthen the construction of digital service infrastructure in the vast rural areas of central and western China and promote the digital transformation of traditional service industries. This could deepen the application of technology in areas such as smart healthcare, digital education and smart elderly care. It also encourages eastern provinces to actively explore the "standardization + digital intelligence + public services" model to promote the continuous improvement of the efficiency and sharing level of SPRs.

There are still some shortcomings in this paper. Due to the availability and completeness of data, the evaluation indicators in this paper are only selected from those with high concern. In addition, digital sharing of SPRs is influenced by various factors, such as the government and socio-economic development. Because most of these factors are difficult to quantify, such as the formulation and implementation of government policies and residents' willingness to share, qualitative indicators are less involved. In the future, qualitative and quantitative methods could be combined to investigating the factors influencing digital sharing of SPRs.

REFERENCES

[1] Wu J, Xiao J. Development Path based on the Equalization of Public Services under the Management Mode of the Internet of Things. Socio-Economic Planning Sciences 2021:101027. https://doi.org/10.1016/j.seps.2021.101027

[2] Dwivedi YK, Hughes DL, Coombs C, Constantiou I, Duan Y, Edwards JS, et al. Impact of COVID-19 Pandemic on Information Management Research and Practice: Transforming Education, Work and Life. International Journal of Information Management 2020; 55:102211. https://doi.org/10.1016/j.ijinfomgt.2020.102211

[3] Zhang Q, Wang L, Chai J, Pei D, Jiang Z. Research on Incentive Policies of Medical Information Sharing of Medical Consortium in China Based on the Principal-Agent Theory. 2016 Ieee International Conference on Industrial Engineering and Engineering Management (ieem, New York: Ieee; 2016, p. 1274–8.

[4] Li B, Li T, Yu M, Chen B. Can Equalization of Public Services Narrow the Regional Disparities in China? A Spatial Econometrics Approach. China Economic Review 2017; 44:67–78. https://doi.org/10.1016/j.chieco.2017.03.010

[5] Romanelli M. Towards Sustainable Ecosystems. Systems Research and Behavioral Science 2018; 35:417–26. https://doi.org/10.1002/sres.2541

[6] Pouri MJ, Hilty LM. Digitally Enabled Sharing and the Circular Economy: Towards a Framework for Sustainability Assessment. In: Schaldach R, Simon K-H, Weismüller J, Wohlgemuth V, editors. Advances and New Trends in Environmental Informatics, Cham: Springer International Publishing; 2020, p. 105–16. https://doi.org/10.1007/978-3-030-30862-9_8

[7] Li S, Jiang F. An Empirical Analysis of Social Public Resources Digital Sharing System: Dissipative Structure Theory. PLOS ONE 2022; 17: e0271300. https://doi.org/10.1371/journal.pone.0271300

[8] Cheng L, Wen Y. Research on the Measurement and Influencing Factors of Equalization of Basic Public Services from Different Urbanization Perspectives. Economic and Management Review, 2018;34:106–15.

[9] Li S, Zhao Z. Research on the Measurement of China's Social Public Resources Networking Urban and Rural Sharing Level. Survey the World, 2020:32-7.

[10] Zhang X, Yang S. Research on the Equalization Level of Basic Public Services in Heilongjiang Province. E3S Web of Conferences 2021; 292:03044. https://doi.org/10.1051/e3sconf/202129203044

[11] Wang L, Liu G. Research on Information Sharing Mechanism of Network Organization Based on Evolutionary Game. 3rd International Conference on Advances in Energy Resources and Environment Engineering, vol. 113, Bristol: Iop Publishing Ltd; 2018, p. 012183. https://doi.org/10.1088/1755-1315/113/1/012183

[12] Zhu P, Shen J, Xu M. Study on the evolution of information sharing strategy for users of online patient community. Pers Ubiquitous Comput 2020. https://doi.org/10.1007/s00779-020-01464-6

[13] Mazurova B, Kollar J. Unproductive Government Expenditure in Context of Fiscal Policy. Sgem 2016, Bk 2: Political Sciences, Law, Finance, Economics and Tourism Conference Proceedings, Vol I, Sofia: Stef92 Technology Ltd; 2016, p. 761–72.

[14] Halaskova R. Approaches to Evaluate Government Expenditures on Services in EU Countries. Ostrava: Vsb-Tech Univ Ostrava; 2019.

[15] Sanogo T. Does Fiscal Decentralization Enhance Citizens' Access to Public Services and Reduce Poverty? Evidence from Côte d'Ivoire Municipalities in A Conflict Setting. World Development 2019; 113: 204–21. https://doi.org/10.1016/j.worlddev.2018.09.008

[16] Cheng Y, Shi Y, Andrew S. Exploring the Link between Fiscal Arrangements and the Quality of Public Services: Evidence from Major US Urban Park Systems. Public Performance & Management Review 2020. https://doi.org/10.1080/15309576.2020.1781215

[17] Pick JB, Sarkar A, Johnson J. United States Digital Divide: State Level Analysis of Spatial Clustering and Multivariate Determinants of ICT Utilization. Socio-Economic Planning Sciences 2015; 49: 16–32. https://doi.org/10.1016/j.seps.2014.09.001

[18] Meijer AJ. Networked Coproduction of Public Services in Virtual Communities: From a Government-Centric to a Community Approach to Public Service Support. Public Administration Review 2011; 71: 598–607. https://doi.org/10.1111/j.1540-6210.2011.02391.x

[19] Shah GH, Badana ANS, Robb C, Livingood WC. Cross-Jurisdictional Resource Sharing in Changing Public Health Landscape: Contributory Factors and Theoretical Explanations. Journal of Public Health Management and Practice 2016; 22:110–9. https://doi.org/10.1097/PHH.0000000000000368

[20] Humphries DL, Hyde J, Hahn E, Atherly A, O'Keefe E, Wilkinson G, et al. Cross-Jurisdictional Resource Sharing in Local Health Departments: Implications for Services, Quality, and Cost. Frontiers in Public Health 2018; 6:115. https://doi.org/10.3389/fpubh.2018.00115

[21] Mohd Rasdi R, Tangaraja G. Knowledge-sharing Behaviour in Public Service Organisations: Determinants and the Roles of Affective Commitment and Normative Commitment. European Journal of Training and Development 2020; ahead-of-print. https://doi.org/10.1108/EJTD-02-2020-0028

[22] Enata T, Sato T, Takahashi Y, Yano K. Public Resource Supply-Demand Matching on Distributed Cooperative Scheduling. New York: Ieee; 2018. https://doi.org/10.1109/IIAI-AAI.2018.00142

[23] Pereira HGG, Fong PWL. SEPD: An Access Control Model for Resource Sharing in an IoT Environment. In: Sako K, Schneider S, Ryan PYA, editors. Computer Security – ESORICS 2019, Cham: Springer International Publishing; 2019, p. 195–216. https://doi.org/10.1007/978-3-030-29962-0_10

[24] Pardo-García N, Simoes SG, Dias L, Sandgren A, Suna D, Krook-Riekkola A. Sustainable and Resource Efficient Cities platform – SureCity Holistic Simulation and Optimization for Smart Cities. Journal of Cleaner Production 2019; 215:701–11. https://doi.org/10.1016/j.jclepro.2019.01.070

[25] Zhang Q, Tang X, Marinko RGP. Dynamic Evaluation and Determinants of China's Inter, Regional Equalization of Basic Public Services. Economic Research 2013; 26:49–68. https://doi.org/10.1080/1331677X.2013.11517590

[26] Li B, Li T, Yu M, Chen B. Can Equalization of Public Services Narrow the Regional Disparities in China? A Spatial Econometrics Approach. China Economic Review 2017; 44:67–78. https://doi.org/10.1016/j.chieco.2017.03.010

[27] Lu J, Li B, Li H. The Influence of Land Finance and Public Service Supply on Peri-urbanization: Evidence from the Counties in China. Habitat International 2019; 92:102039. https://doi.org/10.1016/j.habitatint.2019.102039

[28] Liu H, He Q. The Effect of Basic Public Service on Urban-rural Income Inequality: A sys-GMM Approach. Economic Research 2019; 32:3205–23. https://doi.org/10.1080/1331677X.2019.1661005

[29] Cheng H, Yin J. Measurements of Provincial Rural Basic Public Service Levels and Analysis of Regional Differences. Statistics & Decision 2019; 35:100–3. https://doi.org/10.13546/j.cnki.tjyjc.2019.19.022

[30] Qi Y, Qin Y. Research on the Relationship between Public Service Equalization and Economic Development Imbalance in Urban Agglomerations. Statistics & Decision 2020;36:77–81.

[31] Guo M, Li J, Ma C. Under the Background of Digital Village Construction: Development Status and Promotion Strategy of Rural Basic Public Services. China Soft Science Magazine 2021:13–20.

[32] Li S, Tan W. Study on The Coupling Coordination Degree between Digital Sharing of Social Public Resources and Urban-rural Integration Development in China. BCP Business & Management 2022; 18:211–8. https://doi.org/10.54691/bcpbm.v18i.556

[33] Wang Z, Tang C. Dynamic Evaluation and Analysis of Regional Innovation System Performance Based on Overall Entropy Method. Journal of Technology Economics 2020, 39(03: 155-168.

[34] Li S, Jiang F. A Collaborative Evolutionary Model: The Self-organizing Evolutionary Process of Urban–rural Digital Sharing System of Social Public Resources. Journal of Economic Interaction and Coordination 2022. https://doi.org/10.1007/s11403-022-00362-9

[35] Xu Y, Zhao Y. New Urbanization, Local Government Fiscal Capacity and Public Service Supply. Jilin University Journal Social Sciences Edition 2015; 55:24-35+171-172.

[36] Tajudeen OS, Tajudeen IA, Dauda RO. Quantifying Impacts of Macroeconomic and Non-economic Factors on Public Health Expenditure: A Structural Time Series Model. African Development Review 2018; 30:200–18. https://doi.org/10.1111/1467-8268.12326

[37] Li J, Liu T, Huo J. Spatiotemporal Pattern and Influencing Factors of Rural Public Service Supply Quality in China. Economic Geography 2022; 42:132-43. https://doi.org/10.15957/j.cnki.jjdl.2022.06.014

[38] Ren X. Research on the Supply of Basic Public Services and the Quality of New Urbanization in the Stage of High-quality Development. Urban Problems 2022:16-26. https://doi.org/10.13239/j.bjsshkxy.cswt.220602

[39] Li T, Zhao Y, Kong X. Spatio-Temporal Characteristics and Influencing Factors of Basic Public Service Levels in the Yangtze River Delta Region, China. Land 2022; 11:1477. https://doi.org/10.3390/land11091477

[40] Li Q, Jiang F. Research on The Interactive Relationship Between Fiscal Expenditure, New Urbanization and Urban-Rural Sharing of Public Resources -- Empirical Analysis based on VAR Model. Scientific Journal of Economics and Management Research 2022; 4:186–97.

[41] The 14th Five-Year Plan for Public Services: http://www.gov.cn/zhengce/zhengceku/2022-01/10/5667482/files/301fe13cf8d54434804a83c6156ac789.pdf