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ASSESSING DIGITAL TECHNOLOGY EFFICIENCY IN NATURAL DISASTER PREVENTION: COMPREHENSIVE ANALYSIS OF EMPIRICAL EVIDENCE FROM 30 PROVINCES OF CHINA IN 2012–2021

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Abstract. This paper adopts the entropy value method and the super-efficiency slacks-based measure (SBM) model to measure the level of development of digital technology and the utility of natural disaster prevention. Based on 30 provincial panel data from 2012-2021, the impact of digital technology on natural disaster prevention utility is verified using the two-way fixed effect model, mediated utility model, and spatial Durbin model. Digital technology can significantly improve the utility of natural disaster prevention, with regional differences in the promotion effect of western region > central region > eastern region, as well as heterogeneity depending on the intensity of policy support. Further research found that digital technology can positively affect the efficiency of natural disaster prevention by improving the level of public management, and there is a positive spatial spillover effect on the efficiency of natural disaster prevention in neighboring regions. Therefore, it is important to promote the transformation of the emergency management model towards proactive prevention based on a top-level design, grasp the digital opportunity to achieve high efficiency and precision in the prevention of natural disasters, tailor policies to local conditions to create a favorable digital development environment for disaster prevention; strengthen regional synergy and leverage the radiating effect of digital technology to drive the development of neighboring regions.

1. Introduction

China's emergency management work has gradually transformed from post-event treatment to pre-event prevention, and strengthening disaster prevention can reduce the losses caused by disasters and narrow their impact range. With the advent of the big data era, digital technology has been widely used in all sectors of society. Its powerful resource integration and data analysis capabilities can promote precision, scientific substantiation, and efficiency in disaster prevention work. Digital empowerment for disaster prevention can reserve ample response time for disaster response and add a safety barrier to ensure the safety of people's lives and property. Moreover, China invests a large amount of manpower, material resources, and

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funds in digital technology research and development, disaster prevention and control investment, and environmental protection every year. However, the efficiency of digital technology empowerment in disaster prevention has yet to be effectively verified and requires further verification through quantitative research.

Currently, research on disaster prevention is primarily focused on three aspects: first, the theoretical study of disaster prevention. From a holistic research perspective, the most representative is the 4R Crisis Management Theory proposed by Robert Heath in 1988, which includes reduction, readiness, response, and recovery [9]. Taking disaster prevention measures to prevent the occurrence of disasters or mitigate their impact is the main content of the reduction phase, and there is a risk correlation between disasters and between measures for preventing, alleviating, and dealing with disasters [12]. A systemic governance system should be formed from an overall perspective. From a risk management perspective, traditional risk management models tend to focus more on "treatment over prevention" in the emergency management process, emphasizing disaster relief and neglecting pre-disaster warning and risk avoidance [20]. With the influx of emerging risks, catastrophic disasters, and transboundary crises, the fourth-generation emergency management system, centered on enhancing adaptability, proactively guards against "gray rhinos" while efficiently responding to "black swans" [33], achieving "prevention and control simultaneously." The advent of the digital governance era has propelled emergency management from "department integration" to "platform integration" [19], thereby enhancing the efficiency of emergency management. Secondly, disaster prevention technology is considered. Macro-level research, supported by big data, permeates the three stages of emergency management: before, during, and after the event [17]. This facilitates the effective integration of resources and provides scientific, objective methods and technical support for decision-making in emergency management [22]. Micro-level research primarily focuses on the application of geological disaster prevention and meteorological monitoring. In geological disasters, some scholars have utilized airborne LiDAR for disaster identification and interpretation in key areas of geological disaster prevention, effectively identifying and preventing geological hazards [3]. It can also be applied to the investigation and evaluation of geological disasters. In meteorological monitoring [1], some scholars have identified existing issues with China's meteorological monitoring forecast warning (MMFW) software and suggested addressing shortcomings in development environments, tools, and other foundational and application support software, actively promoting the application of artificial intelligence technology in meteorological monitoring [38]. The third aspect is the assessment of disaster prevention capabilities. Research in this area mainly focuses on risk prediction, loss estimation, and evaluating prevention efficiency. For risk assessment, some scholars use spatiotemporal feature analysis to deduce the future development trend of meteorological disasters and potential risks [25]. Others use the replacement cost method to measure the losses caused by disasters [30]. For the efficiency evaluation of disaster prevention, some scholars use the data envelopment analysis (DEA) model to assess the efficiency of disaster prevention investments [11]. Disaster prevention, through risk prediction, loss estimation, and efficiency evaluation, can effectively enhance the capability to prevent disasters, thereby reducing the probability of disaster occurrence and mitigating the impact of disasters.

In summary, the academic community has discussed disaster prevention from prevention theory, technology application, and capability assessment. The research mainly starts by improving disaster prevention capabilities, focusing on internal factors as the basis for research. At the same time, there needs to be more research on the impact of the development and changes in the current social environment and natural conditions on the efficiency of disaster prevention. Based on the above considerations, this study aims to use the super-efficiency SBM model and the spatial econometric model to quantitatively evaluate the efficiency of digital technology in natural disaster prevention and to explore its potential spatial spillover effects. The key findings and innovations of this research are outlined below: 1. A comprehensive analysis framework is proposed to link the application of digital technology in disaster prevention with its prevention efficiency, providing a new theoretical perspective for the field of disaster prevention; 2. Through empirical research, the actual efficiency of digital technology in disaster prevention is revealed, and its spatial spillover effects are explored, providing an empirical basis for related policy-making; 3. New research tools and methods are provided for researchers and practitioners in the field of disaster prevention, which helps to evaluate and improve disaster prevention strategies more accurately. Through this study, we hope to provide new insights and support for academic research, practical operations, and policy-making in disaster prevention and emergency management.

2. Theoretical analysis and research hypotheses

2.1. Theoretical Analysis.

With the advent of the risk society, the difficulty of social governance has increased, testing countries'ability worldwide to respond to risk challenges. The emergence of digital governance theory has undoubtedly brought a new perspective to social governance and has also provided strong management tools for emergency management. Digital governance, as a risk governance model under the background of informatization, is based on digital technology and actively responds to the uncertainty of emerging risks through intelligent governance methods such as rapid identification, tracking learning, and continuous iterative upgrading [32]. With the continuous development of digital technology, digital governance has gradually shown its unique governance potential and advantages. Digital technology has revolutionized emergency management, making emergency responses more efficient, coordinated, and intelligent. Its key purpose is to fully tap the potential of digital technologies such as big data, cloud computing and artificial intelligence, and build a government system that is more responsible, more transparent and more efficient.

In the current environment where emergencies are increasing, digital technology has unique advantages in disaster prevention. First, it can improve the efficiency of emergency management. Digital technology, by changing the governance structure and operation mechanism, promotes the overall or partial reshaping of the emergency governance system in terms of decision-making procedures, information exchange, and resource distribution and enhances governance efficiency [5]. Second, it can reduce disaster losses. By effectively integrating and using these technologies, it is possible to calculate the efficiency of disaster prevention, plan resource distribution reasonably, and make up for shortcomings [35], significantly enhancing the ability and resilience of all sectors of society to respond to disasters, and ultimately reducing the losses and impacts brought by disasters.

Therefore, based on risk governance theory and digital governance theory, and considering the uncertainty of natural disasters and the efficiency of digital technology, this paper constructs a dynamic policy adjustment analysis framework with the government as the governance subject, digital technology as the governance means, and prevention efficiency as the comprehensive governance result.

2.2. **Research Hypotheses.**

2.2.1. *The Direct Benefits of Digital Technology on the Utility of Natural Disaster Prevention.* Human triumph over major disasters and pandemics is inseparable from scientific development and technological innovation [27]. Digital technology's progress results from modern science and technology's rapid growth and is a prominent technological manifestation in today's social advancement. The broad utilization of digital technologies like big data, cloud services, and AI has quickened the transfer, dispersion, and overflow of knowledge and technology between different countries[31], promoting the development of human society and facilitating people's lives. In natural disaster management, digital technology can achieve a series of functions such as risk perception, real-time monitoring, loss assessment, and development trend prediction [21], providing data support and creating conditions for early handling. Moreover, digital technology is capable of dissecting colossal volumes of data, expeditiously sieving and distilling valuable information, thereby buttressing efficacious decision-making within the ambit of disaster management [36]. Digital technology is not omnipotent in the disaster management process. It is often constrained by technical, organizational, and environmental factors (such as technical capabilities, subject participation, and community capabilities). It may also need to show more resilience in the empowerment process [4]. However, overall and long-term, the development of digital technology will promote innovation in disaster prevention methods, thereby improving disaster prevention capabilities and efficiency. In brief, the following hypothesis is put forward.

H1: The development of digital technology can improve the efficiency of natural disaster prevention.

2.2.2. *Mechanisms of Digital Technology's Impact on the Efficiency of Natural Disaster Prevention.* The subject of disaster prevention is the government, a crucial manifestation of governmental governance activities. The core of government governance is efficiency, which directly determines the outcomes of other related governance issues [15]. Digital technology injects new vitality into government public management, promoting more efficient, convenient, and faster public service processes, effectively facilitating the transformation from management to service and significantly reducing the administrative costs of government public services [28]. Promoting digital technology in national governance processes can effectively enhance government governance efficiency, reduce governance costs, and minimize resource consumption, becoming a vital means to advance environmental management transformation and improve supervision and public services [26]. The efficiency of public management (willingness and capability to implement it) directly affects the specific outcomes of its behavior.

For example, in the disaster management process, using digital technology can enhance emergency management departments'disaster risk prediction capabilities and improve the efficiency of emergency management personnel, improving disaster prevention efficiency. The mechanism is shown in Figure. 1.

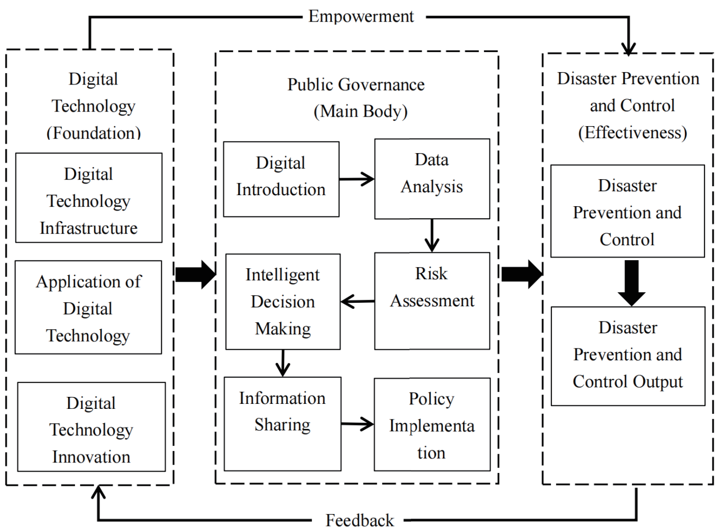

FIGURE 1. Flowchart of digital technology's role in disaster prevention efficiency

Therefore, considering the potential impact of the current development of digital technology on the level of public management, the following hypothesis is proposed:

H2: Digital technology can improve the efficiency of natural disaster prevention by enhancing the level of public management.

2.2.3. *Spatial Spillover Effects of Digital Technology on the Efficiency of Natural Disaster Prevention.* Additionally, digital technology's strong mobility, knowledge exchange, and cross-temporal and spatial transmission characteristics should be considered. Compared to traditional factors such as technology and human capital, digital technology better demonstrates the efficiency of knowledge spillovers [23]. Studies have shown that digital technology promotes industrial structure upgrading in neighboring cities through spatial spillover effects [6].Furthermore, digital technology impacts the carbon emission intensity of adjacent cities, lessening it and spurring the formation of a carbon reduction pattern for inter-regional coordinated development [13]. Digital technology can be applied in various fields, promoting regional communication and collaboration. Therefore, spatial spillover effects of digital technology on the efficiency of natural disaster prevention should be considered. Based on this, the following hypothesis is proposed:

H3: Digital technology, through spatial spillover effects, affects the efficiency of natural disaster prevention in neighboring areas.

3. Model specification and variable explanation

3.1. **Model Design.** In light of the research hypotheses and the characteristics of the selected data, to effectively control for unobservable heterogeneity, enhance the precision of the model, flexibly respond to various research contexts, and accurately test the impact of digital technology on the efficiency of natural disaster prevention, the following baseline econometric model is established:

$$Dpu_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \epsilon_{it} \tag{3.1}$$

where Dpu_{it} is the dependent variable that indicates the natural disaster prevention efficiency of province i during time t, while Dig_{it} is the level of digital technology development in province i during time t. A series of control variables is included, primarily encompassing urbanization (Urb), education level ($Lnedu$), ecological governance intensity ($Lneco$), and openness level ($Open$). Moreover, μ_i and ν_t denote province-fixed and year-fixed effects, respectively, and $\epsilon_{i,t}$ is the stochastic disturbance term.

A model of mediation analysis is utilized to investigate the pathway by which digital technology influences the effectiveness of natural disaster mitigation. Building on the significant coefficients in Model 1, the following regression models are established:

$$Pml_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 X_{it} + \mu_i + \nu_t + \epsilon_{it} \tag{3.2}$$

$$Dpu_{it} = \gamma_0 + \gamma_1 Dig_{it} + \gamma_2 Pml_{it} + \gamma_3 Urb_{it} + +\mu_i + \nu_t + \epsilon_{it} \tag{3.3}$$

where Pml_{it} is the intermediate public management level variable. Model 2 examines the impact of digital technology Dig_{it} on the intermediate variable Pml_{it}, and Model 3 assesses the joint impact of digital technology Dig_{it} and the intermediate variable Pml_{it} on the efficiency of natural disaster prevention.

Given the propagative and penetrative characteristics of digital elements, breaking geographical limitations and facilitating cross-regional circulation and collaboration, and considering the regional impact of disasters, a spatial Durbin model is introduced into Model 1 to examine the influence of digital technology development on the efficiency of natural disaster prevention in adjacent regions:

$$\begin{aligned} Dpu_{it} = {} & \alpha_0 + \rho W \times Dpu_{it} + \alpha_1 Dig_{it} + \theta W \times Dig_{it} \\ & + \alpha_2 X_{it} + \phi W \times X_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{3.4}$$

where ρ is the spatial autoregressive coefficient, measuring the potential spatial correlation in natural disaster prevention efficiency among different provinces; θ is the spatial regression coefficient of the explanatory variable level of digital technology development; φ signifies the coefficient in spatial regression analysis for the control variables; W is the spatial weight matrix, constructed as the geographical adjacency matrix to quantify the degree of connectivity between different regions. The expression is as follows:

$$W_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ are spatially adjacent} \\ 0, & \text{if } i \text{ and } j \text{ are not spatially adjacent} \end{cases} \tag{3.5}$$

3.2. **Variable Measurement and Explanation.**

3.2.1. *Natural Disaster Prevention Efficacy. (1) Choice of Measurement Method*

Assessing natural disaster prevention efficiency involves considering both post-prevention benefits and the impacts caused by disasters, encompassing expected and unexpected outputs. Traditional DEA models face challenges in handling slack variables and accurately calculating efficiency values involving unexpected outputs. Therefore, this study employs the Super-efficiency SBM model, which includes unexpected outputs, to assess each province ’ s natural disaster prevention efficiency. The specific model is constructed as follows:

$$\min \rho = \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}}+\sum_{t=1}^{q_2}\frac{s_t^{b-}}{b_{tk}}\right)}$$

$$\text{s.t.} \begin{cases} \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j - s_r^+ \geq y_{rk} \\ \sum_{j=1,j\neq k}^{n} b_{tj}\lambda_j - s_t^{b-} \leq b_{tk} \\ 1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_t^+}{y_{rk}}+\sum_{t=1}^{q_2}\frac{s_t^{b-}}{b_{rk}}\right) > 0 \\ \lambda \geq 0, \quad s^- \geq 0, \quad s^+ \geq 0, \quad s^{b-} \geq 0 \\ i=1,\dots,m; \quad r=1,\dots,q_1; \quad j=1,\dots,n(j\neq k) \end{cases} \tag{3.6}$$

Here, ρ is the value of natural disaster prevention efficiency, j is the number of decision-making units (provinces), $x_{ij}(i$=1,2…,m)is the inputs of decision-making unit, q_1 and q_2 are the expected and unexpected outputs of decision-making unit, respectively; and $y_{rj}(j$=1,2…,q_1) denotes desired outputs of natural disaster prevention,$b_{tj}(j$=1,2…,q_2) denotes non-desired outputs of natural disaster prevention,λ is the weight of cross-sectional observations for each decision unit. Subscript is the weight of the observation value for the decision-making unit. s_i^-, s_r^+,s_t^{b-} is the slack vector of inputs, desired outputs, and undesired outputs.

(2) Selection of Measurement Indicators

The indicators for natural disaster prevention efficiency include various prevention activities as input indicators, prevention benefits as expected output indicators, and losses caused by disasters as unexpected output indicators. In particular, nine adherence and implementation strategies for enhancing China's capacity for natural disaster prevention and control have been introduced at the Third Plenary Session of the Central Financial and Economic Affairs Commission of China [24].

Based on this and drawing on existing research results [11, 16, 8], a system of input-output indicators for assessing natural disaster prevention efficiency was formulated, as detailed in Table 1.

Table 1. Natural disaster prevention efficiency index system

Primary indicators	**Secondary indicators**	**Description of secondary indicators**
Input indicators	Prevention and control of capital investment	Forestry and grassland investment completed this year (million RMB)
		Expenditures on natural resources, marine meteorology, etc. (billion RMB)
	Infrastructure construction	Number of seismic stations and meteorological operational stations (piece)
		Density of drainage culverts in built-up areas (km/km^2)
Output indicators	Desired output	Gross output value of agriculture, forestry, animal husbandry, and fishery (billion RMB)
	Non-desired output	Natural disaster economic losses (billion RMB)
		Population affected by natural disasters (10000 person-times)

3.2.2. *Level of Digital Technology Development.* The level of digital technology development is a broad concept that a single indicator cannot measure. Due to the lack of a unified standard in the academic community and referencing existing research results [32, 7], we selected the dimensions of digital technology foundation, application, and innovation as evaluation dimensions for the level of digital technology development. After standardizing the data for each evaluation indicator of digital technology development, the entropy method is employed to obtain the weights of each indicator, and a comprehensive index is calculated to determine the level of digital technology development, as shown in Table 2.

3.2.3. *Control Variables and Mediator Variable.* Referring to previous research [31, 7, 29], this study includes control variables that may affect the efficiency of natural disaster prevention, including urbanization rate (Urb), education level (Lnedu), ecological governance intensity (Lneco), and openness level (Open). Considering that digital technology may affect the efficiency of natural disaster prevention through other pathways and drawing on relevant research [34, 2], the public management level (Pml) is selected as the mediator variable. The specific variable details are presented in Table 3.

Urbanization Rate (Urb). The level of urbanization can reflect the local population aggregation and distribution. Areas with a high urbanization rate have a high population concentration, which may have more resources to deal with disasters. However, they must also bear the high economic losses and casualties after the disaster. This paper employs the proportion of urban residents to the total year-end population in each province and city to determine the urbanization rate.

Education Level (Lnedu). Disaster prevention requires not only scientific technology but also high-quality talent. Education is an important way to cultivate talents and can also strengthen the popularization of disaster prevention knowledge and the training of self-help abilities. This paper uses the logarithm of the number of graduates from ordinary colleges and universities to determine the education level.

*Ecological Governance Intensity (Lneco).*The ecological environment plays an important role in resisting natural disasters. A good ecological environment can conserve water sources and reduce the occurrence of natural disasters such as soil erosion and debris flows. This paper uses the logarithm of the ecological restoration and management investment amount to measure the intensity of ecological governance.

Table 2. Digital technology development level evaluation index system

Variable	Evaluation dimension	Evaluation indicator	Indicator weight
Digital technology development level	Digital technology foundations	Length of fiber optic cable lines (kilometer)	0.099
		Cell phone penetration rate (units/100 people)	0.105
		Internet broadband access port density (pcs/km^2)	0.103
		Number of domain names (ten thousand)	0.087
	Digital technology applications	Software business revenue (million RMB)	0.079
		Total telecommunications business (billion RMB)	0.089
		Percentage of Legal Entities in Information Transmission, Computer Services and Software Industry	0.103
		Technology market turnover (billion RMB)	0.078
	Digital technology innovation	R&D Expenditure of Regulated Industrial Enterprises (RMB 10,000,000)	0.089
		Full-time Equivalent of R&D Personnel of Regulated Industrial Enterprises (person/years)	0.087
		Number of digital economy patents (items)	0.081

Table 3. Description of the relevant variables

Variable category	Variable	Abbreviation	Variable description
Explained variables	Natural disaster prevention utility	Dpu	Measured utility of natural disaster prevention
Explanatory variables	Level of digital technology development	Dig	Measured level of digital technology development
Control variables	Urbanization rate	Urb	Population in cities and towns in each province/population at the end of the year
	Education level	Lnedu	Ln (Number of graduates from general higher education)
	Ecological governance intensity	Lneco	Ln (Investment in ecological restoration and management completed)
	Level of openness to the outside world	Open	Foreign direct investment in each province and city as a share of GDP
Mediating variable	Public management level	Pml	Number of employees in public administration, social security, and social organizations at the end of the year / resident population at the end of the year

*Level of Openness to the Outside World (Open).*The level of opening up to the outside world can promote the flow of resources. Disaster prevention requires support from resources such as funds, experience, talents, and technology.Greater openness could enhance disaster prevention capabilities. This study measures openness by the share of foreign direct investment relative to GDP for each province and city.

3.3. **Data Source and Processing.** This paper selected panel data from 30 provinces in China (excluding Tibet and Hong Kong, Macao, and Taiwan) from 2012 to 2021 for analysis. Data sources include the "China Statistical Yearbook," "China Internet Development Statistical Report," "China Science and Technology Statistical Yearbook," "China Meteorological Disaster Yearbook," and the CNRDS database. A few missing values are supplemented by linear interpolation, and the descriptive statistical results of the main variables are listed in Table 4.

TABLE 4. Descriptive statistical results for primary variables

Variable	**Number of observations**	**Mean value**	**Standard deviation**	**Minimum value**	**Maximum value**
Dpu	300	0.836	0.713	0.101	9.606
Dig	300	0.197	0.129	0.030	0.711
Urb	300	0.596	0.119	0.354	0.942
Lnedu	300	5.224	0.823	2.456	6.520
Lneco	300	13.170	0.769	10.650	14.880
Open	300	0.259	0.277	0.008	1.441
Pml	300	1.315	1.380	0.457	8.776

At the same time, to avoid the bias caused by outliers, all variables are subjected to a 1% trimming at both ends. Although the data selection has a certain representativeness, there are also some limitations. First, the representativeness of some indicators needs to be considered. Due to the lack of intuitive data in disaster prevention, relevant data with stronger correlations are selected as substitute indicators based on existing studies. Second, the data in some years fluctuates greatly. The data from 2019 to 2021 is affected by the epidemic, and the values fluctuate more than in previous years, which will affect the accuracy of the calculation to a certain extent.

4. EMPIRICAL TESTING AND RESULTS ANALYSIS

4.1. **Baseline Regression Results.** Exploring the role of digital technology in the efficiency of natural disaster prevention, the baseline regression data can be found in Table 5. In Column (1), using the OLS method, the estimated coefficient for the digital technology development level is 0.6378, significant at the 1% level. After introducing province and year fixed effects in Column (2), the coefficient for the digital technology development level's influence on disaster prevention efficiency is 2.0362, significant at the 1% level. Columns (3)-(6) sequentially add control variables based on fixed province and year effects. After adding all control variables, the estimated result for the level of digital technology development is 2.1620 in column (6), which is still significant at the 1% level. The baseline regression results indicate that digital technology significantly enhances the efficiency of natural disaster prevention, supporting hypothesis H1.

With all control variables included in column (6), the urbanization rate (Urb) regression coefficient is -2.7197, significant at the 5% level. This suggests that the development of urbanization may increase the difficulty of disaster prevention management. As urban population and density increase, urban management and environmental carrying capacity are being challenged. Once disasters occur, the degree of disaster loss is exacerbated. The regression coefficient for education level (Lnedu) is significantly positive at the 5% level, indicating that promoting awareness of natural disaster prevention through education can effectively enhance disaster prevention efficiency by reducing or avoiding disaster losses. The regression coefficients for ecological governance intensity (Lneco) and openness level (Open) are negative but insignificant.

4.2. **Robustness Tests.** A series of robustness checks have been performed to validate the stability of the baseline regression findings and to mitigate concerns like sample selection bias, incomplete metrics, and omitted variable issues.

1. Change in Estimation Method: The least squares dummy variable (LSDV) method is used to re-estimate the baseline regression model. In column (1) of Table 6, the regression result for the core explanatory variable remains 2.1620 and

Table 5. Benchmark regression results

Variable			Dpu			
	(1)	(2)	(3)	(4)	(5)	(6)
Dig	0.6378***	2.0362***	1.9897***	2.2238***	2.1707***	2.1620***
	(0.2084)	(0.6894)	(0.6859)	(0.6900)	(0.7088)	(0.7101)
Urb			-1.9603**	-2.8130***	-2.7460**	-2.7197**
			(0.9830)	(1.0551)	(1.0754)	(1.0785)
Lnedu				0.5314**	0.5409**	0.5410**
				(0.2493)	(0.2513)	(0.2517)
Lneco					-0.0160	-0.0179
					(0.0473)	(0.0476)
Open						-0.0377
						(0.0809)
Constant terms	0.6793***	0.4049***	1.5825***	-0.7312	-0.5990	-0.5795
	(0.0487)	(0.1364)	(0.6059)	(1.2411)	(1.3031)	(1.3058)
Province fixed effects	NO	YES	YES	YES	YES	YES
Year fixed effects	NO	YES	YES	YES	YES	YES
Sample size	300	300	300	300	300	300
Number of periods	10	10	10	10	10	10
R2	0.0305	0.6338	0.6393	0.6456	0.6457	0.6460

Note: ***, **, and * indicate that the regression results passed the significance test at the 1%, 5%, and 10% confidence levels, respectively; the same table is provided below.

is significant at the 1% level, indicating the robustness of the baseline regression model and results.

2. Sample Adjustment: The sample is adjusted by excluding direct-administered municipalities. Due to their economic and political advantages, strong resource acquisition capabilities, and the ability to promote efficient development and application of digital technology, these municipalities may have a strong impact. Results in column (2) of Table 6 show that after excluding direct-administered municipalities, the regression result remains significant at the 1% level, confirming the robustness of the baseline regression results.

3. Variable Replacement: Digital inclusive finance combines digital technology with traditional inclusive finance, serving various economic and social development fields. The digital inclusive finance index is compiled from three dimensions: depth of use, breadth of coverage, and digital support services, which can reflect the level of digital technology development and application efficiency in a region to a certain extent. Drawing on existing research [37], the level of digital technology development is indicated by the Digital Inclusive Finance Index, which acts as a proxy(Cdig), and the impact of the level of digital technology development on the efficiency of natural disaster prevention is re-examined. The results in column (3) of Table (6) show that the regression coefficient of the core explanatory variable remains positive. The significance level remains unchanged, and the baseline regression results remain robust.

4. Lagging the Explanatory Variable: The variable representing the digital technology development level is delayed by one time period for analysis. Since digital

technology affects not only the natural disaster prevention utility in the current period but also in the next period, the level of digital technology development lagged by one period. According to the results of column (4) in table (6), the coefficient of digital technology development level lagged one period is positive and significant at 1% level, and the previous conclusion is robust.

TABLE 6. Robustness test

Variable	**LSDV**	**Excluding municipalities**	**Replacing explanatory variables**	**Explanatory variables lagged one period**
Dig	2.1620***	1.9031***		(0.0027)
	(0.7101)	(0.5268)		
Cdig			0.0097***	
			(0.0027)	
Dig -1				2.8265***
				(0.7605)
Urb	-2.7197**	-1.4945	-2.1768**	-1.8911
	(1.0785)	(1.1368)	(1.0721)	(1.1666)
Lnedu	0.5410**	0.8745***	0.6114**	0.6075**
	(0.2517)	(0.1990)	(0.2523)	(0.2824)
Lneco	-0.0179	-0.1080***	-0.0618	-0.0399
	(0.0476)	(0.0394)	(0.0462)	(0.0490)
Open	-0.0377	-0.0613	-0.0439	-0.0572
	(0.0809)	(0.0707)	(0.0803)	(0.0919)
Constant terms	0.1636	-1.9017*	-2.6862*	-1.2252
	(1.3174)	(1.1083)	(1.5451)	(1.4393)
Province fixed effects	YES	YES	YES	YES
Yearly fixed effects	YES	YES	YES	YES
Sample size	300	260	300	270
Number of periods	10	10	10	10
R2	0.6460	0.7347	0.6508	0.6793

4.3. **Endogeneity Analysis.** Although fixed effects for provinces and years were included in the baseline regression, and control variables were added to alleviate the problem of omitted variables, the impact of digital technology on the efficiency of natural disaster prevention may still be affected by measurement errors and reverse causality due to unobservable factors such as cultural environment and policy systems. This paper uses instrumental variables to alleviate the endogeneity problems it brings. Drawing on existing research [10], the ownership of fixed telephones in each province in 1984 is selected as the instrumental variable. On the one hand, considering the relevance requirement of the instrumental variable, the iterative upgrade of traditional communication technology has laid the foundation for the development of today's digital technology, and provinces with more fixed telephones historically tend to have a higher level of digital technology development in the future. On the other hand, considering the exogeneity requirement of the instrumental variable, there is a nearly 30-year span in time, which has a small impact on the efficiency of natural disaster prevention and does not directly affect the efficiency of natural disaster prevention. To make this instrumental variable have a time-varying effect, drawing on existing research [13], the cross product of the number of fixed telephones owned by each province in 1984 and the number of internet broadband access users in each province in the previous year is constructed, and two-stage least squares (2SLS) regression is performed.

The results in columns (1) and (2) of Table 7 show that the estimated coefficients of the first and second stages of the instrumental variable method are significantly positive at the 1% confidence level, so after considering the endogeneity problem, the promoting effect of digital technology on the efficiency of natural disaster prevention is still significant, consistent with the baseline regression results, and the research conclusion is robust. In addition, according to the statistical test results of the instrumental variable, the instrumental variable constructed in this paper meets the identification requirements of the instrumental variable. It addresses the issue of weak instruments and ensures the efficacy of the chosen instrumental variable.

TABLE 7. Endogenous testing

Variable	**Phase 1 (1)**	**Phase 2 (2)**
Dig		2.6176***
		(2.69)
IV-Dig	0.0001***	
	(14.95)	
Urb	0.1793**	-2.7682
	(2.58)	(-1.53)
Lnedu	0.0237	0.5620***
	(1.42)	(2.64)
Lneco	-0.0068**	-0.0111
	(-2.26)	(-0.19)
Open	-0.0032	-0.0364
	(-0.61)	(-0.58)
Constant terms	-0.0950	-0.1391
	(-1.01)	(-0.09)
Kleibergen-Paap rk Statistics of LM		131.1599
		[0.000]
Kleibergen-Paap rk Statistics of Wald F		223.642
		16.38
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Sample size	300	300
Number of periods	10	10
R2	0.9772	0.5859

Note: P-values in [ ]; critical values at the 10% level for the Stock-Yogo weak identification test in { }

4.4. **Heterogeneity Analysis.**

4.4.1. *Regional Heterogeneity.* Due to differences in natural resource conditions, policy environments, and the level of digital technology development, the promotion effect of digital technology on the efficiency of natural disaster prevention may vary across regions. The research partitions the sample into three distinct regions: the East, the Central, and the West[The eastern region includes 11 areas: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes eight areas: Shanxi, Jilin, Heilongjiang, Henan, Hubei, Hunan, Anhui, and Jiangxi; the western region includes 11 areas: Inner Mongolia, Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.]. Columns (1)-(3) of Table 8 illustrate the notable regional heterogeneity in the efficiency-enhancing effect of digital technology on natural disaster prevention, with efficiency ranking from highest to lowest as Western, Central, and Eastern regions.The reasons for this difference may be: In recent years, national policy preferences for the central and western regions, as well as the unique resource endowments of these areas, have promoted the rapid rise of regional digital technology, which in turn has facilitated the upgrading of the local industrial structure and technological transformation. As a result, digital technology has played a significant promotional role.

4.4.2. *Policy Intensity Heterogeneity.* To investigate whether the effect of digital technology on natural disaster prevention is influenced by policy support, provinces designated as "Comprehensive Experimental Zones for Big Data" in the "Action Plan for Promoting Big Data Development" in 2015[Big Data Comprehensive Pilot Zones: Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Shanghai, Henan, Guangdong, Chongqing, and Guizhou] are considered as having high policy intensity, while others are categorized as having normal policy intensity.

Results in columns (4) and (5) of Table 8 show that both groups exhibit positive coefficients, but the coefficient for high policy intensity is greater than that for normal policy intensity. This suggests that under high policy intensity, the promotion effect of digital technology on the efficiency of natural disaster prevention is higher than under normal policy intensity. Thus, if the country implements strong policy support for central and western regions while applying normal policies in the Eastern region, the effect of digital technology on natural disaster prevention is likely to be higher in China's central and western regions.

5. Comprehensive analysis

5.1. **Analysis of Impact Mechanisms.** Building upon the theoretical analysis of the impact mechanisms of digital technology on the efficiency of natural disaster prevention from the perspective of public management, this study employs a stepwise approach to conduct intermediary effect tests. The testing process comprises three steps: (1) examining the impact of digital technology on the efficiency of natural disaster prevention; (2) contingent upon the significant results from step (1), investigating the influence of digital technology on the intermediary variable of public management level; and (3) introducing the intermediary variable of public management level into the regression equation for digital technology and the efficiency of natural disaster prevention. If both the coefficients of the digital technology development level and the intermediary variable of the public management level are significantly positive, it indicates that public management plays an intermediary role in the process by which digital technology enhances disaster prevention efficiency.

The results in columns (1)-(3) of Table 9 correspond to these three steps. The coefficients in all three steps are significantly positive, with the estimate in column

Table 8. Heterogeneity test results

Variable	**Eastern**	**Central**	**Western**	**High policy intensity**	**Normal policy intensity**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dig	0.7051	2.7048**	5.4514***	2.7959*	1.9456***
	(1.3635)	(1.3472)	(1.2404)	(1.6393)	(0.7150)
Urb	-1.0798	4.4104**	-3.1103	-3.4503	-0.8196
	(2.0211)	(2.0342)	(2.6636)	(2.1789)	(1.4067)
Lnedu	-0.7798	-0.2577	0.7778**	0.5789	0.4782*
	(0.9399)	(0.3995)	(0.3057)	(0.5494)	(0.2625)
Lneco	-0.0276	-0.2476***	0.0920	0.0184	-0.0441
	(0.0779)	(0.0687)	(0.1177)	(0.1015)	(0.0497)
Open	-0.0427	-0.1186	0.0158	0.0843	-0.1246
	(0.2044)	(0.1770)	(0.1469)	(0.1898)	(0.0847)
Constant terms	6.2027	2.5496	-3.3705*	-0.7507	-1.0133
	(4.8521)	(2.1733)	(1.8207)	(2.5046)	(1.6118)
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Sample size	110	80	110	100	200
Number of periods	10	10	10	10	10
R2	0.53845	0.88225	0.67427	0.5108	0.7489

(3) being smaller than that in column (1), suggesting that the public management level serves as a mechanism through which digital technology promotes the efficiency of natural disaster prevention, thus confirming hypothesis H2.

Table 9. Mediation effect test results

Variable		**Dpu**	
	(1)	**(2)**	**(3)**
Dig	2.1620***	0.6343***	1.8009**
	(0.7101)	(0.2296)	(0.7097)
Pml			0.5694***
			(0.1904)
Urb	-2.7197**	0.2485	-2.8612***
	(1.0785)	(0.3486)	(1.0632)
Lnedu	0.5410**	-0.0420	0.5649**
	(0.2517)	(0.0814)	(0.2480)
Lneco	-0.0179	0.0377**	-0.0394
	(0.0476)	(0.0154)	(0.0474)
Open	-0.0377	0.0217	-0.0501
	(0.0809)	(0.0262)	(0.0798)
Constant terms	-0.5795	0.7583*	-1.0112
	(1.3058)	(0.4221)	(1.2941)
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Sample size	300	300	300
R^2	0.6460	0.9958	0.6580

5.2. **Spatial Spillover Effects'Analysis.**

5.2.1. *Spatial Correlation Test.* This research employs a global Moran's I index, grounded in a matrix of spatial contiguity, to determine if there's a spatial relationship between the level of digital technology development and the efficacy of disaster prevention measures.

The results in Table 10 imply that, except for the negative value in 2021, Moran's I values for the efficiency of natural disaster prevention from 2012 to 2021 are positive and significant for more than half of the years. Similarly, Moran's I values for the development level of digital technology from 2012 to 2021 are positive and significant, indicating a certain degree of spatial dependence between the efficiency of natural disaster prevention and the development level of digital technology. Therefore, it is deemed necessary to employ spatial econometric models to test the relationship between the two.

TABLE 10. Global Moran index

Year		**Dpu**			**Dig**	
	Moran's I	**The value of z**	**The value of p**	**Moran's I**	**The value of z**	**The value of p**
2012	0.162*	1.557	0.060	0.190**	1.868	0.031
2013	0.183**	1.725	0.042	0.147*	1.522	0.064
2014	0.052	0.686	0.246	0.142*	1.476	0.070
2015	0.400***	3.754	0.000	0.173**	1.731	0.042
2016	0.128*	1.304	0.096	0.191**	1.876	0.030
2017	0.002	0.378	0.353	0.221**	2.114	0.017
2018	0.031	0.522	0.301	0.178**	1.790	0.037
2019	0.161*	1.585	0.056	0.176**	1.781	0.037
2020	0.012	0.971	0.166	0.168**	1.721	0.043
2021	-0.181	-1.162	0.123	0.220**	2.147	0.016

Based on the above, the study further employs a local Moran scatter plot to analyze the spatial clustering characteristics of the efficiency of natural disaster prevention and the development level of digital technology.

Figure 2 illustrates that coastal regions such as Shandong, Hainan, and Jiangsu exhibit high-value clustering for the efficiency of natural disaster prevention, while central and southwestern regions such as Hunan, Shaanxi, Chongqing, and Sichuan exhibit low-value clustering. Concerning the development level of digital technology, eastern coastal regions like Shandong, Shanghai, Jiangsu, and Zhejiang similarly show high-value clustering. In contrast, northwestern regions, including Qinghai, Gansu, Ningxia, and Xinjiang, exhibit low-value clustering. Overall, a positive spatial correlation exists between the efficiency of natural disaster prevention and the development level of digital technology, demonstrating an east-high-west-low pattern. However, a few provinces are located in the second and fourth quadrants. Provinces in these quadrants do not form positive clustering with neighboring areas regarding the efficiency of natural disaster prevention and the development level of digital technology. These provinces include Beijing, Tianjin, and Guangdong in the eastern region, reflecting the need for further improvement in the radiative driving effect of the eastern region on neighboring areas regarding natural disaster prevention and digital technology development.

5.2.2. *Selection of Spatial Regression Model.* Initial LM tests are conducted on OLS regression residuals to select the spatial econometric model. Results indicate that both LM and Robust LM tests are significant at the 1% level, suggesting the presence of spatial error and spatial lag effects. Consequently, the Spatial Durbin Model

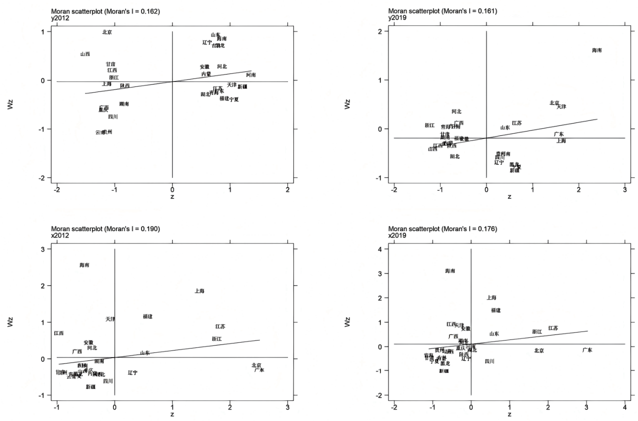

FIGURE 2. Local Moran scatter plot of natural disaster prevention utility and digital technology development in 2012 and 2019

(SDM) is deemed more appropriate. After selecting the SDM, it is essential to ascertain whether the SDM would degenerate into a Spatial Error Model (SEM) or a Spatial Lag Model (SLM). Both LR and Wald tests pass the 1% significance level, indicating the stability of the SDM. Moreover, the Hausman test findings recommend opting for a fixed effects model rather than a random effects model.

5.2.3. *Spatial Regression Analysis.* Based on the model selection, this paper employs a two-way fixed spatial Durbin model for spatial econometric empirical analysis. It uses the partial derivative method to decompose the impact of digital technology development on the efficiency of natural disaster prevention into direct and indirect effects.

The results are shown in Table 11. Columns (1) and (2) of Table 12 show that the estimated coefficient of the digital technology development level on the local natural disaster prevention efficiency is 1.2141, which passes the 10% significance level test, indicating that digital technology can indeed enhance the prevention efficiency of local natural disasters, consistent with previous research conclusions. Additionally, the spatial regression coefficient of the digital technology development level is 2.3129. The result is highly significant at the 1% level, suggesting a pronounced spatial externality, where enhancements in local digital technology can markedly boost the efficiency of natural disaster prevention in neighboring areas. The decomposition of the spatial effect shows that the direct effect of the digital technology development level on natural disaster prevention efficiency is 1.2764, the indirect effect is 2.5709, and the total effect is 3.8472, all of which pass the significance test. This further illustrates that the development of digital technology improves the efficiency of local natural disaster prevention and helps enhance the efficiency of neighboring areas. Hypothesis H3 is verified.

6. Conclusions and policy recommendations

6.1. **Conclusions.** Employing a dataset that includes 30 provinces in China from 2012 to 2021;this study employed the entropy method and Super-efficiency SBM

TABLE 11. Regression results and effect decomposition of spatial Dubin model

Variable	Direct effect (1)	WX (2)	Direct effect (3)	Indirect effect (4)	Total effect (5)
Dig	1.2141*	2.3129***	1.2764*	2.5709***	3.8472***
	(1.7682)	(2.7622)	(1.8216)	(3.1285)	(4.1001)
Urb	-2.7285***	-0.5546	-2.7925***	-0.8181	-3.6106
	(-2.7006)	(-0.2974)	(-2.8561)	(-0.3933)	(-1.6121)
Lnedu	0.0936	1.1531***	0.1408	1.1953***	1.3361***
	(0.3523)	(2.6543)	(0.5588)	(2.7900)	(3.3518)
Lneco	-0.0295	0.1225	-0.0278	0.1361	0.1084
	(-0.6554)	(1.3627)	(-0.6446)	(1.3743)	(0.9064)
Open	-0.0879	0.0948	-0.0858	0.0975	0.0117
	(-0.7261)	(0.5904)	(-0.7392)	(0.5949)	(0.1117)
N	300	300	300	300	300
R2	0.003	0.003	0.003	0.003	0.003
$Sigma^2$			0.0711***		
Log-likelihood			-29.2023		

model to measure the development level of digital technology and the efficiency of natural disaster prevention, respectively. Subsequently, various models, including bidirectional fixed models, intermediary effect models, and spatial Durbin models, were applied to investigate the impact of digital technology on the efficiency of natural disaster prevention, resulting in these subsequent findings:

1. Digital technology significantly promotes the efficiency of natural disaster prevention, a conclusion robust to various estimation methods, variable replacements, exclusion of direct-controlled municipalities, one-period lag of explanatory variables, and introduction of instrumental variables.
2. Digital technology's impact on the efficiency of natural disaster prevention exhibits regional heterogeneity. The Western region leads in promotional effectiveness, the Central region comes in second, and the Eastern region trails with the least promotion effect.Furthermore, the effect of promotion varies with different policy intensities.
3. Through intermediary effect tests, it is revealed that digital technology can enhance the efficiency of natural disaster prevention by promoting improving public management levels.
4. Spatial spillover effects are identified in the impact of digital technology on the efficiency of natural disaster prevention. The findings indicate that digital technology not only enhances the local capacity for natural disaster prevention but also has a beneficial effect on the efficiency of such efforts in adjacent regions.

6.2. **Policy Recommendations.** Digital technology is a vital force driving the transformation of traditional emergency management collaborative governance. It is also an important safeguard for dealing with lex siturgencies and enhancing collaborative efficiency [14]. Digital empowerment of emergency management conducts research through technological empowerment, communication empowerment, and decision-making empowerment, promoting the transformation of the emergency management system towards integration and high efficiency [18]. Against the backdrop of the country's establishment of a large safety and emergency framework and the establishment of the Big Data Bureau, this study on the impact of digital technology on the efficiency of natural disaster prevention proposes the following policy recommendations:

1. *Based on top-level design, promote the transformation of emergency management models towards pre-event prevention:* Integrate digital technology with top-level institutional design, supported by the development of digital technology, to build a framework for large-scale safety and emergency management. Comprehensively apply digital technologies such as 5G, big data, and blockchain to various scenarios and stages of emergency management; address the compatibility issues between digital technology and the systems, mechanisms, and legal frameworks of emergency management by establishing cross-departmental coordination mechanisms to ensure effective communication and resource sharing among different departments; establish effective pre-event prevention decision-making mechanisms, responsibility division mechanisms, and early warning response mechanisms to enhance emergency monitoring and early warning capabilities, achieving pre-event prevention and monitoring, early warning response, and pre-positioned disposal; encourage public participation in disaster prevention activities by providing regular disaster management training and drills.

2. *Grasping digital opportunities for efficient and precision development of disaster prevention:* Firstly, to enhance the efficiency of disaster prevention work, it is necessary to increase the application and development of digital technologies such as the Internet, big data, and the Internet of Things in the prevention of natural disasters, and to combine "prevention by people" with "prevention by technology". To promote disaster prevention efficiency, develop intelligent early warning systems based on artificial intelligence to improve early warnings'accuracy and response speed. Secondly, it strengthens the precision of natural disaster prevention information. The most powerful function of digital technology is intelligent data analysis and prediction of developments. In conjunction with the needs of departments such as meteorology, water conservancy, and natural resources, establish a unified data-sharing platform to achieve real-time data sharing and analysis and implement disaster early warning monitoring, analysis, and prediction. Implement precise control and information release for specific areas and groups; provide policy support and financial incentives to encourage enterprises and research institutions to innovate in disaster prevention technology.

3. *Tailoring policies to local conditions and create a favorable digital development environment to aid disaster prevention:* Considering the regional disparities in resource endowments and the diverse effects of digital technology on enhancing natural disaster prevention efficiency, tailor the progression of digital technology advancement to align with each region's resources, and incrementally adopt policies that leverage local resource strengths for digital technology development. Conduct detailed assessments of natural disaster risks in different areas and formulate targeted prevention measures, encouraging the development of technology solutions adapted to local conditions. For example, the eastern and central regions should fully leverage their innate advantages in developing digital technology, explore the

integration of digital technology with natural disaster prevention at the highest level, and maximize the marginal utility of digital technology in natural disaster prevention. The Western region can further strengthen the construction of digital technology infrastructure and increase investment in digital technology innovation and research and development, introduce advanced disaster prevention equipment and methods, and further enhance the efficiency of disaster prevention. At the same time, community-based disaster management strategies should be promoted to improve communities'self-management and recovery capabilities.

4. *Strengthen regional coordination and leverage digital technology's radiative effect for development in neighboring area:* Harnessing digital technology's radiating and driving role is crucial for coordinating regional development and strengthening joint prevention and control among regions.By leveraging digital technology to build a platform for regional collaborative development in emergency management, the integration of digital technology with disaster prevention can be deepened and broadened. This fosters technical exchange and collaboration on digital technology and disaster prevention between regions and establishes an effective framework for cross-border disaster management to create a mechanism for joint prevention, control, and collaboration between regions. This leads to a division of labor and cooperation across regions, reduces regional development gaps, and improves regional disaster prevention and response capacity.

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