Evaluating the resilience of social license to operate towards NIMBY facilities: a cloud model-based approach

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A B S T R A C T

This research aims to enhance the understanding of Social License to Operate (SLO) resilience in Not-In-My-Backyard (NIMBY) facilities. The dynamic nature of SLO acquisition is explored, and its implications for the relationship between industries and local communities in NIMBY contexts. Employing a systematic literature review, the study identifies indicators for SLO resilience, categorizes them through principal component analysis, and constructs an evaluation framework from diverse stakeholder perspectives. A cloud model approach is developed for SLO resilience evaluation, departing from traditional models. The study combines qualitative and quantitative methods, ensuring a comprehensive analysis of the chosen NIMBY facility. The research reveals that SLO resilience in NIMBY facilities is a complex system influenced by such factors as information disclosure, fairness, and community education. Government, community, and business resilience are essential components, with the study identifying specific indicators for each. A Quzhou case study provides valuable insights into the proposed evaluation model's practical application and validity. The findings offer actionable recommendations for stakeholders involved in NIMBY facility construction and operation. Emphasizing transparency, fairness, and strengthened legal frameworks for public participation, the study guides for improving the resilience of SLOs in the face of evolving community dynamics. It contributes to the existing literature by integrating resilience theory with the SLO concept, offering a novel perspective on social licensing in NIMBY facilities. Introducing a cloud model approach for SLO resilience evaluation adds a methodological contribution to the field. The research's value lies in its potential to guide governments and enterprises in managing NIMBY facility challenges and balancing the interests of diverse stakeholders.

Keywords: Cloud modeling; Not-In-My-Backyard facilities; Social License to Operate; Evaluation; Resilience theory; Environmental risk avoidance

1. Introduction

The term NIMBY (Not-In-My-Backyard) emerged in the 1970s and was first introduced in academic literature by O'Hare (1988). It refers to economic projects or public facilities that, while providing societal benefits, impose negative externalities on local residents. As a result, these projects often face opposition from the communities directly affected by their presence (Michael, 1992). NIMBY facilities, such as municipal solid waste disposal and nuclear power facilities, are crucial for a country’s economy and society globally (Xu et al., 2023). However, by definition, they are often opposed by local residents due to potential environmental or health hazards or property loss (e.g., Wang et al., 2019), as seen in China’s Hangzhou Jiufeng waste-to-energy incineration plant (Liu et al., 2019) and Xiamen P-Xylene plant (Sun et al., 2016). Although some economists, such as Fischel (1986) and Esaiasson (2014), have argued that NIMBYism may lead to excessive local government intervention and restrictive construction policies, potentially impeding economic and social development, the growing prevalence of anti-NIMBY movements worldwide has elevated the question of how to enhance and secure social acceptance of NIMBY facilities to a critical issue.

Social License to Operate (SLO) has its origins in the extractive industries (Jijelava and Vanclay, 2018) and is used by academics and practitioners to evaluate local residents' acceptance of NIMBY facilities. SLO is non-linear, dynamic, and better suited for providing feedback on the complex attitudes and behaviors of NIMBY facilities than the

PA (Public Acceptance) framework, which originated in the nuclear power industry (Xu et al., 2023). However, it is ‘at risk of collapse’ (Wolsink, 2010) due to its dynamic nature and potential destabilization over time or environmental changes (Dare et al., 2014). For example, while nuclear power plants have been granted an SLO (Hoadl, 2018), the nuclear leakage accident in Fukushima has led to a decline in trust in nuclear power plants (Kim and Song, 2018), highlighting the need for further research and development.

Maintaining SLO can be interpreted as SLO *resilience*, which refers to the ability to withstand external shocks to social infrastructure (Adger, 2000). Resilience is dynamic, uncertain, and non-linear scientific thinking based on the same system-sustaining characteristics as SLO (Smits et al., 2016). Studying the complexity, dynamics, and comprehensiveness of NIMBY facilities from the perspective of resilience theory can help better cope with external factors and perturbations. Research has illuminated the pivotal role of Environmental Impact Assessments (EIA) in shaping the permitting process for large capital projects (de Souza Hacon et al., 2018). Additionally, environmental production and investment standards are crucial in determining the feasibility of mining operations (Yıldız, 2021). These elements not only shape SLO but also enhance its resilience. Therefore, this study raises the following research questions: What are the indicators of SLO resilience of NIMBY projects, and how do these differ among various stakeholder groups?

Most current research into SLO focuses on its formation mechanism and analytical framework, with little attention to its maintenance. Theoretical research combining SLO with resilience is relatively slow. Extant studies mainly examine resilience measurement methods in disaster management (Qiang et al., 2023; Saja et al., 2018), the role of social capital in enhancing community resilience (Carmen et al., 2022; Pfefferbaum et al., 2017; Zhang and Sung, 2023), and resilience attributes at community and individual levels (Abramson et al., 2015, Shapira et al., 2020). However, these studies mainly focus on urban disaster contexts, with studies of SLO social resilience for NIMBY facilities only recently emerging. Existing research is also mainly qualitative (Saja et al., 2018; Pfefferbaum et al., 2017; Khalili et al., 2015), and the absence of quantitative evaluation frameworks or a mature indicator system.

The present study identifies SLO resilience indicators through a resilience theory lens through a systematic literature review. It constructs a robust evaluation model using cloud modeling and principal component analysis. Validated in a case study, it enhances the adaptive capacity of NIMBY facilities and fortifies system resilience post-risk. This research bridges the existing gap and advances understanding in the field, providing a clearer roadmap for its contribution to the broader knowledge landscape. In addition, the developed knowledge system of the SLO’s maintenance mechanism offers insights for governmental bodies and enterprises involved in NIMBY infrastructure projects by acting as a roadmap for constructing and operating NIMBY infrastructures, contributing to the existing SLO resilience knowledge base.

In summary, this study delves into the resilience of SLO within NIMBY facilities. It pinpoints essential indicators, constructs an extensive evaluation model utilizing cloud modeling and principal component analysis, and validates these methodologies through a case study with Everbright Environmental Energy (Quzhou) Co. Ltd., significantly contributing to existing knowledge. This novel approach offers actionable insights for stakeholders. It advances the broader discourse on SLO resilience, providing a clearer roadmap for understanding and addressing critical gaps in the current research landscape.

2. Literature review

2.1.Social License to Operate

As part of impact assessment, Social License to Operate (SLO) is gradually becoming an important dimension in evaluating the social feasibility and sustainability of projects (Bice, 2017). The concept of SLO had been applied to industries such as mining, forestry, wind and bioenergy, and a range of frameworks for assessing(Edwards and Trafford, 2016, O'Brien et al., 2015), constructing and maintaining SLO had emerged. As Prno and Slocomb point out, natural capital was becoming increasingly important as the public had more power to influence the development of government decisions and the concept of sustainability, and businesses needed to acquire, maintained, and improve SLO

(Prno and Slocombe, 2014). Because SLO has similar characteristics to formal regulatory permits, it requires a set of processes with clear logic and standardized conditions of use (Ford and Williams, 2016). SLO is dynamic and sustainable, and prevents companies from taking into account people's wishes only at the initial stage of project decision-making, while ignoring public opinion after the project is put into operation (Boutilier et al., 2012).

Access to SLO is dynamic and non-permanent, and beliefs, opinions, and perceptions may change as new information is acquired. For the first time, the Three-Step Process clarifies how to maintain SLO (Thomson and Boutilier, 2011). In the SLO concept, social acceptance is not simply defined in linear terms such as ‘low’ or ‘high,’ but can be defined in terms of thresholds that separate different states of acceptance, and this focus on states, thresholds, and nonlinear change links the SLO concept to systems thinking. The maintenance and enhancement of SLO is characterized by systematic uncertainty and nonlinear changes that cannot be explained by simple determinism or reductionism.

2.2 Social Resilience

Resilience was often used in the fields of engineering (Shen and Ying, 2022), disasters (Saja et al., 2018), urban and planning (Lu et al., 2021), and sociology (Liang and Cao, 2021), was a diverse and interconnected set of non-linear attributes in complex and dynamic social system that typically vary over time (Abenayake et al., 2016). Adger first extended the concept of resilience from the ecological domain to the human social domain, exploring the link between social resilience and ecological resilience, defining it as ‘the ability of a group or community to withstand external shocks to the social infrastructure’. (Adger, 2000)

In their study of resilience in cities, neighborhoods, and infrastructure, Moya and Goenechea (2022) constructed a conceptual framework for social resilience by synthesizing the characteristics of community resilience and integrating different approaches in sociology to view community resilience as a dynamic, multilevel, and evolutionary process. Saja et al. (2018) proposed an inclusive and adaptive ‘5S’ social resilience framework based on discussions in the existing literature, including social structure, social capital, social mechanisms, social equity, and social beliefs. In addition, the development of systematic resilience assessment methods and tools is also extremely important, and some scholars have proposed a number of resilience assessment frameworks that combine different contexts and perspectives. Peacock et al. proposed the CDRI framework in 2010 by analyzing and studying several communities along the U.S. Gulf of Mexico Coast, focusing on surveying their community leaders to identifying their social, economic, human, and material capitals (Peacock, 2010). Alshehri et al. in 2014 used the AHP method through a combination of quantitative and qualitative methods to construct the CRDSA framework, which contains dimensions related to social, economic, physical and environmental, governance, health and well-being, and information and communication (Alshehri et al., 2015). Therefore, further research on the 'resilience' of SLO needs to be carried out with a systemic approach, which will also help to improve enterprise-land relations and enhance social acceptance in the long term.

2.3 SLO Resilience

A comprehensive review of the relevant literature reveals that research on SLO has gradually advanced, leading to the development of a relatively mature theoretical framework that effectively addresses the degree of acceptance of NIMBY facilities by local residents. Meanwhile, resilience-related research has yielded even more significant advancements in fields such as urban systems, social-ecological systems, public safety, and individual psychology. Given that individual views and attitudes can evolve over time and across changing environments, SLO is inherently dynamic and sustainable. This characteristic prevents companies from focusing solely on public preferences during the initial stages of project decision-making while neglecting public opinion once the project is operational (Boutilier et al., 2012). In particular, adaptation plays a more critical role in sustaining SLO than in establishing it, making it a key variable in assessing SLO resilience (Prno and Slocombe, 2014). In this regard, Baumber (2019) further emphasizes the importance of considering adaptation as an independent factor in the context of SLO resilience.

The majority of current research on SLO focuses on its formation mechanisms and analytical frameworks, while studies on strategies for maintaining SLO remain relatively insufficient. By integrating the concept of SLO with the systems thinking approach to resilience, it becomes evident that the level of SLO fluctuates when a project is impacted by external risks (Moffat and Zhang, 2014; Smits et al., 2017). During such instances, the system's inherent resilience mitigates the risk of a complete loss of SLO. Subsequently, the resilience and adaptability within the SLO system operate sequentially to restore and stabilize the SLO level. Research on social resilience is often embedded within broader studies on urban resilience or social-ecological system resilience (Saja et al., 2021). Critical factors such as social capital, social support, community participation, and social identity constitute foundational elements in the development of a resilience theory for SLO. Resilience research enhances the ability of SLO systems to manage risks and remain renewable, as Joyce and Thomson (2000) noted, emphasizing that SLO systems must possess the capacity to adapt to contingencies in order to maintain their stability and sustainability. The theoretical framework for this study is illustrated in Fig 1.

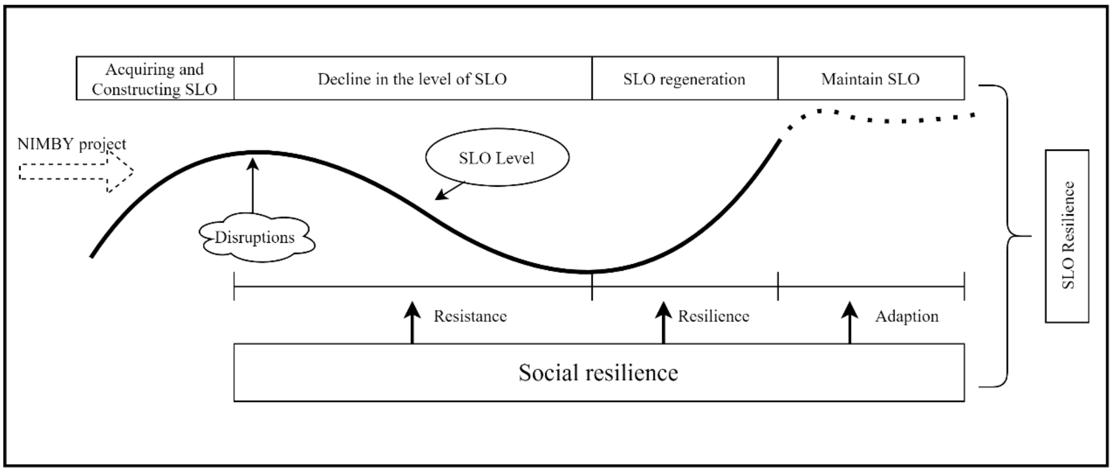


Fig.1 Theoretical framework

3. Materials and methods

Fig. 2 shows the overall analytical framework. This study contains the following three steps:

Step one: The SLO resilience evaluation indicators are identified by the systematic literature review method to screen related literature in the China Knowledge Network database and the Web of Science Core Collection with 'resilience/resilient', 'community', 'social resilience', 'social license/permission' as keywords.

Step two: The basic data are obtained by questionnaire, and the questionnaire results are factor analyzed using Kaiser's principle (Kaiser, 1960) and Scree's test (Ledesma et al., 2015). The weight calculation results are introduced into the cloud model to generate an SLO resilience evaluation benchmark cloud map, which is used to construct a SLO toughness evaluation model.

Step three: A classic case validates the SLO toughness evaluation model. Evaluation of the selected cases by local residents is obtained through field research. The obtained data are imported into the constructed SLO resilience evaluation model to obtain the evaluation cloud of the case and compared with the benchmark cloud to obtain the final evaluation results. The evaluation results are then compared with the actual situation to verify the scientific rationality of the model.

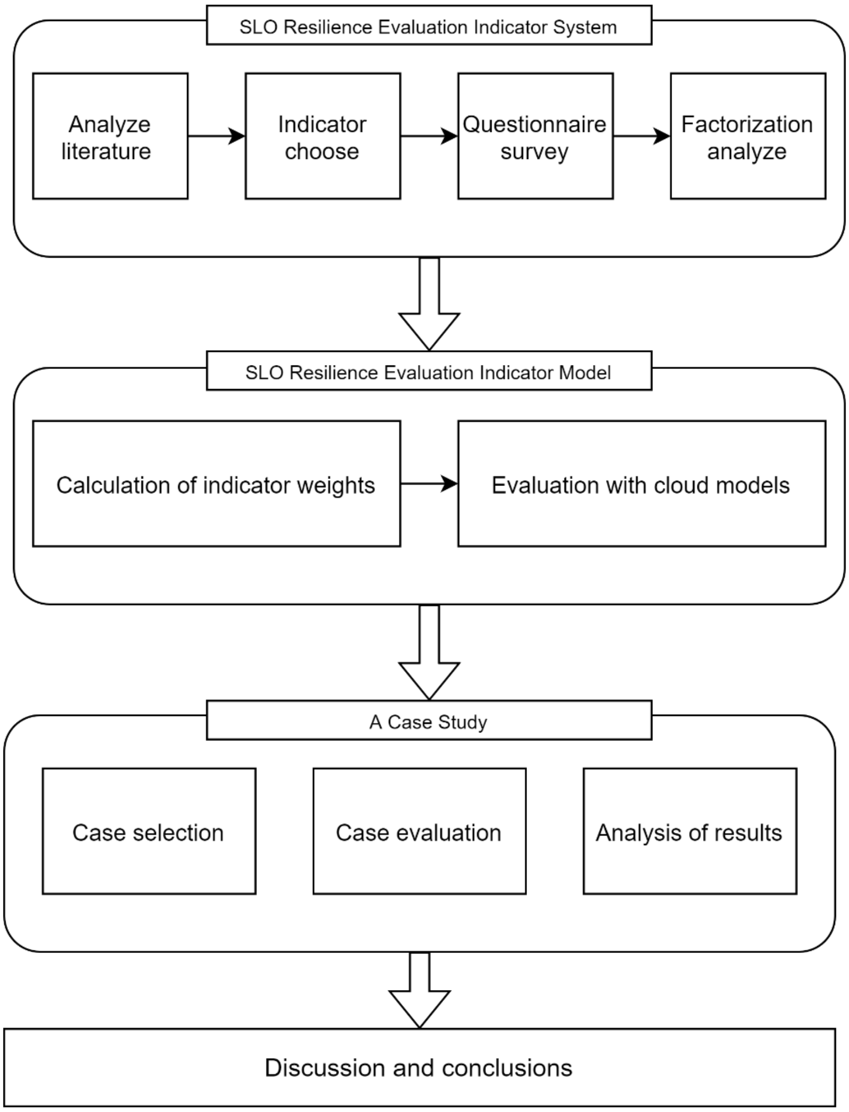


Fig. 2. The overall research framework

3.1. Identifying SLO resilience evaluation indicators

To explore the indicators of resistance, resilience, and adaptability within the government, community, and business subsystems, principal component analysis was conducted firstly based on Kaiser's principle and Scree's test to extract the number of factors for each stakeholder. Secondly, the component matrices corresponding to each indicator were analyzed using the maximum variance method after several rotation iterations. The rotation method used was orthogonal rotation with Kaiser normalization. The final feature set, which captures the amount of information present in the dataset, is obtained (See Tables B-D in the Appendix). In the SLO Resilience Evaluation Metrics System for NIMBY Facilities, the *secondary indicator* weights can be calculated using the principal component analysis discussed earlier, reflecting the correlation and interdependence among multiple indicators. The process of calculating the weights involves the following three main steps:

In the first step, calculating the coefficients of the factors in a linear combination requires dividing the initial factor loading coefficients by the square root of the corresponding eigenvalues. In the second step, the coefficients of the composite score model were calculated using the variance contribution. The linear combination coefficients were then accumulated by multiplying them with the rotated variance explained rate and dividing by the cumulative variance explained rate. In the third step, the weight coefficients were calculated for each factor, and the model coefficients were normalized for each factor’s composite score.

3.2. Selection of indicators

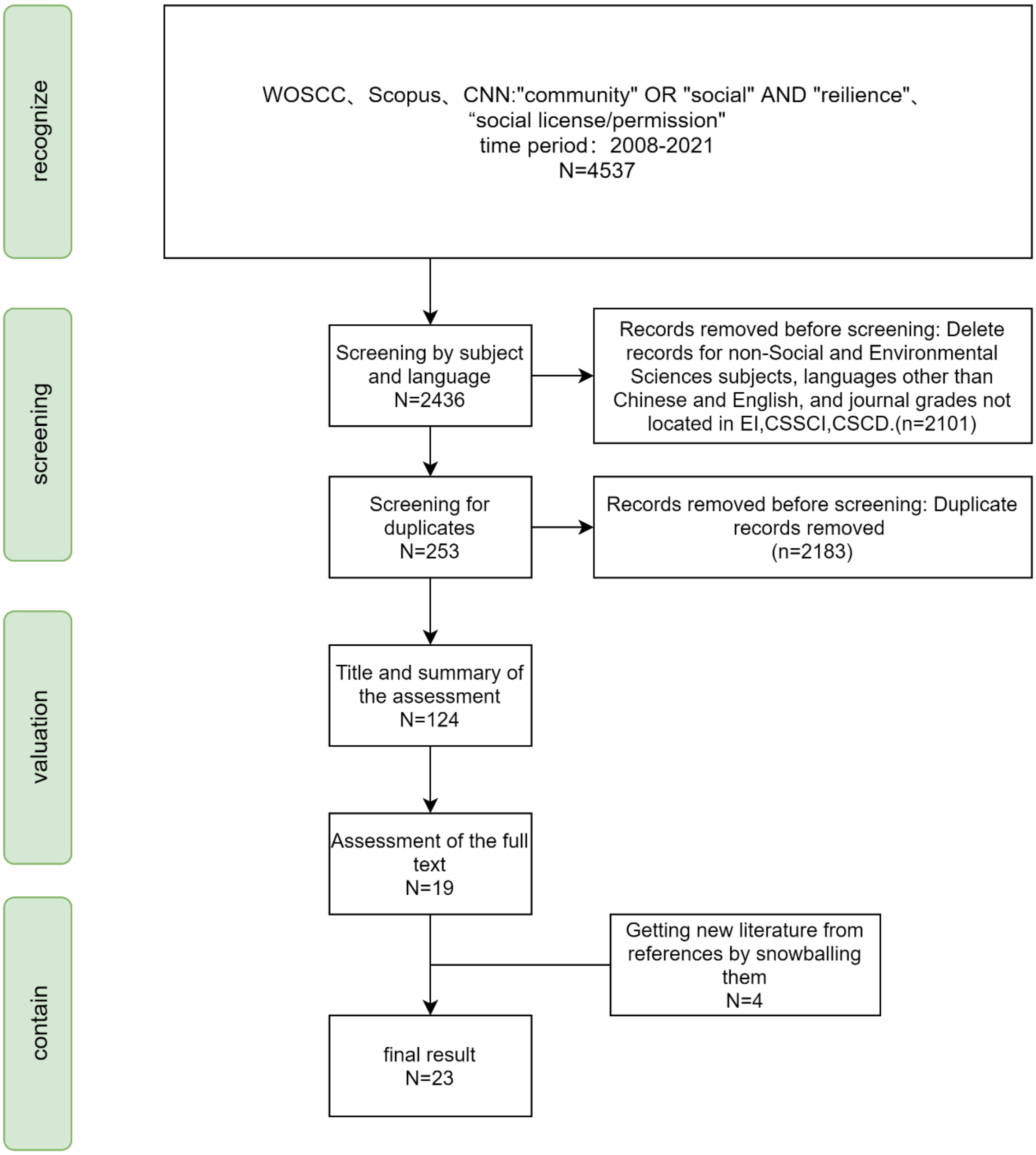


Fig. 2. Flow of literature search and screening

SLO resilience-related indicators are screened based on past social/community resilience evaluation indicators combined with NIMBY facilities’ SLO characteristics and influencing factors in the 23 screened items of literature, with cross-cutting and similar indicators merged. The literature screening process is shown in Fig. 3.

Based on a structured Expert Workshop, an electronic questionnaire was distributed to a total of nine people, including experts in the relevant fields from universities, Master's and doctoral students, and people managing NIMBY facilities, to inquire about the reasonableness of the indicators, as well as whether any are missing or need to be added. The list of indicators for evaluating the resilience of SLO for NIMBY facilities is categorized according to the three stakeholders in the complex system of SLO: government, community, and business. Tables 1 to 3 provide the indicator labels with specific interpretations for each subsystem.

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Liberati et al., 2009) guidelines were used to screen the literature from multiple databases, establishing the foundation for selecting the SLO resilience metrics for NIMBY facilities. The screening process is shown in Fig.3, which resulted in 23 documents. Drawing from previous social/resilience evaluation indicators and considering the unique characteristics and influencing factors of SLO in NIMBY facilities, a preliminary list of indicators is formed. The list can be found in the Appendix (see Table A), followed by the merging of cross-cutting and similar indicators.

Invitations for the structured expert workshops were extended *via* email to a diverse group, including university experts in the relevant fields, master’s and doctoral students, and NIMBY facility administrators. Nine people agreed to participate in the online workshop facilitated through Tencent conferencing software. Participants engaged in an electronic questionnaire, providing valuable insights on the reasonableness of the indicators and suggesting any necessary additions or modifications. The indicators designed to assess SLO resilience at NIMBY facilities are categorized according to the three stakeholders within the complex system of SLO: government, community, and business.

Government: The relevant authorities at the prefecture-level city responsible for overseeing and regulating the project;

Community: The local communities adjacent to the project site that are affected by the presence and operations of the NIMBY facilities;

Business: The corporation or entity tasked with project design, construction, and operational management.

Tables 1 to 3 provide indicator labels and specific explanations for each subsystem.

Table 1
Interpretation of evaluation indicators on the government

Serial	Indicators	Interpretation of indicators

G1	Government credibility	Local residents' satisfaction with local government
G2	Emergency preparedness	The government has prepared a more comprehensive emergency plan for the project
G3	Popularization of science	Grassroots government science outreach to surrounding communities in NIMBY facilities
G4	Equitable distribution	Transparent and fair distribution of financial compensation by the government
G5	Supervision of enterprises	The government can monitor businesses
G6	Disclosure of information	The government will publicize the EIA report and information related to government decisions
G7	Pacified communities	Grassroots government will provide psychological comfort and emotional relief to community residents
G8	Government governance	The enterprise can assume its responsibilities under the governmental governance structure and governance mechanisms
G9	Specialized working groups	The government will set up a thematic working group for the project
G10	Laws and regulations	Improvement of laws related to protecting the environment, public participation processes, etc.
G11	Modulating effect	Government becomes the link between business and the community and plays a moderating role

Table 2

Interpretation of evaluation indicators in the community

Serial	Indicators	Interpretation of indicators
C1	Age structure	Proportion of young adults in local communities
C2	Educational attainment	Educational attainment of local community residents at the tertiary level and above
C3	Sense of community	Residents have a strong sense of identity and belonging to the region
C4	Learn about the program	Community members took the initiative to learn about the program
C5	Community leadership	There are trusted community leaders in the community
C6	Local committee	The local committee informs the community about important developments in the project
C7	Community expectations	The needs and expectations of community residents can be met
C8	Expression of opinion	Community residents have the opportunity to express their wishes
C9	Key figure	There are key people in the community who know the right people to help with tasks
C10	Moral of the population	Community members have a strong sense of morality
C11	Shared vision	Community residents can work together with government and businesses to solve related problems
C12	Risk awareness	Risk awareness among community members themselves

Table 3

Interpretation of evaluation indicators for the business

Serial	Indicators	Interpretation of indicators
E1	Corporate reputation	Word of mouth, reputation, and satisfaction of the business in the surrounding community
E2	Emergency drills	Businesses conduct regular drills for unforeseen events
E3	Popularization of science	Enterprises educate residents of neighboring communities about the facility's publicity and science
E4	Views of the population	Businesses listen to and respect community residents
E5	Emergency measures	Enterprises have a comprehensive emergency protection system for emergencies
E6	Disclosure of information	Enterprises organize field trips to projects for local residents, public annual reports
E7	Protecting the environment	Maintenance of local future sustainability of groundwater, farmland
E8	Corporate decision-making	Businesses consider local residents in some of their decisions
E9	Quality of communication	Business engagement with local residents can be effective in solving residents' problems
E10	Frequency of communication	Enterprises will hold symposiums to communicate with local residents' representatives frequently
E11	Corporate governance structure	The government regulates businesses to meet the needs of society
E12	Long-term monitoring	Businesses pay long-term attention to the opinions and sentiments of community residents

3.3. Validation of indicators

The questionnaire used the evaluation indicators as variables. It was distributed online through the Questionnaire Star software and offline by hard copy distributed face-to-face and collected on the spot. Snowball sampling was used to reduce the chances of random or invalid questionnaires. Data collection took two months, with 145 and 67 questionnaires issued online and offline, respectively, of which 142 and 65 were retrieved. Those with extreme ratings and no significant differences were considered invalid (Zhong Xiaoyu, 2020). The total number of valid questionnaires for analysis after screening is

204, with an effective recovery rate of 96.23%. Table 4 summarizes the respondents' socio-demographic information.

Table 4

Sample basic information statistics

Profile (N=204)	Category	Frequency	Proportion
Genders	Male	113	55.39%
	Female	91	44.61%
Work unit	Universities and research institutions	59	28.92%
	Government branch	49	24.02%
	NIMBY facilities businesses	70	34.31%
	Other businesses	26	12.75%
Education level	Specialized and below	45	22.06%
	Undergraduate	88	43.14%
	Bachelor's degree	50	24.51%
	PhD and above	21	10.29%
Working experience	5 years and under	55	26.96%
	5-10 years	32	15.69%
	10-20 years	40	19.61%
	More than 20 years	77	37.75%

Worthy of mention is that the number of males is slightly higher than that of females, with a ratio of 11:9. Their work units are mainly NIMBY facilities and university research institutions, accounting for 34.31% and 28.92% of the total sample, respectively. In terms of academic qualifications, Bachelor's degrees account for the vast majority of respondents, with 88 people, or 43.14% of the total, and respondents with Master's and doctoral degrees account for 34.8% of the total. Hence, respondents generally have higher academic qualifications. In the statistics of working experience, the respondents with more than 20 years of experience account for 37.75%, indicating that the survey respondents have more seniority and work experience in the industry. Overall, the sample characteristics are more evenly distributed, and the sample data are credible and representative.

3.4. Cloud model-based approach for SLO resilience evaluation

Deyi Li and Du (2016) initially proposed Deyi Li and Du (2016)the cloud model concept in the 1990s by combining the stochastic functions of traditional probability theory with the theories of modern fuzzy mathematics as models that can be interchanged between qualitative concepts and quantitative data. The model is widely used in the evaluation of complex systems and uncertainty risks, such as in the study of urban disaster emergency response capacity (Xu et al., 2022) and ecological risks(Yang et al., 2018), and in recent years it has also begun to be applied in resilience evaluation(Qiao and Pei, 2022). In this study, the cloud model approach is used to calculate the SLO resilience, and a questionnaire evaluates the resilience of NIMBY facilities' SLO during the case evaluation process.

The evaluation steps for the resilience of NIMBY facilities' SLO are based on the cloud model implementation process, which is obtained in combination with the weights of the indicators identified in the previous section. The Benchmark Cloud is generated by dividing the rubric set after organizing and categorizing each stakeholder's indicator and guideline layers. The resilience indicators are calculated by determining the membership through the forward and inverse cloud generators. Fig. 4 shows the steps for the comprehensive evaluation of the cloud model. This approach has the randomness and fuzziness of cloud modeling. Fuzziness and randomness are co-expressed throughout the data processing process, and the cloud model materializes both characteristics. The number of comments can better respond to the model's differences in new data.

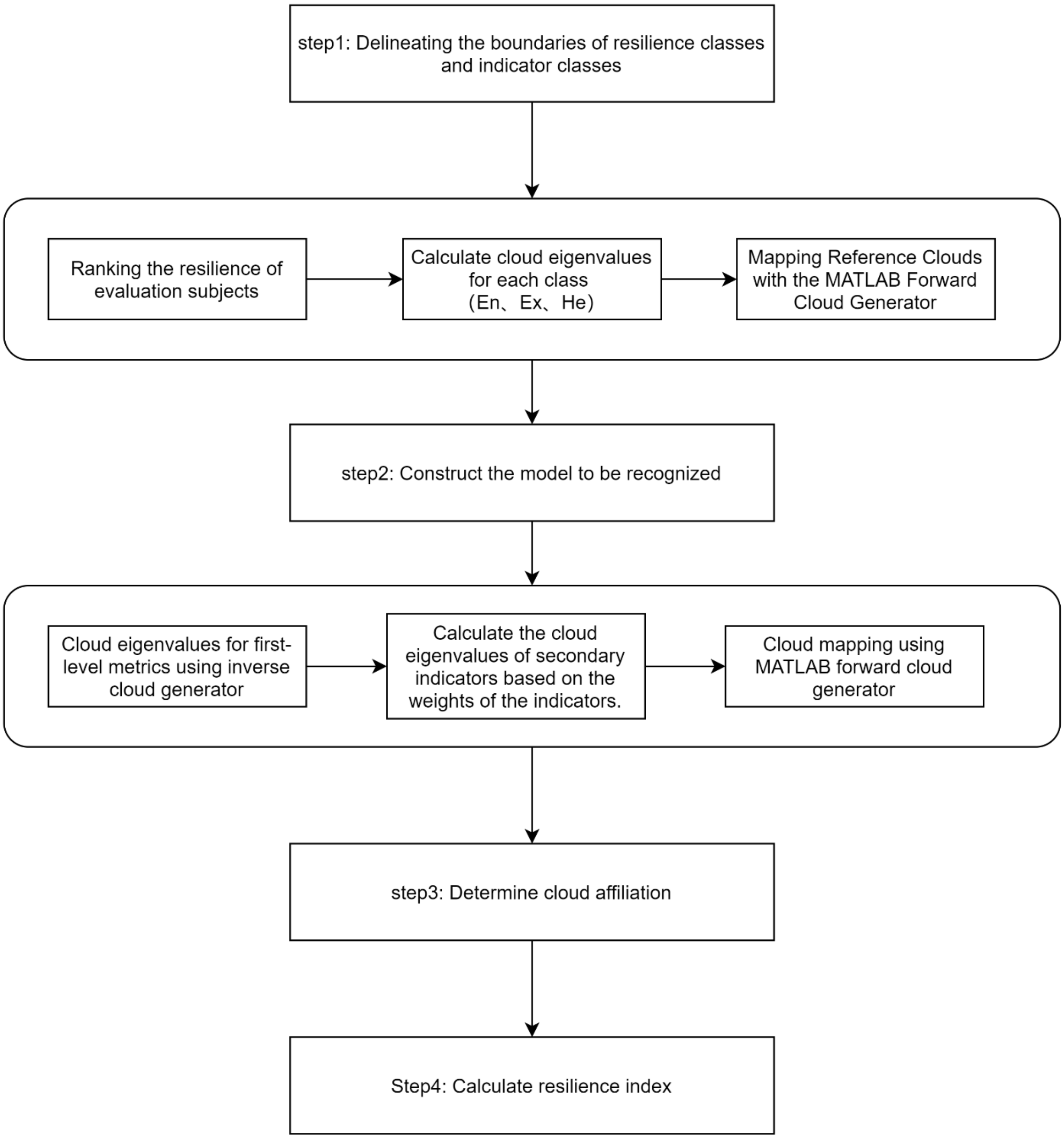


Fig. 4. Cloud modeling evaluation steps

3.5. Validating models with a case study

The case object selected for this study is the Everbright Environmental Energy (Quzhou) Co. Ltd. Waste disposal facility in Kecheng District, Quzhou City, Zhejiang Province, established on August 28, 2017, which treats 1,500 tons of domestic waste daily. It has gained the support of local residents during the construction and operation process, and has won many awards, such as the Luban Award and Top Ten Environmental Protection Facilities, and has become a benchmark enterprise in the construction and operation of NIMBY facilities.

To assess the resilience of NIMBY facilities' SLO, the questionnaire is divided into three main sections based on stakeholders – government, residents, and businesses – and the questions are determined according to the developed indicator system. To understand the respondents' background information, the questionnaire established relevant options before the SLO Resilience Measurement Scale, including age, gender, and education level. The question items remain on a 5-point Likert scale, ranging from 1 ("not at all") to 5 ("fully") conforming. The primary respondents were residents within 3km of the project, as studies such as Ren et al. (2016) indicate that these are more likely to be opposed to the project and involved in mass demonstrations.

4. Results

4.1. The model

(1) Reliability and validity

Because the absolute skewness value of each indicator is less than 1.2 and kurtosis is less than 1, the sample indicators are approximately normally distributed, so they can continue to be analyzed for reliability and validity. The overall Cronbach α coefficient for the government respondents is 0.88, indicating good reliability, and is above 0.9 for community and enterprise, with very good reliability. For all the indicators, Cronbach's α values are still greater than 0.8 after deleting the question item, so the scale has good reliability. Therefore, each question item meets the requirements. Subsequently, the KMO test and Bartlett's test for sphericity are performed. The KMO values of the various subjects of interest are all greater than 0.7, and the probability of significance of Bartlett's test of sphericity is 0.000, much less than 0.01, so the data have good validity.

(2) Exploratory factor analysis

Kaiser's principle determines how many of the main factors can be retained, which is satisfied before the extracted components can be considered to explain the original variables better. There are three main steps in the extraction and categorization of public factors; the first step is to interpret the total variance by Kaiser's principle, the results of which are shown in Table 5; the second step is to test whether the extraction results are ideal or not by Scree's test, and the third step is to categorize the extracted public factors according to the results. The results of the categorization are shown in Table 6. Table 5 shows the total explained variance. The eigenvalues of the public factors extracted for government, community, and business are greater than unity, and the cumulative variance contributions are greater than 60%, explaining most of the variance. The Scree plots similarly show steeper slopes for the first three factors with eigenvalues greater than unity for government, community, and business, with the slopes leveling off after the third factor, which suggests that the appropriate number of principal components are extracted.

Table 5

Total explained variance ratio

Interested parties	Factor	Initial eigenvalue			Extracted sum of squares loadings			Rotation sum of squares loadings		
		Total	Variance contribution ratio(%)	Cumulative (%)	Total	Variance contribution ratio(%)	Cumulative (%)	Total	Variance contribution ratio(%)	Cumulative (%)
Government	1	5.07	46.093	46.093	5.07	46.093	46.093	2.883	26.209	26.209
	2	1.458	13.251	59.344	1.458	13.251	59.344	2.467	22.428	48.637
	3	1.252	11.378	70.722	1.252	11.378	70.722	2.429	22.084	70.722
Community	1	6.074	50.619	50.619	6.074	50.619	50.619	3.398	28.319	28.319
	2	1.229	10.24	60.859	1.229	10.24	60.859	2.798	23.314	51.634
	3	1.155	9.625	70.485	1.155	9.625	70.485	2.262	18.851	70.485
Business	1	6.479	53.99	53.99	6.479	53.99	53.99	3.138	26.152	26.152
	2	1.385	11.54	65.53	1.385	11.54	65.53	3.056	25.469	51.62
	3	1.181	9.843	75.373	1.181	9.843	75.373	2.85	23.753	75.373

Orthogonal variable rotation for government, community, and business sides with Kaiser normalization converges after five iterations. Since the loading of every indicator is greater than 0.5, there is no need to modify or delete the indicators. Based on the adaptive cycle theory, which was originated by Holling and Gunderson (2001), indicators are categorized as resistance, adaptation, and resilience indicators (Gunderson, 2003). Table 6 shows the categorization.

Table 6

Indicator categorization

	Government	Community	Business
Resistance	G3 Popularization of science	C1 Age structure	E2 Emergency drills
	G5 Supervision of enterprises	C2 Educational attainment	E3 Popularization of science
	G2 Emergency preparedness	C3 Sense of community	E5 Emergency measure
	G8 Government governance		E6 Disclosure of information
Adaptation	G9 Specialized working groups	C5 Community leadership	E1 Corporate reputation
	G10 Laws and regulations	C6 Local committee	E10 Frequency of communication
	G11 Modulating effect	C7 Community expectations	E11 Corporate governance structure
		C9 Key figure	E12 Long-term monitoring
		C11 Shared vision	
Resilience	G1 Government credibility	C4 Learn about the program	E4 Views of the population
	G7 Pacified communities	C8 Expression of opinion	E7 Protecting the environment
	G4 Equitable distribution	C10 Moral of the population	E8 Corporate decision-making
	G6 Disclosure of information	C12 Risk awareness	E9 Quality of communication

(3) Constructing the SLO resilience evaluation model

For the *public factor* weights, the three common factors are first extracted. Then, the weighted variance explained is obtained by dividing the rotated variance explained of the common factors by the rotated cumulative variance explained. Table 7 shows the weights of each common factor.

Table 7

Weight of each metric factor

Interested party	Factor	Weighted variance explained ratio	Weight
Government	GR1	37.059%	0.371
	GR2	31.713%	0.317
	GR3	31.226%	0.312
Community	CR1	40.177%	0.402
	CR2	33.077%	0.331

	CR3	26.745%	0.267
Business	ER1	34.697%	0.347
	ER2	33.791%	0.338
	ER3	31.514%	0.315

For the *government factor*, GR1 > GR2 > GR3 is obtained after the weighting process, corresponding to resistance, adaptability, and resilience dimensions. Of these, resistance is the most heavily weighted and important. Adaptation and resilience weights are not very different, and their importance is comparable. In the *community factor*, CR1 > CR2 > CR3 correspond to the dimensions of adaptability, resilience, and resistance, respectively, and the adaptive weights are significantly greater than the remaining factors. For the *business factor*, resilience is of low importance — ER1 > ER2 > ER3. They correspond to the adaptability, resilience, and resistance dimensions, respectively, with their order of importance similar to the community dimensions. However, the weights of the dimensions are similar, as is their importance.

Tables 8 to 10 show the overall and intra-group ranking of the indicators yielded in this way, providing a good basis for the subsequent use of the assessment methodology.

Table 8

Government indicator weights

Dimension	Dimension weight	Evaluation indicator	Weighting within groups	Group ranking	Combined weight	Comprehensive ranking
Resistance	0.371	Emergency preparedness.	0.236	4	0.087	9
		Popularization of science.	0.251	3	0.093	4
		Government governance.	0.278	1	0.103	1

		Supervision of enterprises.	0.267	2	0.099	3
Resilience	0.312	Government credibility.	0.291	3	0.070	11
		Pacified communities.	0.268	4	0.089	8
		Equitable distribution.	0.318	1	0.089	7
		Disclosure of information.	0.293	2	0.091	6
Adaptation	0.317	Specialized working groups.	0.226	2	0.092	5
		Laws and regulations.	0.285	3	0.085	10
		Modulating effect.	0.285	1	0.101	2

Table 9

Community indicator weights

Dimension	Dimension weight	Evaluation indicator	Weighting within groups	Group ranking	Combined weight	Comprehensive ranking
Resistance	0.267	Educational attainment.	0.183	2	0.049	11
		Sense of community.	0.183	3	0.049	12
		Age structure.	0.351	1	0.094	4
Resilience	0.331	Learn about the program.	0.244	4	0.081	10
		Expression of opinion.	0.259	3	0.086	7
		Risk awareness.	0.292	1	0.097	2
		Moral of the population.	0.292	2	0.096	3
Adaptation	0.402	Community expectations.	0.220	3	0.088	6
		Local committee.	0.249	1	0.100	1
		Shared vision.	0.226	2	0.091	5
		Key figure.	0.209	5	0.084	9
		Community leadership.	0.212	4	0.085	8

Table 10

Business indicator weights

Dimension	Dimension weight	Evaluation indicators	Weighting within groups	Group ranking	Combined weight	Comprehensive ranking
Resistance	0.315	Popularization of science.	0.262	2	0.082	8

		Emergency measure.	0.259	3	0.082	9
		Emergency drills.	0.219	4	0.069	12
		Disclosure of information.	0.276	1	0.087	3
Resilience	0.338	Protecting the environment.	0.241	2	0.081	10
		Views of the population.	0.218	4	0.084	6
		Corporate decision-making.	0.252	1	0.085	5
		Quality of communication.	0.230	3	0.078	11
Adaptation	0.347	Corporate governance structure.	0.255	2	0.089	2
		Frequency of communication.	0.242	4	0.084	7
		Long-term monitoring.	0.271	1	0.094	1
		Corporate reputation.	0.246	3	0.085	4

(4) Building the benchmark cloud model

Based on the characteristics of SLO and other studies on infrastructure resilience, the SLO resilience evaluation ratings are categorized into five levels (Table 11). The comment sets are {lower, low, medium, high, and higher}. The value field is [0,5]. The intervals corresponding to each evaluation level are [0,2.25), [2.25,3), [3,4), [4,4.5), [4.5,5]. The entropy value is obtained after several experimental adjustments using MATLAB, and the value of k is finally determined to be 0.02. A benchmark cloud model of NIMBY facilities' SLO resilience is then computed.

Table 11

SLO resilience evaluation delineation

Evaluation	Rating	Evaluation interval	Ex	En	He
Lower	I	[0,2.25)	1.125	0.955	0.02
Low	II	[2.25,3)	2.625	0.318	0.02

Medium	III	[3,4)	3.5	0.425	0.02
High	IV	[4,4.5)	4.25	0.212	0.02
Higher	V	[4.5,5]	4.75	0.212	0.02

Based on the three numerical features calculated, the baseline cloud map for SLO resilience evaluation is generated using MATLAB's forward cloud generator with the number of cloud droplets set to 1500 (Fig. 5).

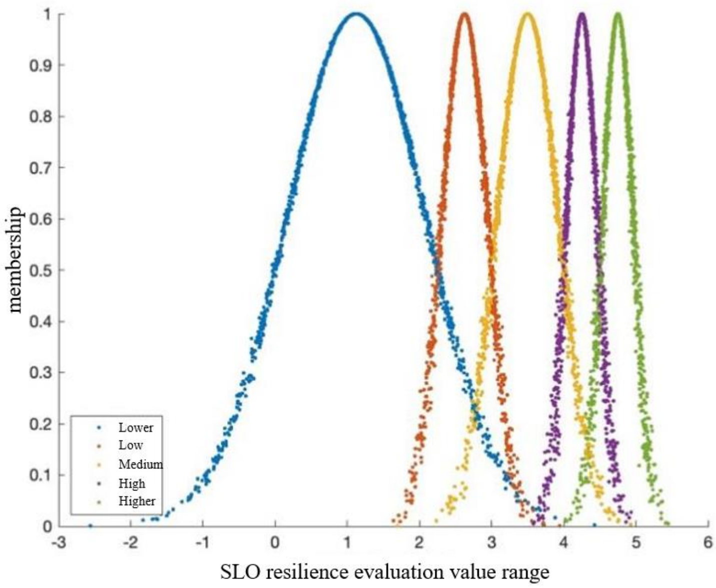


Fig. 5. SLO resilience evaluation benchmark cloud

In evaluating SLO for NIMBY facilities, a larger Ex indicates a higher average resilience and a greater horizontal position on the graph; a larger En implies a wider range of data, reflecting a broader span on the image, with more dispersed and volatile individual evaluations of the project. A larger He suggests a thicker cloud, representing less stable resilience.

4.2. Case evaluation

(1) Implementation

On November 5, 2022, the research team organized relevant members to visit Quzhou Everbright Environmental Energy Company for a week-long visit. The returned questionnaires identified the relevant study villages as Shandi Village, Siqian Village, Zhangjia Village, Jangyao Village, Shangzhu Village, and Huangjia Village.

One hundred fifty questionnaires were distributed in this case study, of which 146 were considered valid, with a percentage of 97.33%. Since the project perimeter was mostly located in suburban and rural areas, the residents were generally less educated and may be unable to complete the questionnaire independently. Hence, the team members interacted with the respondents face-to-face and verbally explained the questionnaire to help them understand the content and complete it on the spot.

Table 12
Sample demographic information

Profile	Category	Frequency	Proportion
Gender	Male	61	41.78%
	Female	85	58.22%
Age	18-25	6	4.11%
	26-35	10	6.85%
	36-44	30	20.55%
	45-60	64	43.84%
	⩾60	36	24.66%
Highest degree	Junior high school and below	88	60.27%
	High school or junior college	34	23.29%
	Senior college	18	12.33%

Undergraduate	4	2.74%
≥Graduate	2	1.37%

Table 12 shows the respondents' demographics, with 39.3% more females than males, over two-thirds over 35, and many not even receiving a secondary education. This is because of the remoteness of the villages where the project is located and that most of the male and young labor force is out of work. It was also found during the field research that most of the women who stayed behind were middle-aged and above.

(2) Comprehensive cloud evaluation

BCG was used to calculate *Ex*, *En*, and *He* for each metric in the collected NIMBY facility SLO resilience data through MATLAB. These represent the indicator stratocumulus cloud eigenvalue. The weights of each indicator obtained above are then used to calculate *Ex*, *En*, and *He* for the criterion layer using the indicator layer cloud eigenvalues. This process resulted in the final cloud model for each party (Tables 13 to 15).

Table 13

Government cloud modeling

Standardized layer	Standardized layer cloud model (Ex, En, He)	Indicator	Indicator layer cloud model (Ex, En, He)
Resistance	(3.1135,1.0634,0.2477)	G_{11} Popularization of science	(3.0479, 1.2064, 0.4099)
		G_{12} Supervision of enterprises	(2.9658, 0.9498, 0.0118)
		G_{13} Emergency preparedness	(3.0205, 0.9943, 0.2924)
		G_{14} Government governance	(3.0411, 0.9819, 0.2620)
Resilience	(3.2054,1.0917,0.2310)	G_{21} Government credibility	(3.0959, 0.8276, 0.0961)
		G_{22} Pacified communities	(3.1233, 1.0426, 0.2324)
		G_{23} Equitable distribution	(2.7877, 1.0101, 0.1029)

		G_{24} Disclosure of information	(2.8151, 1.0953, 0.3890)
Adaptation	(2.6497,0.7991,0.2039)	G_{31} Specialized working groups	(3.0342, 0.8183, 0.3688)
		G_{32} Laws and regulations	(2.9041, 0.9396, 0.2710)
		G_{33} Modulating effect	(3.1096, 0.9723, 0.0753)

Table 14

Community cloud modeling

Standardized layer	Standardized layer cloud model (Ex, En, He)	Indicator	Indicator layer cloud model (Ex, En, He)
Resistance	(2.8687, 0.6428, 0.1967)	C_{11} Educational attainment	(1.6164, 0.9313, 0.2236)
		C_{12} Sense of community	(3.8288, 0.6756, 0.3576)
		C_{13} Age structure	(2.2192, 0.9944, 0.2575)
Resilience	(3.7630, 1.0366, 0.2866)	C_{21} Learn about the program	(3.0479, 1.2358, 0.3963)
		C_{22} Expression of opinion	(3.3219, 1.0908, 0.3953)
		C_{23} Risk awareness	(3.6370, 0.9011, 0.1657)
		C_{24} Moral of the population	(3.7534, 0.6463, 0.1328)
Adaptation	(3.3300, 1.1852, 0.2654)	C_{31} Community expectations	(2.7877, 0.9992, 0.2918)
		C_{32} Local committee	(2.8904, 1.1519, 0.2648)
		C_{33} Shared vision	(3.1096, 1.0696, 0.2835)
		C_{34} Key figure	(2.9726, 1.0391, 0.0673)
		C_{35} Community leadership	(3.1644, 1.0325, 0.2693)

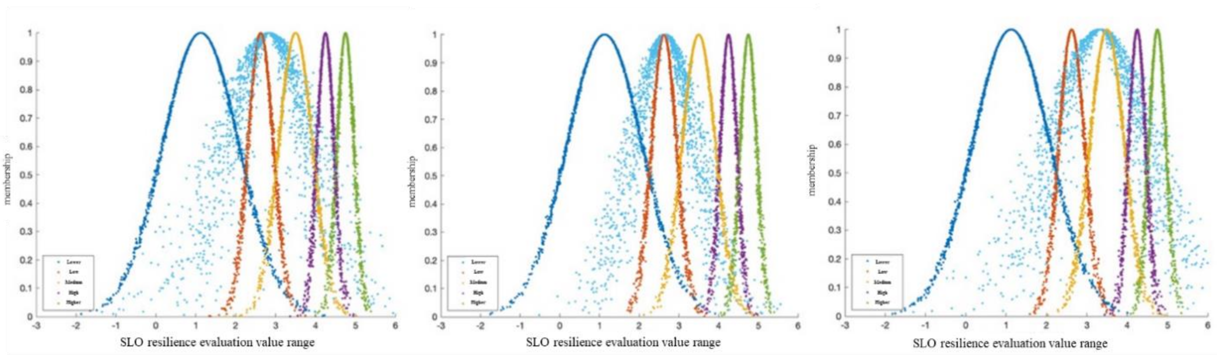
Table 15

Business cloud modeling

Standardized layer	Standardized layer cloud model (Ex, En, He)	Indicator	Indicator layer cloud model (Ex, En, He)
Resistance	(2.8293, 1.0501, 0.3061)	E_{11} Popularization of science	(2.7260, 1.1519, 0.3839)
		E_{12} Emergency measure	(3.1096, 0.9647, 0.1507)
		E_{13} Emergency drills	(2.5753, 1.0473, 0.3839)
		E_{14} Disclosure of information	(2.7123, 0.9789, 0.2996)
Resilience	(2.6288, 0.9537, 0.3631)	E_{21} Protecting the environment	(3.0890, 0.7942, 0.3560)
		E_{22} Views of the population	(2.6164, 1.0790, 0.3922)
		E_{23} Corporate decision-making	(2.5068, 0.9892, 0.3463)
		E_{24} Quality of communication	(2.6164, 1.0633, 0.4018)
Adaptation	(2.6069, 0.9942, 0.3485)	E_{31} Corporate governance structure	(2.5822, 1.0674, 0.3493)
		E_{32} Frequency of communication	(2.5274, 0.9195, 0.3129)
		E_{33} Long-term monitoring	(2.5274, 0.9981, 0.3530)

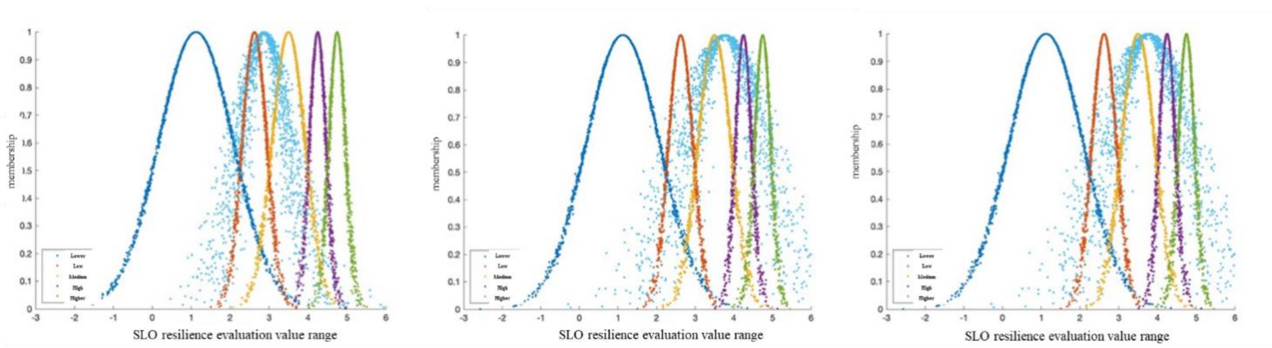
E_{34} Corporate reputation	(2.6507, 0.9313, 0.3580)

There are two main steps involved in applying the cloud model for assessment. One compares and judges the resulting evaluation cloud map with the baseline cloud map. At the same time, the other calculates the affiliation between the evaluated cloud model and the baseline cloud model and decides the resilience level according to the principle of maximum affiliation.



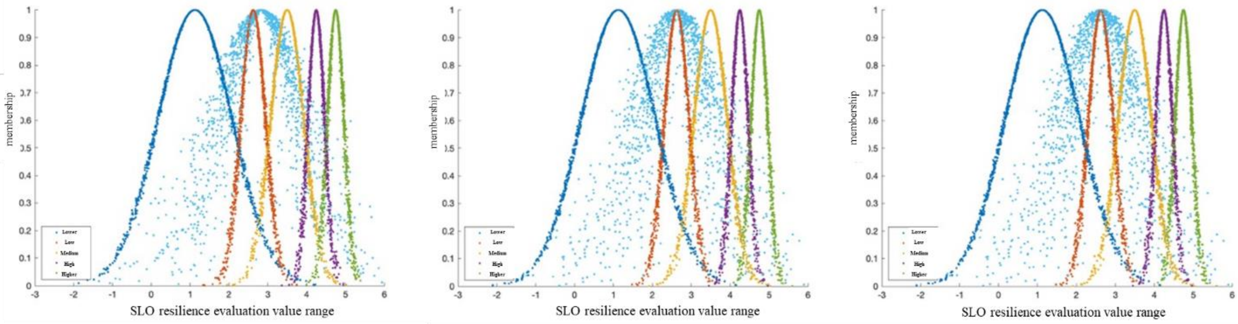
(A) Resistance (B) Resilience (C) Adaptation

Fig. 6. Stage-by-stage cloud map of government



(A) Resistance (B) Resilience (C) Adaptation

Fig. 7. Stage-by-stage cloud map of community



(A) Resistance (B) Resilience (C) Adaptation

Fig. 8. Stage-by-stage cloud map of business

For the analysis of the criterion layer, a forward cloud generator is used to generate a cloud map of the evaluation results for each dimension (Fig. 6). Each of these cloud drops is a potential assessment of the resilience of the NIMBY facilities' SLO. The horizontal axis represents the evaluation score, and the vertical axis is the likelihood of this value occurring.

The resistance, resilience, and adaptability cloud eigenvalues as a benchmark parameter calculate its corresponding resilience evaluation level affiliation, which, according to the principle of maximum affiliation, can be divided into its resilience level. Tables 16 to 19 show the calculation results for the resilience level affiliation for each dimension.

Table 16

Affiliation to the government's resilience hierarchy across dimensions

Dimension	Membership				
	Lower	Low	Medium	High	Higher
Resistance	0.1170	0.2624	0.2714	0.2033	0.1459
Resilience	0.1061	0.2535	0.2689	0.2150	0.1565
Adaptation	0.1441	0.3758	0.2712	0.1365	0.0724

Table 17

Affiliation to the community's resilience hierarchy across dimensions

Dimension	Membership				
	Lower	Low	Medium	High	Higher
Resistance	0.0808	0.4167	0.3128	0.1290	0.0608
Resilience	0.0566	0.1896	0.2786	0.2633	0.2119
Adaptation	0.1064	0.2338	0.2668	0.2198	0.1732

Table 18

Affiliation to the business's resilience hierarchy across dimensions

Dimension	Membership				
	Lower	Low	Medium	High	Higher
Resistance	0.1458	0.2972	0.2629	0.1721	0.1219
Resilience	0.1597	0.3397	0.2576	0.1461	0.0969
Adaptation	0.1671	0.3262	0.2487	0.1536	0.1045

In the case of government-side resilience, for example, the maximum affiliation is 0.2714 in medium resilience. The resistance resilience evaluation cloud is closest to the medium resilience criteria cloud, indicating that the government side of resistance has a medium resilience level. The maximum affiliation for resilience is 0.2689. The Resilience Evaluation Cloud is closest to the Medium Resilience Criteria Evaluation Cloud, indicating that the government side has a medium resilience level. The adaptive maximum affiliation is 0.3758. The Adaptive Resilience Evaluation Cloud is closest to the Lower Resilience Criteria Evaluation Cloud, suggesting that government-side adaptation has a lower resilience level.

The resilience coefficients e1, e2, e3, e4, and e5 are assigned values of 1, 2, 3, 4, and 5 for each of the five classes. Based on the affiliation of the government side of the dimensions, it is possible to calculate the resistance indicators of the government side as 2.9987, the resilience indicators as 3.0622, and the adaptability indicators as 2.6175.

Table 19

Indicators of resilience across stakeholder dimensions

	Government	Community	Business
Resistance	2.9987	2.6725	2.8271
Resilience	3.0622	3.3842	2.6807
Adaptation	2.6175	3.1195	2.7022

(3) Analysis of synthesized evaluation results

In the previous section, the levels at which the government side, the community side, and the business side are at each stage when uncertain risks perturb the NIMBY facilities are calculated separately. The overall cloud eigenvalues of each stakeholder are calculated, and their results are derived from the affiliation calculation program written in MATLAB (Table 20).

Table 20

Cloud modeling and membership for each stakeholder

Stakeholders	Cloud eigenvalue	Membership				
		Lower	Low	Medium	High	Higher
Governments	(2.9951, 0.9884, 0.2286)	0.1180	0.2874	0.2771	0.1872	0.1302
Community	(3.3498, 0.9910, 0.1116)	0.0778	0.2447	0.2822	0.2265	0.1689
Business	(2.6844, 0.9982, 0.3401)	0.1626	0.3202	0.2495	0.1615	0.1062

Based on the Table 20 eigenvalues, a three-way resilience cloud comparison is plotted using a forward cloud generator (Fig. 9). Blue, red, and yellow represent the government-, community-, and business sides, respectively. Most of the cloud droplets generated by the government side are concentrated around the medium resilience level. On the other hand, the cloud droplets generated by the community side lie between lower and medium resilience. The cloud drops generated by the business side are focused on a lower level of resilience. This also corroborates the values obtained from the affiliation calculations – the maximum affiliation of the government side of 0.2874 has a low resilience level, while the maximum affiliation of the community side is 0.2822 at a medium level, and the maximum affiliation of the business side is 0.3202 at a low level.

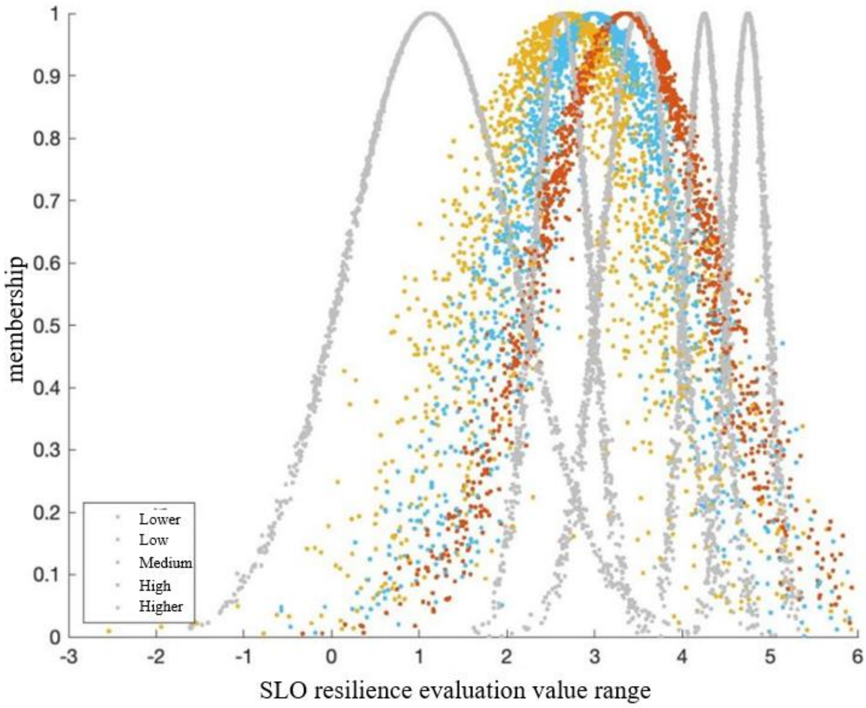


Fig. 9. Comparative cloud diagram of resilience evaluation of SLO subsystems

In terms of the overall resilience of each stakeholder, the results show the government-, community-, and business-side resilience indicators to be 2.9240, 3.1639, and 2.7286, respectively. After evaluating the SLO resilience evaluation model, it is concluded that the government has a medium resistance and resilience level and a high capacity to withstand disturbances. Surrounding neighborhoods are generally in the moderate range of resilience and adaptive improvement. Business-side SLO resilience is low for all stages, with only the 'Emergency Response' and 'Protecting the Environment' indicators in the medium range.

5. Discussion

Research indicates that SLO acquisition is neither a single approval-seeking process nor permanent. Early support from local populations may be affected during operations, potentially causing SLO to diminish (Ford and Williams, 2016). Resilience, a non-linear form of scientific thinking based on dynamics and uncertainty, is similar to the system maintenance characteristics of SLO. The present study introduces resilience theory into SLO to expand its application and enrich research results related to SLO and social risk.

For NIMBY facilities, the SLO system is a complex system (Shi et al., 2021) that involves negotiations between businesses, communities, and government actors (Filer and Gabriel, 2018). The local government plays a crucial role in project promotion, providing guidance and publicity to residents and regulating enterprises (Renn and

Schweizer, 2009). The local community is the most directly affected by the project, and the SLO awarded is the subject of the SLO. NIMBY facilities are constructed and operated by companies that listen to community concerns and offer financial compensation to reduce potential threats to the living environment (Kirsch, 2007). Therefore, the present study selects three stakeholders (i.e., government, community, and business) to construct the resilience evaluation indicators system.

The study uses a cloud model approach for evaluating SLO resilience, a departure from traditional models like the resilience matrix (Mosleh et al., 2023; Mustajoki and Marttunen, 2019; Zebardast, 2022), hierarchical factor analysis (Santos et al., 2018; Alshehri et al., 2015, Javari et al., 2021), multidimensional analysis (Saja et al., 2018), and TOPSIS (Qiao and Pei, 2022, Xun and Yuan, 2020). This method converts qualitative assessments to quantitative values, effectively addressing uncertainty and stochastic attributes in NIMBY facilities. The cloud model, guided by an algorithm system, efficiently handles events with dual attributes, eliminating redundant calculations and large sample data. Its ability to integrate both qualitative and quantitative aspects enhances its suitability for this study, providing a more nuanced and contextually relevant evaluation of SLO resilience.

A typical case was introduced in this study to validate the feasibility of the model. This case was honored with the 2022 Top Ten Environmental Protection Facilities Open Unit award. During the field research, it was also found that, in the initial stage of the project, the village committees of the surrounding villages, acting as grass-roots representatives of the government, conducted scientific briefings for the residents to raise their understanding and support of the project. This clearly shows that the model's evaluation results align with reality. The selected case in this study received positive evaluations across all aspects. The project exemplifies notable practices when compared to other NIMBY facilities that have experienced conflicts or poor practices. This distinction may lead to different outcomes when applying the model to their assessments. In project communities facing NIMBY conflicts, local governments and companies implement laws, regulations, technical norms, and economic compensation. However, residents frequently perceive these efforts as insufficient, resulting in resilience indexes that may not accurately reflect the situation.

Although the metrics used to construct the cloud model in this study are derived from a broad review of existing global literature, the supporting evidence in this paper is limited to a single case study located within China. It is well understood that significant differences exist between China's social structure and political system and those of Western countries. Eakin et al. (2017) argue that efforts to enhance social resilience must account for variations in social and political environments, as factors such as political decision-making, resource allocation, and policy prioritization across different countries can influence the resilience of SLO in NIMBY facilities. Poelzer (2023) found that variations in the values of native communities across different countries necessitate distinct approaches to securing SLO. Zhang and Moffat (2015) concluded that the economic development stage of mining communities or nations likely influences how people perceive the impacts and benefits. This study has shown that the model is applicable in social environments similar to China's. However, further cross-sectional studies are necessary to extend its applicability to countries with different cultural contexts.

The study elucidates that various factors shape government resilience in the context of NIMBY facilities. For instance, the extent of information disclosure, the fairness of decision-making processes, the modulating effect on public concerns, the establishment of specialized working groups, and adherence to relevant laws and regulations collectively contribute to the overall resilience of governmental entities involved in these facilities. However, these factors contribute to a low overall resilience. The community is primarily governed by age structure and education, which are difficult to change regionally. High-impact indicators on the business side include long-term monitoring, corporate governance structure, communication frequency, corporate reputation, and information disclosure. Therefore, to improve the resilience of NIMBY facilities' SLO, stakeholders can start with the following.

(1) The government should provide timely and accurate information to community residents regarding the implementation of the NIMBY program (Kou and Yang, 2023). Establishing a robust complaint mechanism empowers residents to

monitor enterprises effectively, address concerns, and manage environmental issues promptly. Moreover, the government should also strengthen its supervision of enterprises and form a relevant working group for public opinion surveys, ensuring every resident can understand the project and its advantages (Wu and Tham, 2023). It is important to implement a framework for public participation in formulating relevant laws and regulations (Smits et al., 2017). Additionally, rigorous government monitoring is essential to ensure these measures are implemented.

(2) The community plays a vital role in cultivating a positive atmosphere among residents. By enhancing residents' understanding of scientific principles related to NIMBY facilities and providing emotional support during internal community meetings (Luke, 2017), the community can foster greater understanding and solidarity. Strengthening community cohesion is essential for improving resilience (Dare et al., 2014). Typically, communities will implement the policy recommendations proactively to ensure stability, maintain smooth community operations, and safeguard their rights and interests.

(3) Businesses need to actively engage with the local community and pay long-term attention to the sentiments of their residents (Moffat and Zhang, 2014). Elevating employee training and developing a scientifically sound and reasonable emergency management program is crucial. At the same time, companies should

be clear that while profits are important, they need to focus on long-term benefits to sustain community support rather than jeopardizing it for short-term gains (Saenz, 2023).

6. Conclusions

The study uses a literature review and expert surveys to identify indicators for SLO resilience in NIMBY facilities. It categorizes indicators and constructs an evaluation framework from diverse stakeholder perspectives. The model is rigorously calculated based on factor contributions and loading matrices, and its reliability is confirmed through application to the Quzhou Everbright Waste Incineration Power Generation Project.

The theoretical framework enhances the study of NIMBY facilities' SLO by analyzing resilience characteristics and system components, providing a new perspective in social licensing research. Combining theoretical insights with practical indicators and evaluation models ensures deeper theoretical understanding and practical application.

The study provides insightful recommendations for governments and businesses involved in the construction and operation of NIMBY facilities, emphasizing the importance of transparency, fairness, community education, and effective business communication. It calls for enhancing legal frameworks to facilitate public participation and promote a comprehensive approach to environmental risk management. In essence, this study explores the intricate dynamics of SLO resilience within the context of NIMBY facilities, bridging the theoretical foundations of SLO with the practical implications of resilience theory. The study presents a novel approach using the cloud model to evaluate SLO resilience, departing from traditional models. It identifies the crucial factors influencing the resilience of government, community, and business stakeholders. The findings underscore the importance of maintaining a stable SLO throughout the project lifecycle, shedding light on specific strategies for enhancing resilience. By addressing the complexities of NIMBY facilities, these insights provide valuable guidance for stakeholders, policymakers, and industries involved, paving the way for more robust and socially accepted infrastructure projects in the future.

The focus on the Quzhou Everbright Waste Incineration Power Generation Project limits its inclusivity of resilience factors. Its reliance on subjective methods, such as literature reviews and expert surveys, hinders the model's universality. Improvements are needed for the reliability of indicators and the applicability of recommendations for stakeholders in NIMBY facilities. Future research should enhance the indicator selection process, broaden the evaluation scope, and integrate comparative analyses to create a balanced framework for evaluating SLO resilience and explore adaptability across different regions and communities.

Highlights

1. A set of SLO resilience evaluation indicators system is constructed

2. Constructed a resilience evaluation model using cloud modeling as a methodology

3. Validated the rationality of the model using case studies

4. Helping to clarify the mechanism of SLO resilience maintenance

Declaration of competing interest

The authors declare that they do not have any competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Table A

Initial Summary of SLO Resilience Indicators

Topics	Evaluation indicators			
Social license to operate	Government credibility (4)	Distributional equity (3)	Environmental impact assessment (4)	Government governance (2)
	Leadership (3)	Supervise and manage (1)	Environmental monitoring (2)	Regulatory capacity (1)
	Corporate reputation (5)	Public Information (3)	Shared vision (3)	Community consolation (2)
	Community expectation (3)	Governance structure (2)	Community views (3)	Local committee (3)
	Communication frequency (4)	Confidence level (3)	Thematic working groups (2)	Expression of opinion (3)
	Public participation (5)	Good reputation (2)	Follow-up testing (3)	Local economies (2)
	Frequency of interaction (2)	Social communication (4)	Resident expectations (4)	Observation monitoring (3)
	Sense of belonging (2)	Community connections (2)	Government interventions (2)	Community Leaders (2)
	Laws and regulations (3)	Expression of opinion (3)	Quality of communication (3)	moral sense (1)
Social/community resilience	Age structure (10)	Knowledge (7)	Emergency plan (11)	Community expectations (5)
	Educational attainment (9)	Community Leaders (3)	Social trust (6)	Communication skills (7)
	Community involvement (6)	Disaster education (4)	Safeguard (7)	Open and transparent (3)
	Risk perception (6)	Planning exercises (5)	Disclosure of information (6)	Community identity (7)
	Attachment to a place (8)	Government governance (6)	Community pacification (9)	Key figure (3)
	Accidental drills (7)	Community views (5)	Community cohesion (8)	Sense of belonging (5)
	popular science (8)	Leadership (6)	Disaster prevention training (4)	Program policy (3)
	Collective effectiveness (6)	Standard (7)	Risk perception (3)	Information sharing (4)

Table B

Government-side rotated component matrix

Serial	Indicators	ingredient		
		1	2	3
G2	Emergency preparedness	0.851		
G3	Popularization of science	0.846		
G8	Government governance	0.81		

G5	Supervision of enterprises	0.67		
G9	Specialized working groups		0.868	
G10	Laws and regulations		0.851	
G11	Modulating effect		0.818	
G1	Government credibility			0.811
G7	Pacified communities			0.728
G4	Equitable distribution			0.715
G6	Disclosure of information			0.652

Extraction methods: Principal component analysis

Rotation method: Orthogonal rotation method with Kaiser normalization.

The rotation converges after 5 iterations.

Table C

Community-side rotated component matrix

Serial	Indicators	ingredient		
		1	2	3
C7	Community expectations	0.78		
C6	Local committee	0.78		
C11	Shared vision	0.755		
C9	Key figure	0.754		
C5	Community leadership	0.708		
C4	Learn about the program		0.79	
C8	Expression of opinion		0.787	
C12	Risk awareness		0.76	
C10	Moral of the population		0.712	
C2	Educational attainment			0.798
C3	Sense of community			0.779
C1	Age structure			0.738

Extraction methods: Principal component analysis

Rotation method: Orthogonal rotation method with Kaiser normalization.

The rotation converges after 5 iterations.

Table D

Business-side rotated component matrix

Serial	Indicators	ingredient		
		1	2	3
E11	Corporate governance structure	0.87		
E10	Frequency of communication	0.81		
E12	Long-term monitoring	0.786		
E1	Corporate reputation	0.731		
E7	Protecting the environment		0.849	
E4	Views of the population		0.803	
E8	Corporate decision-making		0.782	
E9	Quality of communication		0.719	
E3	Popularization of science			0.836
E5	Emergency measures			0.823
E2	Emergency drills			0.754
E6	Disclosure of information			0.673

Extraction methods: Principal component analysis

Rotation method: Orthogonal rotation method with Kaiser normalization.

The rotation converges after 5 iterations.