

Article

Research on the Factors Influencing the Epidemic Resilience of Urban Communities in China in the Post-Epidemic Era

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Abstract: In the aftermath of the COVID-19 pandemic, people are gradually realizing that urban community resilience is pivotal for effectively managing public health emergencies. This study employed grounded theory to establish a theoretical framework for epidemic resilience of urban communities (ERUC) in the post-pandemic era. Subsequently, the decision-making trial and evaluation laboratory (DEMATEL)-interpretive structural modeling (ISM) method is utilized to discern the significance and hierarchical interrelations among influencing factors. The findings delineate that 14 determinants shaping ERUC are organized into five distinct tiers. Notably, nine determinants emerge as principal: vulnerable group; educational attainment; risk perception; medical insurance coverage; communal norms; community emergency response; community services; resident participation; and government efficacy. Among these, the vulnerable group and government efficiency are identified as foundational factors, while medical insurance coverage, resident participation, and community infrastructure are identified as direct influences.

Keywords: post-epidemic era; public health emergencies; urban communities; resilience; influencing factors



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1. Introduction

The World Health Organization defines a Public Health Emergency of International Concern (PHEIC) as an unusual event that poses a threat to the public health of other countries through the international spread of disease and may require an internationally coordinated response. In recent decades, frequent public health calamities have become a global phenomenon [1]. The breakout of the COVID-19 epidemic at the end of 2019 posed a severe test for every country [2], which is the most serious infectious disease pandemic in the world in the past century. By 2023, the world has entered the post-epidemic era. This era is characterized by the return to normalized daily routines following the containment of COVID-19; yet, it necessitates continued navigation through its protracted ramifications [3]. Enhancing society's capacity to resist, adapt to, and recover from public health emergencies in this post-pandemic context, ensuring the seamless and secure functionality of urban environments, has rendered "resilience" an increasingly pivotal paradigm within urban governance discourse.

The term resilience was derived from the Latin "resilio", which originally referred to "reverting to the original state" [4]. An academic inquiry has progressively shifted from a focal point on urban resilience to an emphasis on community resilience, mirroring the evolution of resilience from its roots in engineering and ecological domains to encompass socio-ecological dimensions [5]. Resilience building is particularly important for communities as basic units of governance. Initiatives and programs on community resilience have been established by different organizations, such as the Rockefeller Foundation 100 Resilient Cities initiative [6], which is dedicated to helping communities around the world become

more resilient to physical, social, and economic challenges. The National Institute of Standards and Technology (NIST) has developed two planning guides for community resilience based on a national outreach effort: the Community Resilience Planning Guide for Buildings and Infrastructure Systems (NIST, 2015a) and the Community Resilience Economic Decision Guide for Buildings and Infrastructure Systems (NIST, 2015b). The United Nations Sustainable Development Goals (SDGs) include “inclusive, safe, resilient and sustainable cities and human settlements” as one of their 17 goals [7]. The concept of community resilience can be summarized into three mainstream doctrines: (i) Capability theory, which understands community resilience as the community’s proactive, adaptive capacity to withstand external shocks, absorb adverse impacts, and restore a stable state of affairs [8–11]; (ii) Process theory, which views community resilience as the entire process by which a community learns, manages itself, recovers, and ultimately adapts to a disaster through self-learning, self-management, and self-recovery [12–15]; (iii) Adaptation theory, which means maintaining a state of equilibrium after making timely and effective adjustments in response to a disaster and environmental damage, according to the goals [16–18].

Community resilience is influenced by many factors. Previous studies have focused on the impact of meteorological, geological, and other natural disasters on community resilience, e.g., Moreno, based on the 2010 Chilean earthquake and tsunami in the context of a surviving fishing community, concluded that a sense of community, local knowledge, social capital, organization, cooperation, and trust had positive impacts on the survival of the community in the first few days after the disaster [19]. Boon conducted in a flood-impacted rural Australian town to identify the factors that residents perceived as supporting community resilience to disaster; the interviews and survey showed that community resilience was promoted by social connectedness and a sense of place, a factor that was also negatively linked to the desire to relocate from the community [20]. With the outbreak of the COVID-19 pandemic, scholars have also begun to focus on studying the factors influencing community resilience in the context of Public Health Emergency. Research based on COVID-19 presented that unstable income, weaknesses in the health system, scarcity of resources, and relatively low popular socioeconomic conditions were challenges in containing the pandemic, having negative effects on community resilience [21,22]. Castro examined the relationship between socioeconomic indicators and the morbidity and mortality of COVID-19 based on the spatially dispersed characteristics of the Brazilian socio-demographic population; this research study indicates that the largest urban centers and spaces with the lowest HDI are the most affected by COVID-19 [23]. McElduff, based on people-place relationships, found that people’s concern for community issues, pride, attachment, and sense of belonging largely influenced community resilience [24]. In addition, some scholars, such as Aldrich, have analyzed community resilience from a micro perspective, emphasizing the critical role of social capital for communities in disaster survival and recovery [11]. Karaye argued that vulnerable groups were a key factor in community resilience, and addressing their issues, such as housing, education, the environment, and economic justice, is critical to disaster reduction [25].

The widespread outbreak of COVID-19 has highlighted the vulnerabilities in community governance, prompting scholars to reassess community emergency management strategies, particularly in the face of public health emergencies. In the area of the information age, the existing practices in delivering pandemic-related data and information to the public, the capability to combat the pandemic, and sudden environmental changes (which will likely affect the public health system) are also important and crucial [26]. Quan Lu et al. investigated 133 information release accounts of the Chinese Government and relevant departments at the national, provincial, and municipal levels, focusing on the coronavirus disease 2019 (COVID-19) epidemic in China. The results show that effective coordination of the information released on the COVID-19 epidemic at different levels, departments, and channels guaranteed the rapid success of the epidemic prevention and control process in China [27]. However, public health information in social media must be consistent with public demand [28]. Unlike natural disasters that are confined in time and space, public health emergencies pose complex and pervasive societal risks with significant geographic

contagion [12]. This study used the term “epidemic” as a general reference to public health emergencies. There is a growing consensus among researchers that bolstering community resilience can enhance emergency management capabilities [29–32]. Yet, studies on factors shaping community resilience during public health crises remain scant, especially for developing nations like China. To bridge this gap, we introduce the concept of Epidemic Resilience of Urban Communities (ERUC). ERUC encapsulates the ability of urban communities to harness their resources to weather public health storms. Our objective is to pinpoint factors that influence urban community resilience to epidemics, employing a systematic framework to discern crucial elements for self-improvement. We also seek to elucidate the hierarchical relationships and impact mechanisms at play. Ultimately, the insights aim to inform policymakers.

2. Method and Data

This study employs a comprehensive methodology to discern the determinants of ERUC and elucidate their hierarchical interactions. Initially, grounded theory was utilized to establish a theoretical foundation for urban community resilience in the post-epidemic period. Subsequently, data gathering through questionnaires coupled with Principal Component Analysis (PCA) facilitated the streamlining and optimization of the influencing factors [33]. Building on this foundation, the Delphi technique was implemented to ascertain the causal relationships among these factors. The integrated DEMATEL-ISM approach was then applied to scrutinize the hierarchical relationships inherent to ERUC, subsequently constructing a layered model that represents these complexities. In the final stage, a thorough analysis of the findings was conducted, culminating in the formulation of targeted policy recommendations.

2.1. Step 1: Framework Establishment

The essence of ERUC is seen in the practical processes that transition, integrate, and adapt communities between standard and non-standard governance systems. To create a theoretical framework for ERUC that fits the Chinese scenario, it is essential to go beyond merely adapting analytical approaches from previous research. Instead, we must engage in necessary qualitative research based on real-world situations and capture and refine relevant theories so as to create a functional theoretical framework.

As a result, this study uses the grounded theory methodology for this research, with the specific procedure outlined in Figure 1. This methodology, a qualitative research approach proposed by American sociologists Barney Glaser and Anselm Strauss, highlights the crucial role of actual data and information in establishing the theoretical foundation of a concept. It supports the bottom-up creation of empirical theory through the careful collection, generalization, and analysis of research data, as well as the mutual impacts between the data and the analytical processes [34]. The layered coding of information is fundamental to grounded theory and includes three levels: open coding; axial coding; and selective coding [35]. Using grounded theory to examine ERUC after an epidemic has significant theoretical importance.

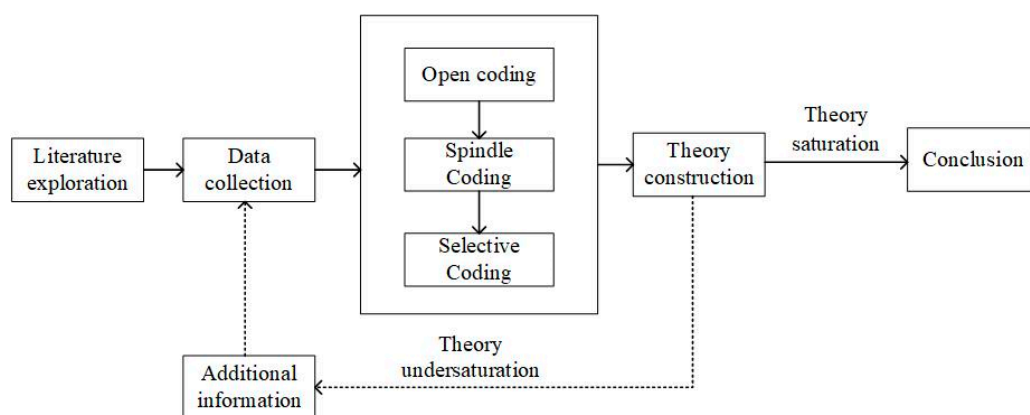


Figure 1. The flow chart of grounded theory.

2.2. Step 2: Influencing Factor Identification

(1) Data collection

The data for this study were primarily sourced from community residents and community workers, who represented the two most crucial stakeholder groups within a community. Among these, community workers are tasked with the critical role of relaying and issuing information, acting as a vital link in the implementation of policies and measures released by higher authorities and their execution at the grassroots level. These workers possess an intricate understanding and detailed oversight of the entire process of community epidemic prevention. Meanwhile, community residents, as the primary targets of epidemic prevention and control measures and subjects of community oversight, can directly perceive and evaluate the efficacy of community initiatives.

To delve deeply into the factors influencing ERUC, this research adopted a semi-structured approach, commencing with a predefined set of questions forming an interview guide. The specific interview outline is presented in Section S1, with each interview lasting between 15 to 40 min. Interviews were recorded and subsequently transcribed into textual data, and the final unified data format was imported into Nvivo11 qualitative analysis software for data collation, coding, and analysis. The specific methods are as follows: (1) Read the data word by word, extract the main points of view in the subjects' language, and extract them from the colloquial language into shorter sentences or phrases that are more concise and can express the subjects' views; (2) Open coding is used to classify phrases and short sentences that express the same or similar meanings, and a more general phrase is used to summarize this category. The final phrase is the axial coding, also known as the category; (3) Spindle coding. Open coding is further compared. Open coding with similar semantic features, attributes, and dimensions is classified. This category is summarized and abstracted into higher-level phrases. The final phase is spindle coding, also known as sub-category; (4) Selectively encode, compare, and classify the spindle code again and extract higher-level categories. At this time, the category is the core category, and all categories at its lower level can be summarized by it;

(2) Sample structure

In line with the research objectives, participants in this study were required to meet specific criteria: (i) Respondents must have been directly involved in the management of the community during the novel coronavirus outbreak; (ii) The community in which the respondent was involved must have been designated as a high-risk area for COVID-19. Given these sampling requirements, a total of 25 respondents were ultimately selected from 2 communities in Nanjing, China. Table 1 summarizes the basic information of the respondents, classified into two categories: S (Staff), representing 5 community workers, and R (Resident), representing 20 community residents.

Table 1. Basic information statistics of interviewees.

Basic Information	Classification	Number	Percentage (%)
Gender	Male	13	52
	Female	12	48
Age	30 and below	6	24
	31–45	12	48
	46–60	5	20
	61 or older	2	8
Educational level	Junior high school or below	4	16
	High school or college degree	5	20
	Bachelor's degree or above	16	64
Length of service/residence	5 and below	5	20
	6–15	13	52
	16–25	5	20
	26 or more	2	8

Upon completion of all interviews, the recorded content was transcribed into textual data. A random selection of 20 interview transcripts was analyzed using Nvivo11 software for line-by-line coding. Following the completion of three-level coding, the remaining five interview transcripts were utilized to test theoretical saturation.

(3) Open coding

The 20 interviews selected at random were meticulously organized, yielding 59 initial concepts after the excision of statements deemed meaningless or repetitive. These concepts were then synthesized into 20 preliminary categories, a process guided by their inherent connotations and extensions. The specific coding procedure is outlined in Table 2. Due to spatial constraints, only a subset of the original statements is presented under the initial concepts and preliminary categories.

Table 2. Open coding examples.

Coding	Interview Original Statement	Original Concept	Category
R16	I have rented a house here for nearly 3 years. The landlord's sister lives upstairs. She takes care of me at ordinary times and often sends me some vegetables and fruits from her hometown. I will also buy some gifts for her on New Year's Day. (R16)	Transient population	Demographic Characteristic
S04	Our community has three multitudes: many storefronts; many people in need; and many old houses. The community is a house from the 1980s, with about 1700 households and over 4000 people.	Population density	
R08	I learned about it from watching the news; my son called us, and the community reminded us through loudspeakers to minimize the number of people going out and gathering. After that, I learned about the epidemic by watching the news on TV and reading newspapers.	Information attention	Risk Perception
R02	The present liberalization policy, I think, is more of a demand on our residents themselves to take good personal protection and turn the concept of epidemic prevention into a habit.	Concept of epidemic prevention	
S01	We have not established an emergency plan either, because emergencies are so numerous and complex that a set of emergency plans simply cannot cover them comprehensively, and we, as community workers, need to be on call when emergencies come, which is the best emergency plan.	Community emergency response	Community Governance
S03	The community has a set of emergency plans, and training is given to staff before they start work so that they can do their jobs better.	Community emergency response	
.....			
R01	People around me have gone to graduate school, and I am also in the tide of preparation for graduate school; there are main employment difficulties; undergraduates cannot find a good job, and the impact of the epidemic on finding a job is simply more difficult.	Employment difficulty	Employment Rate
R08	I am on retirement pay, so my income is not much affected.	Income source	Income
R12	The biggest impact on me during that time was the income, not being able to travel to run a business, and do business; there was no source of income.	Income impact	
R01	The government should also prevent the spread of widespread rumors promptly, to avoid the phenomenon of scrambling for food and medicine, which will lead to panic.	Opinion leadership	Government Efficacy
S04	That is, in the 2020 New Year's period, there may have been some shortage of masks, but the goal of our country is to ensure that the system is still relatively good; basically, we have not encountered the problem of stopping the supply.	Material supply	
S11	The elevator will have a regular disinfection record sheet, etc., and every day; there will also be cleaning staff to clean the buildings and the community; the overall health environment of our community is still good.	Hygienic condition	Community Environment
S04	We have special open spaces planned as shelters, and a special floor of workspace was vacated as a quarantine space after the outbreak.	Emergency shelter	Community Infrastructure
R09	Elderly people in the family are less educated, with an old-fashioned mindset, and they simply do not pay attention to the outbreak at first or even think that it does not matter, so we often call them and tell them to do a good job of protecting themselves and to go out less often.	Educational attainment	Educational Attainment

(4) Spindle coding and selective coding

The 20 preliminary categories derived from the open coding phase were subjected to a thorough analysis, comparison, and synthesis to discern their logical interconnections and to organize them into five principal categories. These principal categories, along with their associated preliminary categories, are presented in Table 3.

Table 3. Spindle coding.

Main Category	Initial Category
A. Demographic Characteristics	A1 Vulnerable Group; A2 Educational Attainment; A3 Risk Perception; A4 Health Status
B. Economic Capital	B1 Employment Rate; B2 Resident Income Level; B3 Medical Insurance Coverage; B4 Property
C. Community Governance	C1 Communal Norms; C2 Community Leadership; C3 Community Emergency Response; C4 Community Service
D. Social Capital	D1 Resident Participation; D2 Government Efficacy; D3 Community Learning; D4 Social Network
E. Environment	E1 Building Environment; E2 Community Environment; E3 Community Infrastructure

By further consolidating and refining all categories obtained through axial coding and by extracting and distilling the central themes, we posit that demographic characteristics, economic capital, community governance, social capital, and environment all contribute to community resilience. Consequently, we have identified the core category as the influencing factor of ERUC for the prevention and control of public health emergencies.

(5) Theoretical saturation test

According to grounded theory, in order to check the credibility and sufficiency of the material concept, the main category, and the core category, the theoretical saturation test is needed. The theoretical saturation test means that new theoretical insights and new test categories can no longer be found from the newly collected data [36]. To test the theoretical saturation of the “Theoretical Framework for ERUC”, the remaining five interviews were coded in a three-stage process, and it was found that no new concepts or categories could be derived, and therefore, the research model in this paper was considered to have reached theoretical saturation.

2.3. Step 3: Influencing Factor Reduction

The 20 factors influencing ERUC require further refinement to ensure their scientific validity and effectiveness. This paper utilizes Principal Component Analysis (PCA) to streamline these factors. PCA is a technique that reduces data dimensionality by eliminating redundant indicators, thereby simplifying the indicator system [37]. The goal is to replace complex, interrelated evaluation indicators with a fewer, non-redundant set that still reflects the original data, minimizing bias from subjective indicator selection [38,39].

The questionnaire, grounded in theoretical research, targeted over ten Nanjing communities affected by epidemic lockdowns. We surveyed neighborhood committee leaders, community staff, volunteers, and other practitioners. Additionally, experts in community research were key recipients. Respondent details are outlined in Table 4. The questionnaire comprises two sections: demographic details like gender, age, education level, role, and community involvement years and assessments of factor importance using a five-point Likert scale. Respondents rated each factor’s significance based on experience and knowledge. Scores ranged from “1” (not important) to “5” (very important), as detailed in Section S2.

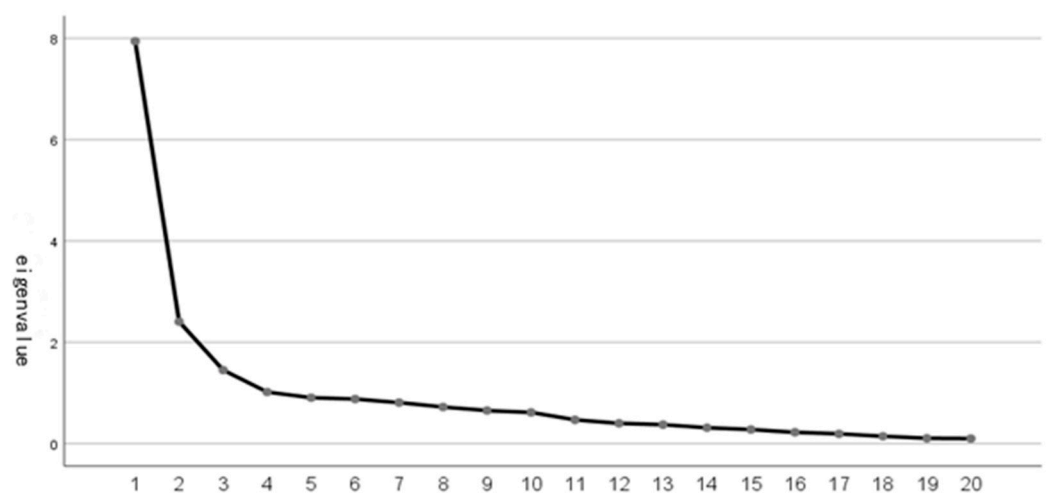
We distributed 70 questionnaires and received 70 responses. After excluding two incomplete surveys, we obtained 68 valid responses—a 97.14% success rate—sufficient for data analysis.

Table 4. Basic information statistics of respondents.

	Classification	Number	Percentage (%)
Gender	Male	18	26
	Female	50	74
Age	18–30	7	11
	31–40	57	84
	41–50	3	4
	51–60	1	1
Educational level	High school	3	4
	Undergraduate	38	56
	Postgraduate and above	27	40
Identities	Neighborhood Council Leader	8	12
	Community Staff	23	34
	Community Volunteer	25	37
	Community Field Specialist	12	17
Years of service/research	5 or under	15	22
	6–10	25	37
	11–15	21	31
	16 or more	7	10

To ascertain the suitability of our collected data for Principal Component Analysis (PCA), we utilized SPSS software (version 22.0) to conduct the KMO and Bartlett's sphericity tests on the sample dataset. The KMO value was found to be 0.808, exceeding the threshold of 0.6, which suggests a high level of reliability in our data. Furthermore, in Bartlett's test, the *p*-value was recorded at 0.000, significantly below the 0.005 threshold, confirming the validity and appropriateness of our sample for PCA.

The cumulative contribution rate of the 20 variables examined through this questionnaire reached 100%, with four variables exhibiting eigenvalues greater than 1. These four variables alone account for a cumulative contribution rate of 64.097%, sufficiently explaining most variances observed in the original 20 variables. Consequently, we extracted four principal components. A scree plot (Figure 2) served as a visual aid, indicating the optimal number of principal components to extract, marked by the point at which the slope of the line changed from steep to smooth.

**Figure 2.** Gravel diagram.

In performing PCA, to enhance clarity in interpreting the principal components, it is crucial to identify components that are highly independent. This means selecting factors (principal components) that are not correlated or have minimal correlation [37]. If the

variable loadings in the initial component matrix are similar and evenly distributed, the interpretation of these principal components becomes ambiguous. Varimax, proposed by Kaiser in 1956, can maximize the sum of variances of each factor load through coordinate transformation. Generally speaking, (1) any variable has a high contribution rate on only one factor, and the load on other factors is almost 0; (2) Any factor only has a high load on a few variables, while the load on other variables is almost zero. To address this and clarify the specific meaning of the principal components, we applied the Kaiser normalized varimax rotation method, which seems to be the best method to ensure factorial invariance [40]. This rotation converged after seven iterations. By filtering out coefficients below 0.4, we derived a clearer component matrix, presented in Table 5, offering a precise realignment of the influencing factors.

Table 5. Component matrix after rotation.

	Index	Component			
		1	2	3	4
A1	Vulnerable Group				0.767
A2	Educational Attainment				0.475
A3	Risk Perception				0.711
B1	Employment Rate		0.649		
B2	Resident Income Level		0.694		
B3	Medical Insurance Coverage		0.730		
C1	Communal Norms	0.763			
C2	Community Emergency Response	0.820			
C3	Community Service	0.833			
D1	Resident Participation			0.573	
D2	Government Efficacy			0.422	
D3	Social Network			0.691	
E1	Community Environment				0.589
E2	Community Infrastructure				0.586

Further approximation and optimization of the 20 influencing factors obtained from the rootedness theory are completed by screening using PCA. According to Table 5, this paper finally identifies the 14 factors contained in the five principal components as the 14 factors affecting the ERUC. At this point, the preliminary interpretation and analysis of the factors influencing the ERUC have been completed.

2.4. Step 4: Analysis of the Factors by DEMATEL-ISM Method

The Decision Making Trial and Evaluation Laboratory (DEMATEL) technique stands out as a highly regarded multi-criteria decision-making (MCDM) approach [41]. This method is based on the empirical knowledge judgment of groups or experts and analyzes the influence relationship between various factors in the system. Its essence is to regard the system as a weighted directed graph. Through the logic between the factors in the system and the direct influencing factor matrix, the influence degree and the affected degree of each factor on other factors are calculated, and then, the centrality and the cause degree of each factor are obtained. Among them, centrality can judge the importance of the influencing factors, and the cause degree can judge the causal attributes of the factors [42]. Currently, the DEMATEL method is extensively employed in analyzing factors impacting various aspects of disaster management, including the economic repercussions of natural disasters and resilience metrics for sustainable constructions, among other applications [43,44].

Interpretive Structural Modeling (ISM) serves as an established technique for system analysis. Its goal is to develop a tiered structural model by breaking down system components, leveraging empirical judgment data, and utilizing computational tools such as MATLAB. ISM adeptly blends qualitative and quantitative approaches, transforming intricate system concepts into an analyzable framework that elucidates the system's inner workings [45].

From the above analysis, although the DEMATEL method and the ISM method are both used to analyze complex systems, the focus of these two methods is not the same. In addition to paying attention to the interaction between various influencing factors, the DEMATEL method pays more attention to the quantitative relationship between nonlinear factors, that is, quantifying the degree of influence between factors, to grasp the importance of each factor in the system. The focus of the ISM method is to classify and sort according to the interrelationship of factors and establish an orderly hierarchical structure in a disorderly system. The single use of any of these methods cannot fully meet the purpose of deep analysis of complex systems. The integration of the DEMATEL method and ISM method can overcome the shortcomings of the two to form complementary advantages. The core of integrating the DEMATEL method and ISM method is to connect them through the correlation between matrices. The comprehensive influence matrix(H) in the DEMATEL method can be transformed into the reachability matrix(K) in the ISM method, and then, the hierarchical structure of the system is derived from the reachability matrix to construct a multi-layer hierarchical structure model.

(1) Model construction

The interview method was used to determine whether there was a relationship between the factors influencing ERUC. Experts in urban emergency management and practitioners with extensive work experience in the community were invited to fill out a questionnaire based on their knowledge and experience to score and determine the relationship between the influencing factors. The scale of pairwise comparisons was categorized into five levels: Scores ranged from “0” (no impact) to “4” (higher impact);

(2) Constructing the direct impact matrix

The scoring results of experts and practitioners are averaged and then rounded to the nearest integer to reduce the subjective differences in judging, and the integrated result is the direct influence matrix $A = [a_{ij}]n \times n$, where a_{ij} indicates the degree of influence of the influence factor X_i on X_j , and $a_{ij} = 0$ when $i = j$.

In order to obtain a unified dimension, matrix A is normalized using the maximum value method according to Equation (1) to obtain the standard matrix $B = [b_{ij}]n \times n$, which makes b_{ij} between the interval [0, 1].

$$B = \frac{a_{ij}}{\max \sum_{j=1}^n a_{ij}} = \begin{bmatrix} 0 & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{n1} & \cdots & 0 \end{bmatrix} \quad (1)$$

(3) Constructing the comprehensive impact matrix

Based on the normalized direct impact matrix B, the direct and indirect impacts of each influencing factor are accumulated to calculate the comprehensive impact of matrix T, as shown in Equation (2).

$$T = \lim_{n \rightarrow \infty} (B + B^2 + B^3 + \dots + B^n) = B(I - B)^{-1} = \begin{bmatrix} t_{11} & \cdots & t_{1n} \\ \vdots & \ddots & \vdots \\ t_{n1} & \cdots & t_{nn} \end{bmatrix} \quad (2)$$

(4) Centrality and Causality Analysis

Based on the comprehensive influence matrix T, the degree of influence f , the degree of being influenced e , the degree of center m , and the degree of cause n are solved for each influencing factor.

The degree of influence, f , refers to the degree to which a particular ERUC factor influences the other factors and is the sum of the values of the corresponding rows of each factor in the matrix T, denoted as f_i .

$$f_i = \sum_{j=1}^n t_{ij}, (i = 1, 2, \dots, n) \quad (3)$$

The degree of being influenced, e , refers to the degree to which a particular ERUC factor is influenced by other factors, and is the sum of the values of the corresponding columns of each factor in the matrix T , denoted as e_i .

$$e_i = \sum_{j=1}^n t_{ji}, (i = 1, 2, \dots, n) \quad (4)$$

Centrality m refers to the degree of importance of a factor in the ERUC system and is obtained by adding the degrees of influencing and being influenced, denoted as m_i .

$$m_i = f_i + e_i \quad (5)$$

The degree of cause, R , focuses on the attributes of the factor; if the degree of cause is greater than 0, it indicates that the factor has a strong influence on other factors and is a cause factor affecting the ERUC; conversely, if the degree of cause is less than 0, it indicates that the other factors have a strong influence on the factor and is an effect factor affecting ERUC. It is obtained by subtracting the degree of influence and the degree of being influenced, which is denoted as n_i .

$$n_i = f_i - e_i \quad (6)$$

(5) Constructing the overall impact matrix

The overall impact matrix only considers the interactions between the influencing factors and ignores the role of the factors themselves. To fully consider the factors themselves, the overall influence matrix H is calculated on this basis.

$$H = I + T = \begin{bmatrix} h_{11} & \cdots & h_{1n} \\ \vdots & \ddots & \vdots \\ h_{n1} & \cdots & h_{nn} \end{bmatrix} \quad (7)$$

(6) Constructing the Reachability Matrix

Firstly, using Equations (8)–(10), the threshold λ is derived by calculating the sum of mean α and standard deviation β in the comprehensive impact matrix T .

$$\alpha = \frac{\sum_{i=1}^n t_{ij}}{n} \quad (8)$$

$$\beta = \sqrt{\frac{\sum_{i=1}^n (t_{ij} - \alpha)^2}{n}} \quad (9)$$

$$\lambda = \alpha + \beta \quad (10)$$

After setting an appropriate threshold λ , the reachable matrix $K = (k_{ij})_{n \times n}$ can be obtained using Equation (11) based on the overall influence matrix H . If the influence value h_{ij} is greater than λ , it represents having influence between h_i and h_j , and the specified value is 1; if it is less than the value λ , it represents no influence, and the specified value is 0.

$$k_{ij} = \begin{cases} 1, & h_{ij} \geq \lambda \\ 0, & h_{ij} < \lambda \end{cases} (i, j = 1, 2, \dots, n) \quad (11)$$

(7) Hierarchy of influencing factors

According to Equations (12) and (13), calculate the reachability set P_i and the antecedent set Q_i , and then use Equation (14) to calculate the common set L_i , classifying the influence factor hierarchy.

$$P_i = \{a_j | a_j \in A, k_{ij} = 1\} \quad (i, j = 1, 2, \dots, n) \quad (12)$$

$$Q_i = \{a_j | a_j \in A, k_{ji} = 1\} \quad (i, j = 1, 2, \dots, n) \quad (13)$$

$$L_i = \{a_j \in A | P_i \cap Q_i = P_i\} \quad (i, j = 1, 2, \dots, n) \quad (14)$$

(8) Model drawing

The central-degree–cause-degree result map is plotted with the center degree on the horizontal axis and the cause degree on the vertical axis. This map is then merged with the hierarchy of influential factors to develop a multilevel hierarchical model. With this step, the entire process of model construction using the integrated DEMATEL-ISM approach is finalized.

3. Case Study

China, as a populous nation with a significant base of vulnerable groups, including those with underlying health conditions, the elderly, and children, requires focused attention during the pandemic. The Second Community of Suojin Village (hereafter called Community S), a typical older community, has a complex internal composition: numerous storefronts, a high concentration of vulnerable populations, many old houses, relatively backward infrastructure, and a weak foundation for resilience, facing formidable challenges in combating the COVID-19 outbreak. During the pandemic, a task force was swiftly formed by community management personnel and members of the neighborhood committee to initiate epidemic prevention and control efforts. Leveraging existing resources, the task force took proactive measures prioritizing residents' needs and interests, effectively addressing their concerns. By implementing "micro-modifications" and age-friendly renovations, the living environment for residents was enhanced; innovative epidemic prevention awareness methods were employed to improve residents' knowledge on the matter. This not only boosted the sense of residential experience and well-being among the inhabitants but also facilitated the optimization and upgrading of grassroots governance capabilities, thereby increasing the community resilience and successfully achieving victory in the battle against the epidemic. For three years, the community has remained vigilant, constantly prepared to face unknown public health emergencies.

This paper selects the Community S in Xuanwu District, Nanjing City, as a case study. Based on expert scoring results, the integrated DEMATEL-ISM method is applied to analyze the factors influencing the community's post-pandemic era resilience against epidemics. It proposes resilience enhancement measures for the community to respond to sudden public health events and offers experiences and references for other similar communities.

3.1. Data Acquisition

Considering the actual response to the COVID-19 of Community S, urban emergency management professionals and community staff with extensive experience were invited to evaluate the factors influencing the ERUC of Community S. This involved 14 indicators across five dimensions. The panel consisted of the head of the Nanjing Center for Disease Control and Prevention, three university professors, two neighborhood committee leaders, and three volunteers—a total of nine experts. The scoring was on a scale of 0–4, where 0, 1, 2, 3, and 4 denoted no impact, low impact, medium impact, high impact, and very high impact, respectively. The scoring results are presented in Section S3.

3.2. Analysis by the DEMATEL-ISM Method

The expert scoring data collected from the questionnaire are presented in the form of a matrix, and the initial direct influence matrix A is obtained. The matrix A is normalized to obtain the standard matrix B, and then, the comprehensive influence matrix T of the

influencing factors of the ERUC is calculated using formulas (3) and (4). Then, according to formulas (5) to (8), the influence degree(f), the affected degree(e), the center degree(m), and the cause degree(n) of each influencing factor are solved, as shown in Table 6.

Table 6. Influence degree, affected degree, center degree and cause degree of ERUC.

	Index	f	f_{rank}	e	e_{rank}	m	m_{rank}	n	Identity
A1	Vulnerable Group	4.141	1	2.960	8	7.101	5	1.182	Cause
A2	Educational Attainment	3.874	3	1.838	13	5.712	11	2.035	Cause
A3	Risk Perception	2.770	10	4.271	3	7.040	6	−1.501	Effect
B1	Employment Rate	2.306	12	2.048	12	4.353	13	0.258	Cause
B2	Resident Income Level	3.209	8	2.560	10	5.768	10	0.649	Cause
B3	Medical Insurance Coverage	2.100	13	4.245	4	6.345	8	−2.144	Effect
C1	Communal Norms	3.444	7	4.448	2	7.892	2	−1.003	Effect
C2	Community Emergency Response	4.047	2	3.763	5	7.810	3	0.284	Cause
C3	Community Service	3.804	4	3.458	6	7.262	4	0.346	Cause
D1	Resident Participation	3.429	6	4.842	1	8.271	1	−1.413	Effect
D2	Government Efficacy	3.642	5	2.402	11	6.043	9	1.240	Cause
D3	Social Network	3.034	9	3.337	7	6.372	7	−0.303	Effect
E1	Community Environment	1.291	14	0.722	14	2.014	14	0.569	Cause
E2	Community Infrastructure	2.727	11	2.925	9	5.651	12	−0.198	Effect

(1) Analysis of the influence degree(f) and affected degree(e)

As shown in Table 6, Table 6, the most influential factor is a vulnerable group (A1), which is lower by untimely community emergency response (C2), educational attainment (A2), community service (C3), and government efficacy (D2). In addition, factors such as resident participation (D1), communal norms (C1), resident income level (B2), and social network (D3) are highly influential. The most affected factor is resident participation (D1), followed by communal norms (C1) and risk perception (A3). Medical insurance coverage (B3), community emergency response (C2), community service (C3), and social network (D3) also have a high affected degree. These results show that the community governance dimension ($f = 3.885$) has the most significant impact on other dimensions, followed by demographic characteristics ($f = 3.595$), social capital ($f = 3.368$), economic capital ($f = 2.538$), and physical environment. It is also the most affected dimension ($e = 3.890$), succeeded by social capital ($e = 3.407$), demographic characteristics ($e = 3.023$), economic capital ($e = 2.951$), and environment ($e = 1.849$);

(2) Analysis of the center degree(m) and cause degree(n)

The top three factors of the center degree are resident participation (D1), communal norms (C1), and community emergency response (C2). These three factors are the most important in the causal system of ERUC and play the most obvious role in the promotion of ERUC. Therefore, to improve the ERUC, we need to focus on these three factors.

Regarding the cause degree, eight factors with positive scores are considered causal factors, highlighting their propensity to influence ERUC overall and underscoring the need for closer attention. Among these, educational attainment (A2) stands out as the indicator with the highest cause degree, signifying its predominant role in the causal group. Concurrently, it ranks among the top three influencing factors, demonstrating the significant impact of educational attainment on other elements. From a micro perspective, enhancing educational attainment can boost risk perception among residents, improving pre-disaster preparations, disaster response, and post-disaster recovery, thereby elevating ERUC. Government efficacy (D2) and income level (B2) are the second and third major factors in terms of causality, influenced minimally yet exerting considerable impact on other factors, leading to a high causality score. Among ERUC's five dimensions, community governance and environment that belong to the causal group are least affected by other factors.

Conversely, six factors scored negatively, classifying them as outcome factors, suggesting that they influence other factors less than they are influenced. Notably, medical

insurance coverage (B3) is foremost, marking it the most crucial outcome group factor, significantly influenced by other elements and exhibiting a strong outcome orientation. The medical insurance coverage is largely affected by the economic capital of the community. The higher the income of people, the higher the purchase rate of medical insurance.

Furthermore, risk perception (A3) and resident participation (D1) are the second and third most significant factors within the outcome group, both ranking in the top three in influence, underscoring their substantial impact on other indicators. Risk perception reflects the residents' awareness and grasp of risk. It is a long-term judgment ability, which is generally related to experience and education level. The realization of resident participation requires the joint efforts of community residents' committees and residents, which is the key to maintaining the order of daily life and cohesion of the community. Therefore, resident participation is largely affected by social network relations.

These findings can be visually represented using scatterplots, with centrality plotted on the horizontal axis and causality on the vertical axis, as depicted in Figure 3.

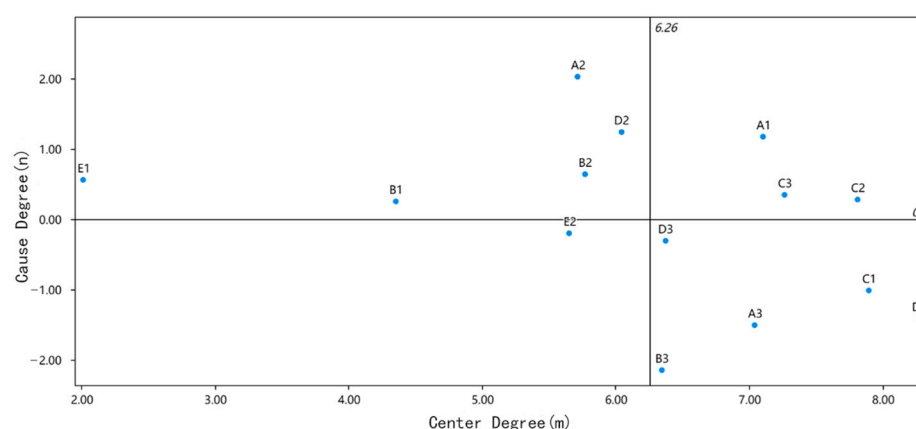


Figure 3. Quadrant distribution of the center degree and cause degree of ERUC.

(3) Model construction

In addition to considering the interactions between influencing factors, the individual roles of these factors must also be thoroughly examined. Utilizing the comprehensive influence matrix as a foundation, the overall influence matrix H is derived using the formula (7). To streamline the system structure, redundant information is eliminated by introducing a threshold λ . Following formulas (8) to (10), the mean α and standard deviation β from the comprehensive influence matrix T are calculated, and the threshold value is determined by summing these values. The computations yield the following results:

$$\alpha = 0.224, \beta = 0.105, \lambda = \alpha + \beta = 0.329$$

This refines the entire matrix, resulting in the reachable matrix K, presented in Table 7.

Based on the final reachability matrix for the influencing factors of ERUC, there are notable disparities in the driving force and dependence among the 14 key factors. For instance, the driving force of the vulnerable group (A1) stands at 6, while its dependence is merely 1, indicating that the vulnerable group exerts a significant influence on other ERUC key factors with minimal impact from them; conversely, the medical insurance coverage (B3) exhibits a dependence as high as 8 but a driving force of only 1, suggesting that it is heavily influenced by demographic characteristics and economic capital without reciprocating significantly.

Further analysis of the reachability matrix K reveals the hierarchical structure of ERUC's influencing factors for Community S, culminating in the processed results shown in Table 8.

Table 7. Reachable Matrix of influencing factors of ERUC.

	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	D3	E1	E2	Driving Force
A1	1	0	1	0	0	1	1	0	0	1	0	1	0	0	6
A2	0	1	1	0	0	1	1	0	0	1	0	0	0	0	5
A3	0	0	1	0	0	1	0	0	0	0	0	0	0	0	2
B1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
B2	0	0	0	0	1	1	0	0	0	1	0	0	0	0	3
B3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
C1	0	0	1	0	0	0	1	1	0	1	0	0	0	0	4
C2	0	0	1	0	0	1	1	1	1	1	0	0	0	1	7
C3	0	0	1	0	0	0	1	1	1	1	0	0	0	0	5
D1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	6
D2	0	0	1	0	0	1	1	1	0	1	1	0	0	0	6
D3	0	0	0	0	0	0	1	0	0	1	0	1	0	0	3
E1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
E2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Dependence Force	1	1	8	1	0	8	8	5	2	9	1	3	1	2	

Table 8. Influencing factors hierarchy decomposition results.

Level	Factor
Level 1 (top floor)	B3, D1, E2
Level 2	A3, C1
Level 3	B1, C2, D3
Level 4	A2, B2, C3, E1
Level 5 (ground floor)	A1, D2

Based on the final reachability matrix and stratification results, an ISM model that captures the key ERUC factors can be developed. This ISM model reveals the intrinsic relationships among the 14 crucial ERUC factors, which are organized into five levels, as shown in Figure 4. Within the ISM framework, higher-tiered factors exhibit increased dependence and decreased driving force, while lower-tiered elements display enhanced driving force and reduced dependence.

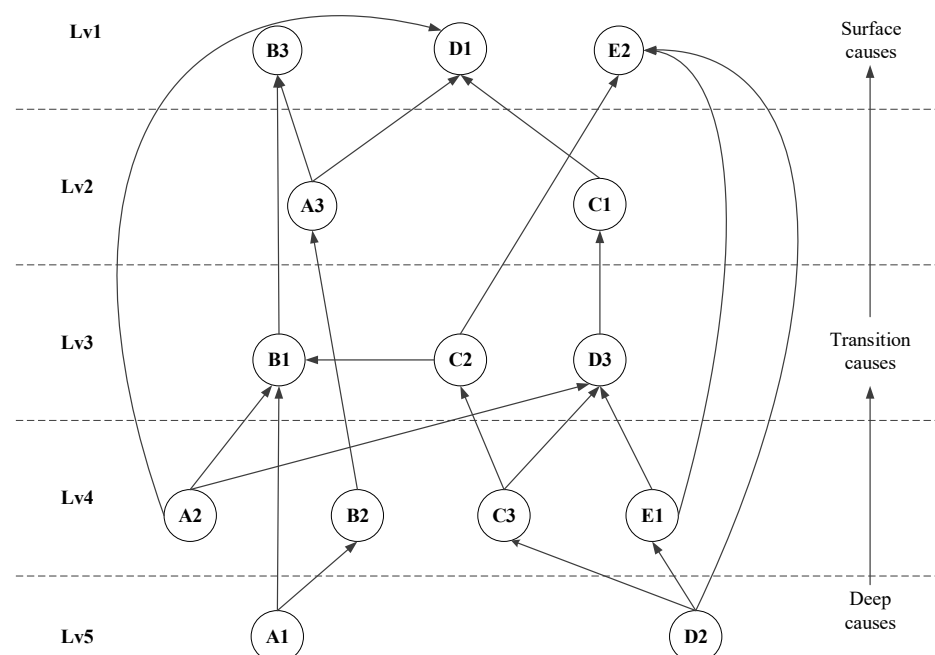
**Figure 4.** Influencer hierarchy model diagram.

Figure 4 shows that among all the influencing factors, the vulnerable group and government efficacy are at the lowest end. This means that these two factors have the strongest driving forces and have strong impacts on other factors. The vulnerable group is determined by community development and is hard to change. However, a larger proportion of a vulnerable group leads to weaker economic capital and higher difficulty in community management. As decision-makers, governments can provide basic guarantees and support for community development through measures such as macro-control, resource supply, financial support, and environmental transformation. This helps create a good natural and humanistic environment, making relationships between residents and communities more intimate and strengthening collective identity and honor.

On the other hand, medical insurance coverage, resident participation, and community infrastructure are at the top of this model. This means that these three factors are highly dependent and vulnerable to other factors affecting ERUC. This is consistent with the result obtained by Ameen et al., who used the Analytic Hierarchy Process to study the ranking and weight of sustainable indicators in developing countries and pointed out that infrastructure was a mandatory factor (must be achieved) in the urban sustainable assessment framework [46]. Medical insurance coverage is a manifestation of risk perception. Residents obtain material security and spiritual comfort through medical insurance purchases to achieve risk prevention and post-risk recovery. Medical insurance coverage is affected by community economic capital; higher income leads to higher purchase coverage. The realization of communal norms and resident participation requires the joint efforts of community resident committees and residents. This is key to maintaining daily life order and community cohesion. Therefore, communal norms and resident participation are largely affected by social network relations. Improving infrastructure also provides communities with “hard conditions” to resist external disturbances, which is key to improving ERUC. The deep-rooted influencing factors affect the surface influencing factors by affecting the intermediate factors. Thus, the remaining influencing factors of ERUC are at levels two to four, playing a connecting role.

4. Discussion

The hierarchical structure model clearly illustrates the internal relationships among the 14 ERUC influencing factors. Based on this model, the relationships between different factors can be further summarized, as shown in Table 9. At this point, the relationships between the 14 factors can be divided into six key influence paths under five dimensions.

Table 9. Key influence paths.

NO.	Key Influence Path between the Factors	Key Influence Path between the Dimensions
1	A1 → B2 → A3 → B3 A1, A2 → B1 → B3	Path1: Demographic characteristics ↔ Economic capital
2	D2 → C3 → D3 → C1 → D1	Path2: Community Governance ↔ Social Capital
3	D2 → E1 → D3 D2 → E2	Path3: Social Capital ↔ Environment
4	A3 → D1	Path4: Demographic Characteristics → Social Capital
5	C2 → B1	Path5: Community Governance → Economic Capital
6	C2 → E2	Path6: Community Governance → Environment

(1) Path 1: Demographic Characteristics ↔ Economic Capital

Among the three demographic factors (A1, A2, and A3), the vulnerable group is a fundamental factor affecting ERUC. Older communities tend to have higher proportions of vulnerable individuals, weakening community capital. Additionally, lower education levels among residents in aging communities lead to weaker risk perception, significantly impacting ERUC. These two influence paths (A1 → B2 → A3 → B3 and A1, A2 → B1 → B3) underscore the profound impact of demographic characteristics on economic capital, though

economic capital can also influence demographic characteristics in some cases. Risk perception reflects residents' understanding and grasp of risks, a long-term judgment ability typically related to experience and educational attainment. Higher-income communities generally exhibit greater educational attainment, thus shaping population characteristics. Medical insurance coverage also reflects risk perception. Residents can obtain material security and spiritual comfort through insurance purchases, aiding in risk prevention and post-risk recovery.

Therefore, focusing on vulnerable groups can help communities better cope with public health emergencies. The government can broaden the coverage of the minimum guarantee policy and appropriately tilt resources to vulnerable groups through policy assistance to reduce the proportion of vulnerable people in the community. In daily life, the community should pay special attention to the needs of vulnerable groups by providing timely services, financial support, and other assistance to help them improve their ability to resist risks. Meanwhile, the community can collaborate with various social actors such as volunteers, hospitals or health clinics, and online platforms under government guidance. Through resource integration, they can establish a support team to promote targeted services for disadvantaged groups in the community;

(2) Path 2: Community Governance $\longleftrightarrow$ Social Capital

This path (D2 $\rightarrow$ C3 $\rightarrow$ D3 $\rightarrow$ C1 $\rightarrow$ D1) clearly shows that social capital and community governance influence each other. In community management and services, the government plays a crucial role by providing comprehensive support such as unified command, force support, and social mobilization. This top-down influence is vital for maintaining normal community operations and ensuring resident well-being. The realization of communal norms and resident participation requires joint efforts from community committees and residents. It is key to maintaining daily order and community cohesion, making communal norms and resident participation heavily influenced by social network relationships. Thus, the government needs to summarize successful domestic and international experiences in responding to public health emergencies, prepare early warnings, and formulate precise policies to guide community responses. This relies on the government's leading role in integrating overall situations and coordinating multiple parties. The government can introduce social organizations, enterprises, and other public-private sector forces into community services, empowering grassroots operations and building a system for emergency response involving government responsibility, social coordination, community cooperation, and resident participation;

(3) Path 3: Social Capital $\longleftrightarrow$ Environment

A good community environment helps residents quickly return to normal life after a disaster and plays a significant role in community reshaping, building a sense of community, and strengthening cohesion. This stimulates the community's strong immunity against future external dangers and shocks. Under the path (D2 $\rightarrow$ E1 $\rightarrow$ D3), the government can formulate policies on community environmental protection programs, strengthen ecological creation, increase environmental supervision, ensure community cleanliness, create a favorable natural environment, and effectively prevent virus spread. Additionally, under the pathway (D2 $\rightarrow$ E2), the government provides communities with "hard conditions" to resist external disturbances by improving infrastructure, which is crucial for enhancing ERUC;

(4) Path 4: Demographic Characteristics $\rightarrow$ Social Capital

Path A3 $\rightarrow$ D1 reveals the influence of demographic characteristics on social capital, mainly through the impact of risk perception on resident participation. Resident participation refers to an individual's sense of belonging and identity within the community. Higher participation allows for more effective integration and utilization of community resources and is an intrinsic motivation and crucial source for building ERUC. Higher risk perception leads to greater self-rescue abilities during emergencies and easier active

participation in community prevention efforts. Therefore, stimulating residents' proactive engagement is beneficial for building epidemic-resilient communities. We can conduct emergency drills simulating various public health scenarios and perform risk reviews to enhance residents' ability to respond to real situations. By spreading knowledge and promoting skills, residents' risk perception, self-help ability, and mutual aid skills can be improved. Simultaneously, it is essential to strengthen community problem-solving, address residents' needs, and enhance community cohesion and action;

(5) Path 5: Community Governance → Economic Capital

The pathway from C2 to B1 suggests that community emergency response is closely linked to employment rates. During emergencies or natural disasters, the need for emergency relief work creates demand for manpower, thereby increasing job opportunities. Enhancing the capacity of community emergency response can stimulate labor demand in related fields and increase employment opportunities. An improved emergency response system can provide businesses with a more stable and secure operating environment, promoting growth and further boosting job creation. An IT-supported emergency response platform can issue early warnings before a public health crisis, efficiently collect information during the community's disaster response, accurately account for the community's various needs, and share resources with superior government. Professionalizing grassroots work can be achieved by strengthening talent training within the community and improving service levels in various aspects. Additionally, professional service agencies and community organizations can be introduced to undertake some service functions in conjunction with the community, allowing residents to enjoy high-level professional services while reducing the grassroots workload;

(6) Path 6: Community Governance → Environment

The pathway from C2 to E2 indicates that community emergency management is closely linked to infrastructure, and emergency planning requires a comprehensive assessment of community infrastructure. This includes categorizing and planning for locations, structures, and potential problems to ensure accurate and rapid search and rescue, evacuation, and supply efforts. Since community infrastructure is fundamental to enhancing ERUC, improving the redundancy and resilience of infrastructure is crucial in minimizing the impact of health emergencies.

Past experiences from public health crises have shown that rational community spatial planning enhances community mobility in responding to risks, helps residents save themselves in emergencies, and alleviates post-disaster tensions and psychological stress. For newly built communities, space design must focus on disaster prevention with both buffer and flexibility, incorporating resilience in architectural design and materials while establishing sufficient evacuation routes and refuge sites. For older neighborhoods, spatial transformation can integrate disaster resilience and mitigation with improved living conditions and, through democratic consultation, ensure community space meets residents' needs. During a public health emergency, the community may take extreme preventive measures, restricting residents' movement and highlighting material supply issues. Therefore, creating a 10–15-minute living circle that combines convenience and epidemic prevention is particularly important. By enhancing medical emergency supplies, logistics, communication and energy supply, isolation points, epidemic prevention points, and other areas within the living circle, we strive to meet residents' daily needs while minimizing their activity range to prevent epidemic spread from large-scale social activities.

5. Conclusions

Risks and disturbances have become a norm in urban development. In the context of public health emergencies, improving the ability of communities to self-organize, adapt, and recover is an urgent task for urban management and construction. Building ERUC is crucial for sustainable global development. Based on the COVID-19 epidemic, this work chooses the method of grounded theory, conducts necessary qualitative research based on

the actual situation, and obtains the theoretical framework of ERUC influencing factors. Then, through a questionnaire survey and PCA method, 14 influencing factors involving five dimensions are identified. The research results have strong practicality and guidance. They can help urban communities in the post-epidemic era to respond to public health emergencies to be able to rapidly shift from normalized to non-normalized governance and to find the key influencing factors of the problem according to the relevant indicators for specific problems, to obtain solutions and enhancement strategies. Using the DEMATEL-ISM method, the logical relationship between the factors influencing ERUC is analyzed in depth. According to the comprehensive relationship matrix, factors were ranked by importance. Resident participation, communal norms, and community emergency response are the top three in terms of importance. The results indicate that population characteristics, community governance, and social capital have a greater impact on the system, while economic capital and environment are more influenced by the other three dimensions. The hierarchical structure model shows that the fundamental factors affecting ERUC are the vulnerable group and government efficacy. Direct influencing factors include medical insurance coverage, resident participation, and community infrastructure. The remaining factors are intermediate causal factors. Through the influence on the causal factors of the intermediate layers, the deep-rooted influencing factors affect the surface influencing factors, which further affect the ERUC. Then, six critical influence paths were discussed, with suggestions provided for implementing each path; understanding the relationships between influencing factors and their action paths can help decision-makers better prioritize strategies to improve ERUC. This knowledge aids in learning from past experiences, seeking strategies to cope with and mitigate external disturbances, and strengthening ERUC to face uncertain disasters.

Combining the DEMATEL method and ISM method to analyze the influencing factors of ERUC can not only quantify the importance of each influencing factor but also obtain the hierarchical relationship between them to ensure a comprehensive understanding of ERUC and avoid missing key factors. However, this paper still has the following limitations. First, this study's scope is limited to communities in regions of Nanjing, and the selected community types may not fully represent factors affecting resilience in other urban communities in China post-pandemic, reducing the universality and persuasiveness of the results. Second, for the construction of the hierarchy of influencing factors (Figure 4), there is only a single influence here (single arrow). Whether there is a mutual influence here (double arrow) must be considered.

Therefore, in future research, the breadth and depth of ERUC in the post-pandemic era can be further explored by observing and researching multiple types of communities in different cities over a long period of time, and in the data acquisition of these communities, different scoring methods and multiplication factors that reflect the statistical significance and importance of the local geographical environment can be supplemented and applied [47]. For the relationship between the indicators in the hierarchical structure, we will try to combine the AHP method with the development of the evaluation system in order to evaluate more accurately [48]. Much relevant work can be performed in the future, and the proposed influence path can also be evaluated in our future research using simulation techniques.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/buildings14092838/s1>, Section S1: Semi-structured interview outline; Section S2: Questionnaire on Factors Influencing epidemic resilience of urban communities (ERUC) in the Post-Epidemic Era; Section S3: Scoring Scale of Role Relationships of Factors Influencing Urban Community Resilience in the Post-Epidemic Era.

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