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Digital Economy, Technological Innovation and Urban Resilience

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Abstract: As an emerging economic form, the digital economy is a crucial force in promoting high-quality economic development, resolving regional development incoherence, and improving the level of urban resilience. In this paper, the urban resilience indicator system is composed of four dimensions: social resilience, economic resilience, infrastructure resilience, and ecological resilience. Meanwhile, the digital economy indicator system is composed of five dimensions: Internet penetration rate, number of Internet-related employees, Internet-related output, number of mobile Internet users, and digital financial inclusion development. The development level was measured using the entropy value method and principal component analysis. On this basis, the impact of the digital economy on the urban resilience of 185 prefecture-level cities in China from 2011 to 2019 was analyzed using a benchmark regression model, spatial econometric model, and mediating effect model. This study shows the following: (1) The development of the digital economy has a positive impact on improving urban resilience. (2) The digital economy affects urban resilience with positive spatial spillover effects, and the temporal heterogeneity and heterogeneity of external openness levels are significant, while the regional heterogeneity is not significant. (3) The digital economy can improve urban resilience through the intermediary role of technological innovation. In the future, we should strengthen digital construction, deeply integrate the relationship between the digital economy, technological innovation, and urban resilience, give full play to the engine role of the digital economy, and further promote the enhancement of sustainable urban development.

Keywords: digital economy; technological innovation; urban resilience; spatial spillover

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Citation: Shi, Y.; Zhang, T.; Jiang, Y. Digital Economy, Technological Innovation and Urban Resilience. *Sustainability* **2023**, *15*, 9250. https://doi.org/10.3390/su15129250

Academic Editors: Colin A. Jones and Steve W. Lyon

Received: 27 March 2023
Revised: 23 May 2023
Accepted: 6 June 2023
Published: 8 June 2023

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1. Introduction

Faced with the frequent occurrence of various natural and human-made disasters around the world and various urban problems, coupled with the rampant coronavirus in the past three years, people are gradually recognizing that the improvement of urban resilience levels is an important element of being able to cope with various exogenous shocks. Therefore, in terms of academic research, the content of urban resilience has involved different fields, such as disaster management [1], urban planning [2], and sustainable development [3]. In terms of policy, in 2013, the Rockefeller Foundation promoted the urban construction process through the "Global 100" resilient cities. The 20th National Congress of the Communist Party of China proposed the implementation of urban renewal initiatives to create livable, resilient, and smart cities. The world is now facing unprecedented changes. The multi-polarization of the world, the deepening of social informatization, and the rise of the digital economy have undoubtedly accelerated the process of urbanization. The study of the digital economy was described for the first time in 1996 by Don Tapscott in the book *Digital Economy: Promise and Peril in the Age of Networked Intelligence*, which elaborated on the impact of the digital economy and the challenges it poses on global development [4]. Later, in September 2016, the G20 Initiative on Digital Economy Development and Cooperation was signed at the G20 summit, which, for the first time, globally connoted the digital economy interpretation; at the same time, the 20th National Congress of the Communist Party of China pointed out the need to accelerate digital economy growth, encourage deep

integration of the digital and real economies, and establish an internationally competitive digital industry cluster. The development of the digital economy not only provides sufficient information support for the construction of resilient cities but also coordinates and optimizes the applicability of different subsystems of resilient cities through big data, as shown in an in-depth study and policy update [5]. Therefore, does the digital economy drive the level of urban resilience? If the hypothesis is confirmed, is there a spatial spillover effect? What is heterogeneity? Additionally, what are the mechanisms of action behind it? These questions of practical relevance need to be explored in depth, seeking to provide some reference for policy research on sustainable urban development.

1.1. Literature Review

The current academic research on the digital economy can be divided into two aspects: the measurement of the digital economy, and the impact mechanism of the digital economy on a particular element of society. In terms of digital economy measurement, it can be roughly divided into four main methods: national economic accounting method research, digital economy value-added measurement, satellite account construction, and index compilation [6], but due to the difficulty of data acquisition, the construction of an evaluation index system has become the primary way for academia and government departments to examine the development level of the digital economy. Liu et al. [7] constructed an intelligent evaluation index system from three aspects: intelligent foundation, intelligent technology, and skillful results. The smart evaluation index system was built to measure the development level of the digital economy. Bryan Tang et al. [8] measured the level of the digital economy from four dimensions: digital infrastructure, digital innovation capacity, digital industry scale, and digital technology application. In 2014, the EU published the "EU Digital Economy and Society Report", which portrayed the development level of the digital economy in EU countries using 31 indicators from 5 main aspects: broadband access, human capital, Internet application, digital economy application, and digital public services. However, not all measures of the digital economy apply to Chinese prefecture-level cities. In terms of the impact mechanism of the digital economy on a certain factor of society, it can be divided into three aspects: economy, environment, and innovation. From an economic point of view, Zhao et al. [9] verified the impact of the digital economy on green total factor productivity using regression models based on panel data of Chinese prefecture-level cities from 2011 to 2019 and concluded that a higher level of the digital economy is more conducive to improving green total factor productivity, and it can also be influenced by the upgrading of enterprise production technology. Guan et al. [10] studied the impact and transmission mechanism of the digital economy development level on industrial structure transformation and upgrading based on panel data of 271 prefecture-level cities in China from 2011 to 2018, concluding that digital economy development can promote industrial structure upgrading, and this impact has non-linear characteristics and spatial heterogeneity. Kim et al. [11] examined the impact of the digital economy on industrial structure transformation and upgrading through "Industry 4.0" to explain the impact of the digital economy on the emerging manufacturing industry in Asia, specifically exploring the readiness of Asia for Industry 4.0 and the factors that determine its enhancement. From an environmental perspective, Hojnik et al. [12] interviewed companies through semi-structured interviews and concluded that the digital economy can optimize products and reduce energy consumption, thus mitigating the environmental impact. Kokina et al. [13] verified the digital economy as an example of the industrial Internet empowering traditional factors of production, reducing energy consumption, and, at the same time, improving the efficiency of all aspects of industry to achieve energy efficiency and promote green development. From the perspective of technological innovation, macroscopically, the digital economy can drive industrial organizational change and innovation in industry by improving resource allocation efficiency and space. The micro digital economy relies on digital technology data homogeneity and other characteristics of

data as the main body of innovation activities, thus driving cost competitive advantage, and helping to optimize production to improve enterprise efficiency and innovation capacity.

Resilience originally referred to the ability of an object to return to its original state after being subjected to external forces [14]. In 1973, ecologist Holling introduced the concept of resilience to the field of ecology [15], and as the research has progressed, "resilience" has been widely used in urban studies. The Resilience Alliance defines urban resilience as follows: the ability of a city to maintain its original structure and critical functions after external disturbances. Meerow et al. [16] reviewed this and argued that urban resilience is the ability of an urban system and all of its constituent socio-ecological and socio-technical networks to maintain or rapidly recover desirable functions in the face of disturbances, to adapt to change, and to rapidly transform systems that limit the current or future adaptive capacity at different temporal and spatial scales.

Current academic research on urban resilience has two parts: comprehensive evaluation, and examination of influence mechanisms. Regarding the comprehensive evaluation of urban resilience, Tabibian et al. [17] constructed an urban resilience evaluation index system to assess the level of urban resilience in District 8 of Tehran, Iran, and concluded that the level of urban resilience in this region is low. Yang et al. [18] constructed an urban resilience gray evaluation model to evaluate the resilience of 31 provinces in China from 2016 to 2018. They concluded that there is variability among provinces and uncoordinated development at each criterion level, and proposed countermeasures. To study this more concretely, Zhu et al. [19] used the entropy method and ESDA to analyze the urban resilience level of three major urban agglomerations in China, and concluded that the urban resilience level of three major urban agglomerations continues to grow, among which the Beijing–Tianjin–Hebei region is driven by the dual core of Beijing and Tianjin, the Yangtze River Delta has an olive-shaped structure, and the Pearl River Delta has a pyramidal structure. Regarding the urban resilience impact mechanism test, it can be analyzed from both economic and disaster aspects. From the economic side, taking 41 prefecture-level cities in the Yangtze River Delta region, one of China's urban agglomerations, as examples, Hu et al. [20] explored the impact and path of the digital economy on urban economic resilience based on panel data from 2011 to 2019, and concluded that the development of the digital economy could significantly enhance the level of urban economic resilience, and there are positive spatial spillover effects and heterogeneity. Through factor and network analyses, Ramezani et al. [21] explored the relationship between urban resilience and urban poverty, where areas with low income that are not subjectively poor were found to have higher levels of urban resilience. Zhang et al. [22] putting aside the relationship between urban agglomerations, discussed the effect of urbanization quality based on panel data from 11 prefecture-level cities in Shanxi from 2003 to 2017, and concluded that high-quality urbanization has a negative effect on flooding, and urban resilience has a significant negative effect as a mediating variable. In a similar vein, Liao et al. [23] studied that all dimensions of urban resilience had a significant positive relationship with residents' well-being.

1.2. Contributions of This Work

In summary, the current academic research on the digital economy and urban resilience is relatively abundant, and most of the studies on the relationship between the digital economy and urban resilience focus on one aspect of investigating the role mechanism of the digital economy and urban economic quality development. Hao et al. [24] explored the impact and mechanism of digital finance on urban economic resilience based on panel data of 276 prefecture-level cities from 2011 to 2019 using the spatial Durbin model and mediating effect model and concluded that digital finance could improve the urban economic resilience level and has a positive spatial spillover effect. Cao et al. [25] studied the impact of the digital economy on high-quality urban economic development based on panel data from 288 prefecture-level cities in China from 2015 to 2018, and concluded that the digital economy could improve the level of high-quality urban economic development, and that there is a threshold effect. However, few studies have directly verified the impact of the

digital economy on urban resilience, and given this, the possible marginal contributions of this paper are as follows: (1) Not limited to the dimension of economic development, this study constructs an urban resilience indicator system composed of four dimensions: social resilience, economic resilience, infrastructure resilience, and ecological resilience, to verify the impact of the digital economy on urban resilience, and to more macroscopically and comprehensively explore the impact of the digital economy on urban development. (2) Few scholars have analyzed the spatial spillover effect of the digital economy on urban resilience at the level of prefecture-level cities. In this study, the selected spatial weight matrix takes into account the single perspective of the spatial adjacency matrix and geographic distance matrix and the double factor of the economic geographic weight matrix. Furthermore, this study explores the profound relationship between regions from multiple perspectives, and conducts heterogeneity analysis from three aspects: time, region, and external opening level. (3) The mediating role of technological innovation in low-carbon pilot policies to promote carbon efficiency was studied by Du et al. [26] However, this paper considers the driving role of technological innovation in promoting urban resilience in the digital economy process, verified the mediating effect of technological innovation using both the Sobel test and Bootstrap test, and further derived the mediating effect ratio, which provides a certain reference basis for policy formulation.

2. Material and Methods

2.1. Index System Construction, Data Sources, and Sample Selection

2.1.1. Indicator System Construction

(1) Relevant indicators to measure urban resilience

Regarding the measurement of the urban resilience level (UR), given that the volatility of measurement and single dimensionality obviously cannot meet the research needs, it has become the consensus of the academic community to conduct comprehensive measurement through a multidimensional indicator system. From the connotation of urban resilience, based on the principles of accessibility and the scientificity of indicators, as well as the studies of Zhou et al. [27], Zhang et al. [28], and Cheng et al. [29], we selected indicators of significance from four dimensions: social resilience, economic resilience, infrastructure resilience, and ecological resilience, as shown in Table 1. To overcome the influence of subjective factors, we used the entropy value method to comprehensively evaluate the resilience of 185 cities at the prefecture level and above. The final comprehensive index of city resilience was obtained using the entropy method.

(2) Relevant indicators for measuring the digital economy

Regarding the measurement of the level of the digital economy (DigE), this paper drew on the study of Zhao et al. [30], starting from five dimensions: the Internet penetration rate, the number of Internet-related employees, Internet-related output, the number of mobile Internet users, and the development of digital financial inclusion. The following specific indicators were used: the number of Internet users per 100 people, the proportion of employees in information transmission, computer services, and software, the total number of telecommunication services per capita, the number of Internet broadband access users per 100 people, and the China Digital Financial Inclusion Index, as shown in Table 1. The China Digital Financial Inclusion Index is jointly compiled by the Digital Finance Center of Peking University and Ant Financial Services Group. Principal component analysis was used to measure and obtain the comprehensive digital economy development index of each city.

(3) Mediating variables

With technological innovation (tech) as the mediating variable, patent-related data are often used to measure technological innovation, and patents include invention patents, utility model patents, and design patents, among which invention patents are more likely to highlight the novelty of technological innovation [31]. In this paper, drawing on the

study of Yu et al. [32], we used the number of invention patents granted/employees to measure the level of technological innovation in cities from the perspective of the output of innovation activities. This indicator not only takes into account the value of patents but also includes the data of employees in the measurement criteria, which can effectively compensate for the drawbacks of using a single patent quantity measurement.

Table 1. Urban resilience and digital economy indicator system.

Target Layer	Guideline Layer	Indicator Layer	Properties	Indicator Weights
Urban Resilience	Social resilience	Unemployment rate	−	0.0486
		Number of college students per 10,000 people	+	0.0847
		Number of basic medical insurance participants	+	0.0760
		Health technicians per 1000 population	+	0.0616
	Economic resilience	GDP per capita	+	0.0578
		Disposable income per capita	+	0.0535
		Per capita consumption expenditure	+	0.0549
		Financial revenue	+	0.0887
	Infrastructure resilience	Road area per capita	+	0.0536
		Number of buses per 10,000 people	+	0.0614
		Number of Internet broadband subscribers	+	0.0486
		Drainage pipe length	+	0.0820
	Ecological resilience	Greening coverage of built-up areas	+	0.0488
		Harmless disposal rate of domestic waste	+	0.0486
		Annual city water supply	+	0.0826
		Urban sewage treatment rate	+	0.0486
Digital Economy	Internet penetration rate	Number of Internet users per 100 people	+	0.1672
	Number of Internet-related employees	Computer services and software employees as a percentage of	+	0.2430
	Internet-related outputs	Total telecom services per capita	+	0.2430
	Number of mobile Internet users	Number of cell phone subscribers per 100 people	+	0.2461
	Digital financial inclusion development	China Digital Inclusive Finance Index	+	0.1006

Notes: A positive sign in an attribute indicates that the larger the value of the indicator in the indicator layer, the better the criterion layer. A negative sign indicates that the larger the value of the indicator at the indicator level, the worse the criterion level.

(4) Control variables

To more fully analyze the effects of the digital economy on urban resilience, it is important to control for variables that may have an impact. In this paper, the level of human capital (human), the level of openness to the outside world (open), the level of economic development (econo), the level of the ecological environment (ecolo), and the level of capital stock (cap) were selected as control variables. Among them, the level of human capital is characterized by the population with a general undergraduate degree or higher/resident population; the level of external openness draws on the study of Liu et al. [33] to characterize the total import and export trade/GDP; the level of economic development is characterized by the average wage of urban workers on the job; the level of the ecological environment is characterized by the area of green park space per capita; and the level of capital stock draws on the study of Zhang et al. [34], using the analysis of this paper. The year 2011 was used as the base period for calculation.

2.1.2. Data Sources and Sample Selection

Considering the accessibility and comparability of variable index data, this paper selected the data of 185 prefecture-level and above cities in China from 2011 to 2019 as the research sample, and the sample data were all obtained from the China Statistical Yearbook, China City Statistical Yearbook, China Statistical Yearbook of Science and Technology, China Statistical Yearbook of each province (autonomous regions and municipalities directly under the Central Government), and Peking University Enterprise Big Data Research Center. The linear interpolation method was used to supplement some missing data. In addition, considering the need for empirical analysis, reducing the quantitative differences among variables, and preventing estimation bias caused by the heteroskedasticity problem,

the natural logarithm values were taken for the digital economy, urban resilience, human capital level, openness level, economic development level, ecological environment level, and capital stock level. The descriptive statistics of each variable of the model are shown in Table 2.

Table 2. Descriptive statistics of variables of the model.

	Variables	Number of Observations	Average Value	Standard Deviation	Minimum Value	Maximum Value
Explained variables	UR	1665	0.2873	0.0674	0.0966	0.6957
Explanatory variables	DigE	1665	2.4000	1.1949	0.0834	13.8360
Intermediate variables	tech	1665	7.5439	9.9766	0.0606	73.1682
Control variables	human	1665	2.0305	2.1889	0.0847	12.7643
	open	1665	0.1838	0.2993	0.0001	3.6397
	econo	1665	10.7475	0.5540	9.0912	13.0557
	ecolo	1665	13.5072	4.1534	1.3600	37.9064
	cap	1665	1.3810×10^8	1.3959×10^8	6,524,260.0000	1.2117×10^9

2.2. Research Strategy

This paper focused on the impact of the digital economy on urban resilience and examined the mediating mechanism of technological innovation. First, the levels of the digital economy and urban resilience were comprehensively assessed using principal component analysis and the entropy method, respectively. Second, the OLS regression model was used to conduct the baseline regression of the digital economy and urban resilience, which was supported by 2SLS using the instrumental variable method to address the possible endogeneity issues. Then, the spatial correlation of the digital economy under different spatial weight matrices was verified using the Moran index, a suitable spatial econometric model was selected via the LM test, and the dynamic spatial model regression results of different spatial weight matrices under this model were calculated to verify the spatial correlation of urban resilience, and to discuss the heterogeneity of national prefecture-level cities, time, region, and the foreign openness level. Finally, the theoretical hypothesis that the digital economy can enhance urban resilience by promoting technological innovation was verified through the mediating effect model.

2.3. Research Methodology

2.3.1. Entropy Value Method

At present, there are many measurement methods for indicator weights. The Delphi method and hierarchical analysis method are subjective and have a certain bias to evaluate the research object. The entropy method is commonly used as one of the objective weighting methods, which can avoid the influence of human factors. The entropy method is a multi-attribute decision analysis method, mainly used to solve decision problems with multiple attribute indicators. The method is based on the concept of entropy in information theory and provides a scientific basis for decision-makers by calculating the relative entropy value between attribute indicators and determining the importance of each indicator in the overall decision problem. At the same time, the entropy method is improved by adding time variables to the original formula, which is more applicable to the panel data in this paper. The specific calculation process is as follows:

The positive and negative indicators are normalized using Equations (1) and (2), respectively:

$$x'_{\theta ij} = \frac{x_{\theta ij} - x_{min}}{x_{max} - x_{min}} \quad (1)$$

$$x'_{\theta ij} = \frac{x_{max} - x_{\theta ij}}{x_{max} - x_{min}} \quad (2)$$

Additionally, the indicator weight $P_{\theta ij}$, entropy value E_j, information utility value g_j, the weight of each indicator, and composite index W_j are calculated for each prefecture-level city in turn according to the following formula:

$$P_{\theta ij} = \frac{x'_{\theta ij}}{\sum_{\theta} \sum_{i} x'_{\theta ij}} \tag{3}$$

$$E_j = -k \sum_{\theta=1}^{r} \sum_{i=1}^{n} P_{\theta ij} \ln P_{\theta ij} \tag{4}$$

$$g_j = 1 - E_j \tag{5}$$

$$W_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{6}$$

where there are r years, n prefectures, and m indicators, and $x_{\theta ij}$ denotes the jth indicator value of prefecture i in the θth year.

2.3.2. Principal Component Analysis Method

The principal component analysis method is based on the idea of dimensionality reduction, converting high-dimensional data into low-dimensional data under the premise of losing less information to achieve the purpose of reducing the complexity of the prediction model. The integrated index after the transformation is the principal component, and the linear combinations of the original variables are composed of the obtained principal components; the principal components are uncorrelated with each other. The basic steps of principal component analysis are as follows [35]:

Data standardization:

$$x^*_{ij} = \frac{x_{ij} - \overline{x}}{\sigma} \tag{7}$$

where x_{ij} denotes the original data, $\overline{x}$ denotes the mean, and σ denotes the standard deviation.

The correlation coefficient matrix of the independent variables is found according to the standardized matrix, assuming that there are samples x, y. The formula is as follows:

$$cov(x, y) = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{(n-1)} \tag{8}$$

The eigenvalues λ_i and eigenvector u_i are calculated, and then the variance contribution e and cumulative contribution E_j of each principal component are found:

$$e = \frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{9}$$

$$E_j = \frac{\sum_{j=1}^{m} \lambda_j}{\sum_{i=1}^{n} \lambda_i} \tag{10}$$

Calculation of the final principal components:

$$y_i = \sum_{j=1}^{p} \sum_{i=1}^{n} u_{ii} x^*_{ij} \tag{11}$$

2.3.3. Spatial Autocorrelation Model

In this paper, the spatial agglomeration trend of the digital economy in Chinese prefecture-level cities was tested using *Moran's I*, which has the widest generalizability. The existence of spatial agglomeration was determined using global *Moran's I*, and the

significance test was performed with the standardized *Z*-value using the following formula:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{12}$$

$$S^2 = \frac{1}{n}\sum_{j=1}^{n}(x_i - \overline{x})^2 \tag{13}$$

$$Z_{score}(I) = \frac{I - E(I)}{\sqrt{VAR(I)}} \tag{14}$$

where x and S^2 denote the mean and variance, respectively, W_{ij} denotes the value of one element of the spatial weight matrix W, and $E(I)$ and $VAR(I)$ are the expected value and variance of $Moran's\ I$, respectively. If global $Moran's\ I$ is positive, there is a positive spatial correlation in the digital economy; if global $Moran's\ I$ is negative, there is a negative spatial correlation in the digital economy; if global $Moran's\ I$ is 0, the digital economy is randomly distributed in space. The p-value determines the significance level of the standardized Z-value; if $p < 0.05$, it is considered that there is no spatial correlation.

2.3.4. Spatial Error Model

The spatial error model (SEM) is one of the commonly used models in spatial measures. This model introduces spatial effects into the perturbation error term, assuming that spatial dependence is reflected in the perturbation error term, and it also measures the impact of error shocks in the dependent variable in the adjacent region on the local dependent variable [36], as follows:

$$Y = X\beta + \mu \tag{15}$$

where $\mu = \lambda W\mu + \varepsilon$, λ is the spatial error coefficient of the dependent variable, and ε is the random error vector.

2.3.5. Mediating Effect Model

There are two common methods for studying mediation effects: one is causal stepwise regression, whose theory was proposed by Wen et al. [37], and the other is the product coefficient method, which can be divided into the Sobel test and Bootstrap test. The first method is simple and easy to understand but less effective; therefore, this paper used the product coefficient method, in which the Sobel test requires the assumption that both the statistic and its product obey a normal distribution, and the Bootstrap test can replace the Sobel test at this time. Considering the feasibility and testing power of the method, this paper used both the Sobel test and the Bootstrap test to verify the mediation effect. The model is as follows:

$$Y = cX + e_1 \tag{16}$$

$$M = aX + e_2 \tag{17}$$

$$Y = c'X + bM + e_3 \tag{18}$$

where the coefficient c of Equation (1) is the total effect of the independent variable X on the dependent variable Y, the coefficient a of Equation (2) is the effect of the independent variable X on the mediating variable M, the coefficient b of Equation (3) is the effect of the mediating variable on the dependent variable while controlling for the effect of the independent variable on the dependent variable, the coefficient c' is the direct effect of the independent variable on the dependent variable, and e_1, e_2, and e_3 are the residuals.

3. Theoretical Mechanisms and Hypotheses

As a new economic form with all-factor digital transformation as an important driving force, the digital economy affects the level of urban resilience from four aspects: society,

economy, infrastructure, and ecology. In terms of society, according to the theory of transaction costs caused by the digital economy, the development of some network platforms in the digital economy has weakened the problem of information asymmetry between enterprises and consumers to a certain extent, and has had an impact on the traditional market structure. In terms of the economy, the application of digital economy platforms has significantly improved the convenience of economic financial services and reduced the difficulty of cross-regional transactions, therefore promoting the inclusiveness and sustainability of financial development. In terms of infrastructure, the development of the digital economy has led to the development of many high-tech industries, which account for an increasing proportion of the industrial structure and optimize it. In terms of ecology, the digital economy reduces the waste of unnecessary resources, frees up labor, and greatly reduces costs, which provides conditions for the improvement of resource allocation.

Based on the above analysis, we propose hypothesis H1: digital economy development has a positive impact on the improvement of urban resilience.

The emergence of the digital economy has brought new factors of production, including both digital technology and digital factors. Based on the digital technology–economy paradigm, data factors break the inherent geographical distance constraint by virtue of their low circulation cost and high utility, and promote the spatial flow of social resources and production factors, meaning that the role of the digital economy in influencing urban resilience shows a strong spatial spillover effect [38]. Based on the characteristics of China's vast territory, the geographical environment, resource endowment, capital stock, and economic policies vary greatly in different regions. Therefore, many scholars have analyzed the heterogeneity of the digital economy in affecting urban resilience based on different perspectives such as time, space, and the city scale. This paper analyzed heterogeneity from three perspectives: time, region, and the level of openness to the outside world.

Based on the above analysis, hypothesis H2 is proposed: the role of the digital economy in influencing urban resilience has a positive spatial spillover effect and is heterogeneous.

In the case of China, General Secretary Xi Jinping pointed out that it is necessary to develop the digital economy, accelerate the promotion of digital industrialization, rely on information technology innovation drive, and constantly give rise to new industries, new business models, and new development with new dynamic energy. The digital economy is characterized by extensive penetration into all aspects of economic development in the form of general-purpose technology, and industrial integration is achieved in the process of penetration, while the innovation of the digital economy spreads rapidly through spillover effects and is accompanied by a large number of technological innovations, in which economic efficiency, market mechanisms, social governance capacity, and other social development indicators are improved, i.e., the level of urban resilience is increased [39].

Based on the above analysis, hypothesis H3 is proposed: the digital economy will contribute to the level of urban resilience through the mediating role of technological innovation.

4. Results

4.1. Examining the Relationship between the Digital Economy and Urban Resilience

The focus of this paper is to test the relationship between the digital economy and urban resilience, and thus the basic regression model was set as follows:

$$UR_{it} = \alpha_0 + \alpha_1 DigE_{it} + \lambda_j \sum_{j=1}^{n} C_{it} + \mu_{it} \quad (19)$$

where i denotes the city, t denotes the year, UR_{it} characterizes the combined level of urban resilience, $DigE_{it}$ characterizes the level of the digital economy in the region, C represents the set of control variables, and μ_{it} is a random disturbance term.

The digital economy and urban resilience may have certain endogeneity problems. There are two common causes of endogeneity: First, concerning endogeneity due to omitted variables, the urban resilience of a region is influenced by a variety of factors related to the

region; although this paper controlled for characteristic variables that may affect the level of urban resilience in different dimensions, such as the level of human capital, the level of foreign openness, and the level of capital stock, it still could not effectively control for all omitted variables. Selection bias, as a special omitted variable, may also lead to endogeneity problems [40]. Second, there is mutual causality, i.e., a correlation effect between the digital economy and urban resilience. To address the above possible endogeneity problems, this paper adopted an instrumental variable approach to mitigate the estimation bias caused by endogeneity problems. Regarding the choice of instrumental variables, this paper referred to the study of Fu et al. [41], which used the distance from prefecture-level cities to Hangzhou to construct the instrumental variables; the spherical distance from each prefecture-level city to Hangzhou can be measured based on the latitude and longitude of each prefecture-level city. This characteristic geographical variable strictly satisfies the homogeneity requirement. These distances are then used as cross-sectional data but do not apply to the regression of panel data in this paper. Referring to Nunn [42], a time-dependent variable was introduced to construct the instrumental variable, and the interaction term between the spherical distance from each prefecture-level city to Hangzhou and the number of digital enterprises nationwide in the previous year was used as the instrumental variable in this paper in conjunction with the Statistical Classification of Digital Economy and its Core Industries released by the National Bureau of Statistics to verify the digital economy's promotion effect on urban resilience.

The regression results in Table 3 show that the basic OLS regression indicates that the digital economy has a significant contribution to urban resilience and passes the 1% significance test; the 2SLS regression still indicates that the digital economy can contribute to the level of urban resilience and passes the 10% significance test. The results of the 2SLS regression in Table 4 satisfy the hypothesis concerning the correlation of the instrumental variables, and the results indicate that there is a significant positive correlation between the digital economy and urban resilience with and without the inclusion of control variables, passing the 1% significance test. This result verifies hypothesis H1 of this paper, i.e., that the development of the digital economy has a positive impact on the improvement of urban resilience.

Table 3. Basic regression results of the digital economy and urban resilience.

Models	**1**	**2**	**3**	**4**
Method	**OLS**		**2SLS**	
Explained Variables	**lnUR**	**lnUR**	**lnUR**	**lnUR**
lnDigE	0.2222 ***	0.07050 ***	0.3099 **	0.1010 *
	(31.8370)	(12.4395)	(2.2120)	(1.8450)
lnhuman		0.008563 **		0.01134
		(2.5771)		(1.1365)
lnopen		0.01288 ***		−0.007399 **
		(6.3182)		(−2.2166)
lnecono		1.0166 ***		0.2077
		(13.1085)		(0.7334)
lnecolo		0.03918 ***		0.08339 ***
		(4.6848)		(8.0605)
lncap		0.1336 ***		−0.07010 ***
		(37.6128)		(−4.3211)
City-fixed	Y	Y	Y	Y
Year-fixed	Y	Y	Y	Y
Phase I F-value			7.1800	21.6300
Observations	1665	1665	1665	1665
Number of IDs	185	185	185	185

Notes: ***, **, * denote significance levels of 1%, 5% and 10% respectively.

Table 4. First-stage 2SLS regression results.

	1		2	
	Coefficient	**T-Value**	**Coefficient**	**T-Value**
Tool variables	0.0274 ***	2.6800	0.0472 ***	4.6500
Control variables	Not included		Included	
Observations	1665		1665	

Notes: *** denote significance levels of 1%.

4.2. Testing the Spatial Spillover Effects of the Digital Economy and Urban Resilience

In this paper, we used the Moran index in the spatial autocorrelation model to verify the "spreading" characteristics of the digital economy, in which the spatial weight matrix is usually set as the spatial adjacency matrix, the geographic weight matrix, or the economic distance weight matrix. Many scholars only set it from a single perspective of geography or economy. Economic factors and geographical factors were considered, and the reliability of the results was ensured by three weight matrices: spatial adjacency matrix, geographic distance matrix, and economic geographic distance matrix. According to the calculation results in Table 5, it can be seen that, regardless of the type of spatial weight matrix, the Moran index of the digital economy is positive during the study period, i.e., it always has a positive spatial correlation. All the matrices pass the 1% significance test, which indicates that the digital economy has an obvious spillover effect in space.

Table 5. "Spreading" characteristics of the digital economy, 2011–2019 (Moran index).

	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Geographic distance matrix	0.0730 *** (9.9130)	0.0810 *** (10.8780)	0.0900 *** (12.0810)	0.0740 *** (10.0950)	0.0730 *** (9.8670)	0.0670 *** (9.1290)	0.074 *** (10.1090)	0.0730 *** (9.9490)	0.0580 *** (8.0740)
Economic geographic distance matrix	0.4780 *** (10.1840)	0.5260 *** (11.1480)	0.5290 *** (11.2850)	0.4750 *** (10.0920)	0.4910 *** (10.4470)	0.4980 *** (10.5740)	0.4570 *** (9.7210)	0.4230 *** (9.0050)	0.3890 *** (8.2860)
Spatial adjacency matrix	0.3720 *** (6.7300)	0.4270 *** (7.6880)	0.3990 *** (7.2260)	0.3820 *** (6.9010)	0.3610 *** (6.5220)	0.3480 *** (6.2860)	0.3290 *** (5.9570)	0.2890 *** (5.2330)	0.2260 *** (4.1220)

Notes: *** denote significance levels of 1%. *Z*-values are in parentheses.

To verify the role of the digital economy in the resilience of the surrounding cities, a suitable spatial econometric model was selected for investigation. The spatial autocorrelation model (SAR), spatial error model (SEM), and spatial Durbin model (SDM) were among the spatial econometric models used, on which the LM test was conducted. Combined with the test results based on Table 6, after the Moran index was found to be significant, the LM-lag and LM-error tests were conducted, with both tests being significant. Then, the Robust-LM-lag and Robust-LM-error tests were carried out. Among the LM-error tests, only the Robust-LM-error test was significant; therefore, the spatial error model (SEM) was chosen as the model for analysis in this paper. Based on the results of the Hausman test, this paper selected the time-fixed effect model to verify the mechanism of action between the explanatory variables and the explained variables.

Table 7 reports the results of the dynamic spatial model regressions of the digital economy on urban resilience under different spatial weight matrices. The lagged term and global Moran index of urban resilience under the three different spatial weight matrices are positive and pass the significance test, indicating a significant positive spatial correlation of urban resilience. Specifically, in the case of the spatial spillover effect of urban resilience, not all the coefficients of the digital economy are significant, but they are all positive, indicating that the digital economy's sprawl promotes the spatial spillover effect of urban resilience while promoting the level of urban resilience, as well as promoting the urban resilience of neighboring areas. This result verifies hypothesis H2 of this paper, i.e., that the digital economy affects urban resilience with positive spatial spillover effects.

Table 6. LM test results.

	Geographic Distance Matrix		Economic Geographic Distance Matrix		Spatial Adjacency Matrix	
Inspection	**Statistical Quantities**	***p*-Value**	**Statistical Quantities**	***p*-Value**	**Statistical Quantities**	***p*-Value**
Moran index	35.062	0.000	8.831	0.000	26.127	0.000
LM-lag	57.224	0.000	15.884	0.000	38.737	0.000
R-LM-lag	0.537	0.464	0.274	0.601	0.796	0.372
LM-error	1071.545	0.000	75.855	0.000	588.533	0.000
R-LM-error	1014.857	0.000	60.244	0.000	550.592	0.000

Table 7. Spatial dynamic model regression results of the digital economy's sprawl and urban resilience.

Models	**1**	**2**	**3**
Spatial Matrix	**Geographic Distance Matrix**	**Economic Geographic Distance Matrix**	**Spatial Adjacency Matrix**
L.lnUR	1.07745 ***	0.90094 ***	0.94686 ***
	(8.1700)	(5.7000)	(5.7900)
lnDigE	0.00965	0.02174 ***	0.03066 ***
	(1.2900)	(3.5600)	(5.0800)
lnhuman	0.01632 ***	0.01664 **	0.01700 **
	(2.6200)	(2.5100)	(2.5500)
lnopen	−0.00263	−0.00238	−0.00341
	(−1.1100)	(−0.9500)	(−1.3200)
lnecono	1.17103	0.39178 ***	0.30665 **
	(1.5100)	(3.1900)	(2.4700)
lnecolo	0.05593 ***	0.07183 ***	0.07300 ***
	(6.9500)	(8.9600)	(9.0200)
lncap	−0.08904 **	0.05241	0.13360 ***
	(−2.5700)	(1.5700)	(3.9600)
Global Moran's I	0.8783 ***	0.6274 ***	0.6201 ***
(*p*-value)	(231.2700)	(36.8560)	(30.8990)
F-test	22.3120	67.4641	53.8042
W-test	290.0564	877.0335	699.4548

Notes: ***, ** denote significance levels of 1% and 5% respectively.

4.3. Heterogeneity of the Digital Economy and Urban Resilience

To further quantify the results of the overall spatial econometric regression of the digital economy on urban resilience for each prefecture-level city in China, the results were estimated using the time-fixed effect, individual fixed effect, and double fixed effect models under three spatial weight matrices. The results are shown in Table 8. The results of the fit of each model under different spatial weight matrices are combined, and it can be seen that the fit is always optimal only under the time-fixed effect model, which again verifies the correctness of the above Hausman test results. Taking model (1) as an example, the λ value is 0.4290 and passes the 1% significance test, which indicates that there is a significant spatial spillover effect of urban resilience in China, and the urban resilience level of a city is not only related to its own economic level and infrastructure level, but also influenced by the resilience level of neighboring cities, and every 1-percentage-point increase in the resilience level of neighboring cities will increase the resilience level of the central city by 0.4290 percentage points. The analysis of other models is similar. It can be seen that the λ values in some of the models do not pass the significance test, which may be due to the heterogeneity between cities, where the heterogeneity of the sample leads to the offset of positive and negative effects [43]. Therefore, heterogeneity analysis is particularly necessary.

Table 8. Spatial error model regression results of the digital economy's sprawl and urban resilience in Chinese prefecture-level cities.

	Geographic Distance Matrix			Economic Geographic Distance Matrix			Spatial Adjacency Matrix		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnDigE	0.0285 ***	−0.0071	−0.0056	0.0275 ***	0.0510 ***	−0.0070	0.0277 ***	0.0673 ***	−0.0050
	(2.8855)	(−1.2005)	(−0.9789)	(2.7744)	(4.2623)	(−1.1824)	(2.8434)	(13.6257)	(−0.8774)
lnhuman	0.0116 ***	0.0169 ***	0.0186 ***	0.0160 ***	0.0411 ***	0.0211 ***	0.0132 ***	0.0469 ***	0.0202 ***
	(3.3964)	(2.7709)	(3.0483)	(4.7193)	(6.0250)	(3.4768)	(3.8742)	(6.8419)	(3.3162)
lnopen	0.0169 ***	−0.0025	−0.0038	0.0178 ***	−0.0042	−0.0036	0.0175 ***	−0.0072 **	−0.0042
	(7.5552)	(−0.9573)	(−1.4829)	(8.2195)	(−1.4041)	(−1.4178)	(8.0496)	(−2.4247)	(−1.6391)
lnecono	1.1798 ***	0.6979 ***	0.7072 ***	1.0849 ***	0.6794 ***	0.7091 ***	1.1464 ***	0.5782 ***	0.6992 ***
	(14.4741)	(6.4415)	(6.8936)	(12.8357)	(5.6270)	(6.9396)	(14.1998)	(4.6985)	(6.8448)
lnecolo	0.0319 ***	0.0938 ***	0.0957 ***	0.0389 ***	0.0931 ***	0.0959 ***	0.0346 ***	0.0976 ***	0.0965 ***
	(3.8147)	(13.8843)	(14.2865)	(4.7593)	(12.6607)	(14.3770)	(4.1420)	(12.4570)	(14.4574)
lncap	0.1290 ***	−0.0624 ***	−0.0698 ***	0.1264 ***	0.0553 ***	−0.0668 ***	0.1288 ***	0.1064 ***	−0.0701 ***
	(35.5124)	(−4.1684)	(−4.9173)	(35.0125)	(2.7211)	(−4.7043)	(35.8736)	(7.5514)	(−4.9804)
λ	0.4290 ***	0.9643 ***	0.2593	0.2075 ***	0.5715 ***	0.1035 **	0.0080	0.1875 ***	0.0252
	(3.2793)	(101.3233)	(1.6282)	(5.2012)	(6.1354)	(2.3216)	(0.2666)	(7.0565)	(0.9068)
Time-fixed	Y	N	Y	Y	N	Y	Y	N	Y
City-fixed	N	Y	Y	N	Y	Y	N	Y	Y
Observations	1665	1665	1665	1665	1665	1665	1665	1665	1665
R-squared	0.7884	0.0000	0.0038	0.7874	0.7229	0.0002	0.7878	0.7558	0.0032
Number of IDs	185	185	185	185	185	185	185	185	185

Notes: ***, ** denote significance levels of 1% and 5% respectively.

This paper conducted heterogeneity analysis based on three classifications: time, region, and level of openness to the outside world. First, the sample was divided into two groups of samples, 2011–2016 and 2016–2019, using the holding of the G20 summit in 2016 as the time node for testing. Specifically, time was set as the time dummy variable (taking the value of 0 for 2011–2015 and 1 for 2016–2019), and the cross-product term of the time dummy variable and the core explanatory variables were included in the regression model. The results are shown in column 1 of Table 9. Then, given the differences in history and culture, natural resources, development patterns, and economic development levels of cities in east, central, and western China, this paper divided the research sample into eastern, and central, and western cities from the perspective of regional variability for the test. Specifically, we set east as the region dummy variable (the eastern region takes the value of 1, while other regions take the value of 0), and included the cross-product of this dummy variable and the core explanatory variables in the regression model. The results are shown in column 2 of Table 9. Finally, based on the connotation and requirements of China's new development pattern of "large domestic circulation and dual domestic and international circulation", creating a high level of openness to the outside world is undoubtedly an important task for China to achieve modernization [44]; therefore, the mean value of the level of openness to the outside world of each prefecture-level city was used as the classification criterion to divide the research sample into high-level and low-level areas of openness to the outside world. The results are shown in column 3 of Table 9.

According to Table 9, from the results in column 1, the coefficient of the cross-multiplier term of the digital economy and the time dummy variable (lnDigE×time) is significantly positive, indicating that the moderating effect of digital policy on the digital economy's promotion of urban resilience has been significantly enhanced with the establishment of digital policy at the 2016 G20 summit. This means that the government's strategic choices are particularly important [45,46]. From the results in column 2, the coefficient of the cross-multiplier term of the digital economy and the region dummy variable (lnDigE × east) is positive, but it does not pass the significance test, indicating that there is no significant difference between the promotion effect of the digital economy on urban resilience in the eastern, central, and western regions, probably because the sample classification is not specific enough to show the characteristics of specific regions. From the results in column 3, the coefficient of the cross-multiplier term of the digital economy and foreign openness

level (lnDigE × level) is positive and passes the 5% significance test, indicating that the effect of the digital economy on urban resilience is more obvious in regions with a high level of openness to the outside world. This result verifies hypothesis H2 of this paper, i.e., that the effect of the digital economy on urban resilience is heterogeneous.

Table 9. Heterogeneity test results.

	Time	Region	The Level of Openness to the Outside World
lnDigE	0.0444 ***	0.0703 ***	0.0644 ***
	(6.4040)	(11.8923)	(10.2189)
lnDigE×time	0.0345 ***		
	(6.3618)		
lnDigE×east		0.0008	
		(0.1405)	
LnDigE×level			0.0157 **
			(2.2309)
lnhuman	0.0103 ***	0.0087 **	0.0079 **
	(3.1325)	(6.5690)	(2.3823)
lnopen	0.0154 ***	0.0128 ***	0.0095 ***
	(7.5100)	(5.7016)	(3.7515)
lnecono	1.0528 ***	1.0156 ***	1.0070 ***
	(13.6980)	(13.0344)	(12.9805)
lnecolo	0.0366 ***	0.0392 ***	0.0404 ***
	(4.4204)	(4.6778)	(4.8205)
lncap	0.1309 ***	0.1336 ***	0.1332 ***
	(37.0187)	(37.1853)	(37.4781)
Observations	1665	1665	1665
R-squared	0.8013	0.7965	0.7971

Notes: ***, ** denote significance levels of 1% and 5% respectively.

4.4. Intermediary Mechanism Test

The Sobel test results are shown in Tables 10 and 11. From the test results, it can be seen that, corresponding to the mediation model (16), the regression coefficient c = 0.0702 is significant at the 1% level, which also indicates the total effect of the digital economy in promoting urban resilience, and the coefficients of the control variables all pass the 1% significance test, indicating that the digital economy, in general, drives the level of urban resilience. Each 1-percentage-point increase in the level of the digital economy significantly drives the level of urban resilience by 0.0702 percentage points. Corresponding to the mediation model (17), the regression coefficient a = 2.5903 is significant at the 1% level, the control variables pass at least the 5% significance test, and each 1-percentage-point increase in the level of the digital economy significantly drives the level of technological innovation by 2.5903 percentage points. Corresponding to the mediation model (18), the regression coefficients $c' = 0.0622$ and b = 0.0031 both pass the 1% significance test, and the control variables pass at least the 5% significance test, where $c' = 0.0622$ is the direct effect of the digital economy in promoting the level of urban resilience, and a×b is the indirect effect with a value of 0.0080. The direct effect accounts for 88.60% of the total effect, and the mediating effect accounts for 11.40% of the total effect.

The Bootstrap test results are shown in Table 12. The existence of direct and indirect effects can be judged according to the confidence interval, and the numerical direct and indirect effect results are consistent with the Sobel test results and pass the 1% significance test. This result verifies hypothesis H3 of this paper, i.e., that the digital economy will promote the level of urban resilience through the mediating role of technological innovation.

Table 10. Results 1 of the Sobel mediating effect test.

	lnUR	Tech	lnUR
lnDigE	0.0702 ***	2.5903 ***	0.0622 ***
	(12.47)	(5.78)	(11.2764)
lnhuman	0.0091 ***	0.5194 **	0.0075 **
	(2.77)	(1.98)	(2.3485)
lnopen	0.0126 ***	1.0033 ***	0.0095 ***
	(6.23)	(6.23)	(4.7817)
lnecono	1.0064 ***	46.1478 ***	0.8622 ***
	(13.06)	(7.53)	(11.3520)
lnecolo	0.0415 ***	−1.8353 ***	0.0473 ***
	(4.99)	(−2.77)	(5.8469)
lncap	0.1330 ***	3.4744 ***	0.1222 ***
	(37.67)	(12.37)	(34.1605)
tech			0.0031 ***
			(10.4365)
Constants	−6.2345 ***	−160.67 ***	−5.7327 ***
	(−34.62)	(−11.22)	(−31.6716)
Observations	1665	1665	1665
R-squared	0.7972	0.4341	0.8098
Adjusted R-squared	0.7965	0.4321	0.8089

Notes: ***, ** denote significance levels of 1% and 5% respectively.

Table 11. Results 2 of the Sobel mediating effect test.

Item	Total Effect c	a	b	Intermediary Effect a × b	c′ Direct Effect	Test Conclusion
X => M => Y	0.0702 ***	2.5903 ***	0.0031 ***	0.0080	0.0621 ***	Some agents

Notes: *** denote significance levels of 1%.

Table 12. Results of the Bootstrap mediating effect test.

Effect	Coefficient	Standard Error	z	95% Confidence Interval
Direct effects	0.0621 ***	0.0053	11.77	[0.0518, 0.0725]
Indirect effects	0.0081 ***	0.0017	4.70	[0.0047, 0.0115]

Notes: *** denote significance levels of 1%.

4.5. Robustness Tests

To ensure the robustness of the results, this paper used two methods to construct the core explanatory variables, which involved replacing them and shortening the sample years for robustness testing. First, we used the construction method to replace urban resilience indicators. The regression analysis was conducted by referring to the method for constructing indicators in the study of Bai et al. [47]. Second, the sample years were shortened. The original years of 2011–2019 were shortened to 2014–2019. The specific results are shown in Table 13, and it can be seen that there is no significant change in the coefficients and significance levels, which suggests that the results of the empirical analysis of this paper are robust.

Table 13. Robustness test results.

Variables	Replacing Urban Resilience Indicators	Data for 2014–2019
lnDigE	0.0649 ***	0.1273 ***
	(12.5502)	(11.2032)
lnhuman	0.0150 ***	0.0035
	(4.9322)	(0.8882)
lnopen	0.0100 ***	0.0119 ***
	(5.3777)	(4.8609)

Table 13. *Cont.*

Variables	Replacing Urban Resilience Indicators	Data for 2014–2019
lnecono	1.1278 ***	0.9913 ***
	(15.9330)	(10.2810)
lnecolo	0.0652 ***	0.0305 ***
	(8.5373)	(2.8950)
lncap	0.0966 ***	0.1300 ***
	(29.7885)	(31.2900)
Observations	1665	1110
R-squared	0.7920	0.8006

Notes: *** denote significance levels of 1%.

5. Discussion and Conclusions

Based on panel data from 185 prefecture-level cities in China from 2011 to 2019, this paper used benchmark regression models, spatial error models, and mediating effect models to explore, in depth, the impact of the digital economy on urban resilience and the mechanism of action. The findings of the study are as follows.

(1) The development of the digital economy has a positive impact on the improvement of urban resilience. The OLS regression and 2SLS regression showed that the positive effect of digital economy development on the enhancement of urban resilience is significant with or without the inclusion of control variables. The instrumental variable method was used to solve the endogeneity problem, which made the test results more robust.

(2) The effect of the digital economy in affecting urban resilience has positive spatial spillover effects and is heterogeneous. The spatial correlation of the digital economy was tested using the Moran index under three different spatial weight matrices, and all of them passed the significance test. The LM test was used to determine the spatial econometric model used in this paper as a spatial error model, based on which it is concluded that the role of the digital economy's spreading in promoting the level of urban resilience has a positive spatial spillover effect. Heterogeneity analysis was carried out in three dimensions: time, region, and external openness level. It is concluded that the promotion effect of the digital economy on urban resilience is significantly enhanced by the moderating effect of digital policy, with no significant difference in the case of this paper's chosen classification, i.e., eastern and central–western. This promotional effect is more obvious in regions with high levels of external openness.

(3) The digital economy will promote the level of urban resilience through the mediating effect of technological innovation. Both the Sobel test and the Bootstrap test were used to verify the mediating effect of technological innovation, and it is concluded that this mediating effect holds significantly and is partially mediated, accounting for 11.40% of the total effect.

Based on the above findings, the following recommendations are made.

(1) Strengthen digital construction and work to improve the level of urban resilience. Vigorously develop digital construction, consider expanding the layout of new infrastructure, enhance digital industrialization, the digitalization of industry, and digital governance, create a new situation of digital economy development, generate new momentum with digital economy development, and use the new momentum to drive the development of urban planning, construction, and governance in all aspects, to improve the level of urban resilience.

(2) Implement dynamic digital economy development strategies to solve the problem of uncoordinated development between regions. Given the spillover characteristics of the digital economy and the spatial spillover of digital economy development into urban resilience, a regional development community should be established to

formulate a dynamic digital economy development strategy to bring into play the driving role of core cities and the radiation capacity of regional specialty industries to solve the problem of uncoordinated development within regions and shorten the development gap between regions.

(3) Deeply integrate the development relationship of the digital economy, technological innovation, and urban resilience. In the process of the digital economy promoting the level of urban resilience, fully consider the importance of technological innovation, improve the top-level design of key core technological innovation, strengthen the key breakthroughs and technological breakthroughs in key areas of core technological shortcomings, deepen the integration of the talent chain, innovation chain, and policy chain, and improve the effectiveness of technological innovation between the digital economy and urban resilience.

Author Contributions: Conceptualization, Y.S. and T.Z.; methodology T.Z.; software, T.Z.; validation, T.Z.; formal analysis, T.Z.; investigation, Y.J.; resources, Y.J.; data curation, Y.J.; writing—original draft preparation, T.Z.; writing—review and editing T.Z. and Y.J.; visualization, T.Z.; supervision, Y.S. and T.Z.; project administration, Y.S., T.Z. and Y.J.; funding acquisition, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (Youth Fund) Project (grant number 70901065); the Ministry of Education Humanities and Social Sciences Planning Fund Project (grant number 21YJA630078); the Soft Science Project of Science and Technology Department of Shaanxi Province (grant number 2021KPM149); and the Xi'an Soft Science Project (grant number 21RKYJ0015).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflict of interest.

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