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CRITIC-TOPSIS-Based Evaluation of Smart Community Safety: A Case Study of Shenzhen, China

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Abstract: As a micro-unit of the smart city, smart communities have transformed residents' lives into a world that connects physical objects. Simultaneously, though, they have brought community safety problems. Most studies of the smart community have only focused on technical aspects, and little attention has been paid to community safety. Thus, this paper aims to develop an evaluation system for smart community safety, which will further promote community safety development. On the basis of identifying evaluation indicators, an evaluation framework was built to assess the level of smart community safety by a comprehensive CRITIC-TOPSIS method. Five smart communities in Shenzhen city were selected as cases to validate the feasibility of the evaluation framework. There was an indication that the indicator with the highest weight was the 'building monitoring', and the indicator with the lowest weight was the 'emergency shelter guidelines'. In addition, the Yucun community showed the highest safety level among these five smart communities. Some suggestions for enhancing the safety level of the smart community are proposed, such as strengthening the training of community safety management talents, establishing good emergency protective measures, and encouraging residents to participate in the development of community safety. This research not only provides an innovative community safety assessment method; it also enriches the knowledge of smart community safety.

Keywords: smart communities; community safety; CRITIC-TOPSIS method; safety evaluation

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1. Introduction

As one of the key directions of urban sustainable development, smart communities have received increasing attention worldwide [1–3]. Generally, a smart community is a new type of community that digitizes and coordinates community residents' daily lives using big data, cloud computing, the Internet of Things (IoT), etc. [4–6]. With the development of such communities, a safer, more convenient, and more comfortable community can be built. Meanwhile, problems related to smart community construction have begun to emerge, such as privacy and security issues, a serious "information Island", and the aggravation of community isolation [7–9]. In particular, community safety has posed one of the toughest challenges for the sustainable development of smart communities, as people's lives and property are seriously affected by safety levels [4,10]. For instance, a large gas explosion accident occurred in the Yanhu community of Shiyan City in China on 13 June 2021, causing direct economic losses of approximately RMB 53.9541 million and 26 deaths [11]. To warn of and to solve community safety-related issues in time, the concept of smart community safety was born, which could turn the community into a place with no safety risks and multi-stability [12–14]. Performance evaluation is considered a valuable tool for ensuring the success of community development [15,16], and the assessment of smart community safety has become important to improve the safety level of smart communities and to promote their sustainable development.

Research into smart communities is also in full swing. The existing research has made progress in smart community studies, including integrated systems of multigeneration energy [17], the encryption scheme of information safety [18], and transportation system assessment for smart communities [19]. Meanwhile, the research field has increasingly focused on community safety. The existing research has mainly focused on the mode of community safety development, technology innovation, and the emergency capacity of communities. In terms of the mode of community safety development, problems with the existing community safety mode were analyzed, and a new community safety mode was put forward [20]. As for technology innovation, a safety system combined with loT equipment and Blockchain (BC) technology was established to deal with the risk factors of community safety. This system can effectively prevent message blocking and help to improve community safety [21]. With regard to the emergency preparedness of communities, the importance of volunteer activities and community activities in reducing community safety risks was discussed, which is helpful for enhancing the emergency response capability of community residents and improving community safety levels [22–24]. However, the majority of studies for community safety have focused only on one aspect of safety. Little research has comprehensively assessed smart community safety, and there is no existing evaluation framework for smart community safety.

Hence, evaluating the safety level of the smart community is crucial to providing a new insight into the safety development of smart communities and improving the community residents' sense of safety. To fill the above gap in the research, this paper aims: (1) to determine the indicators of safety evaluation for the smart community; (2) to develop a safety evaluation framework for smart communities based on the CRITIC-TOPSIS method; (3) to propose several strategies for improving the safety level of smart communities.

The remaining portions of this paper are arranged as follows. Section 2 presents a literature review and related works on smart community safety. Section 3 introduces the research methods of this paper and develops an assessment indicator system for smart communities. Section 4 presents the reasons for choosing the research case and explains the methods of data collection. Section 5 shows the calculation results of weights and total scores. Section 6 discusses the calculation results in depth and puts forward several suggestions to improve the safety level of smart communities. Section 7 explains the research conclusion and lays out the future research directions of this area of study.

2. Literature Review

2.1. The Implementation of Smart Community Safety

Research into smart communities is in full swing. The existing research has made progress in the development of the smart community, including reputation mechanisms for cooperation [25] and the assessment of the smart community transportation system [19]. Specifically, increasing attention has been paid to smart community safety in the research field of smart communities [26–28]. Research on smart community safety mainly focuses on technology innovation, which has improved the capacity of smart communities to cope with emergencies. As for emergencies, a green system of shared photovoltaic (PV) power generation based on vehicle-to-grid (V2G) technology was established to cope with the risk of power outages caused by emergencies; it can realize a stable energy supply in smart communities [29]. At the same time, the Internet of Things (IoT), building performance simulation (BPS), cyber-physical systems (CPS), and other technologies have been used to strengthen the safety level of smart communities to cope with emergencies such as extreme weather disasters, economic instability, insufficient energy supply, and epidemics (e.g., COVID-19) [30,31]. In terms of information safety, information and communications technology (ICT) has experienced very rapid development, and a communication system using non-orthogonal multiple access (NOMA) was proposed to improve the communication safety level in smart communities [32]. Then, based on copy-move forgery detection (CMFD) and Blockchain technology (BC), information transmission in the smart community was updated and classified to reduce deviations in information transmission [33–35]. Meanwhile, the confidentiality of relevant information in the smart community is strengthened through a secure and privacy-preserving mutually dependent authentication and data access scheme, which can improve the safety level of smart communities [36,37]. Furthermore, propaganda and education in smart facilities play an important role in improving public awareness of ICT-based infrastructure, which helps to develop a safer smart community [38].

2.2. The Evaluation of Community Safety

Increasing attention has been paid to community safety. Progress has been made in community safety evaluation, mainly focusing on the evaluation of safety resilience, public safety, and safety management. As for the assessment of community safety resilience, an evaluation indicator system of community risk resilience was developed from ecological, societal, economical, institutional, infrastructural, and community competence [39]. Then, the relevant indicators of residents' individual characteristics were considered in the community resilience assessment, and a more comprehensive evaluation indicator system has been proposed [40,41]. In terms of the evaluation of community safety, the community public safety indicator system was developed from aspects of individuals, communities, and the government [28]. Simultaneously, location information service architecture has been added to the community public safety evaluation system, which can improve the accuracy of the evaluation system [4]. Then, an evaluation system of urban community public safety in emergency management and care service was established to promote the healthy development of urban communities [42]. As for the evaluation of community safety management, 30 evaluation indicators were selected to assess the management level of community safety from the aspects of consciousness, technology, and policy [43]. Further, an indicator system of community safety was proposed to assess the safety performance of the community from a social capital point of view, and the evaluation system included five first-level indicators, for which it is critical to understand the current status of community safety management [44]. Moreover, the fuzzy analytic hierarchy process (FAHP), correlation analysis, the catastrophe progression method (CPM), fuzzy comprehensive evaluation, and other methods have been applied to evaluate community safety levels [4,44–46].

2.3. Research Gap

Extensive studies have been conducted on safety implementation for the smart community and community safety evaluation. As for safety implementation in smart communities, the existing research mainly focuses on technology, but it pays less attention to the safety management of smart communities, especially safety evaluations. There is no safety evaluation for different types of communities; a variety of the evaluation methods depend on the subjective consciousness of the people and questionnaire surveys, and so these research methods lack objectivity. Therefore, three main research gaps can be identified: (1) Several studies have studied smart community safety, but these have mostly focused on only one aspect, and overall, there are relatively few studies on smart community safety. (2) Studies on the systematic evaluation indicators of smart community safety have rarely been reported. (3) An objective and quantitative method is lacking for determining the safety performance of smart communities.

3. Method

To quantify and assess the smart community safety level, a smart community safety evaluation indicator system was developed, and a model of safety assessment was established based on the CRITIC-TOPSIS method. Figure 1 shows the steps involved in the safety evaluation process. Step 1 is to identify the initial indicator system, which is the basis for developing the final indicator system and the basic material for expert interviews. Step 2 is to determine the final indicator system for smart community safety, which is the basis for obtaining indicator weight through the CRITIC method. Step 3 is to determine the indicator weight, which is an essential part of the TOPSIS method in order to calculate the total score.

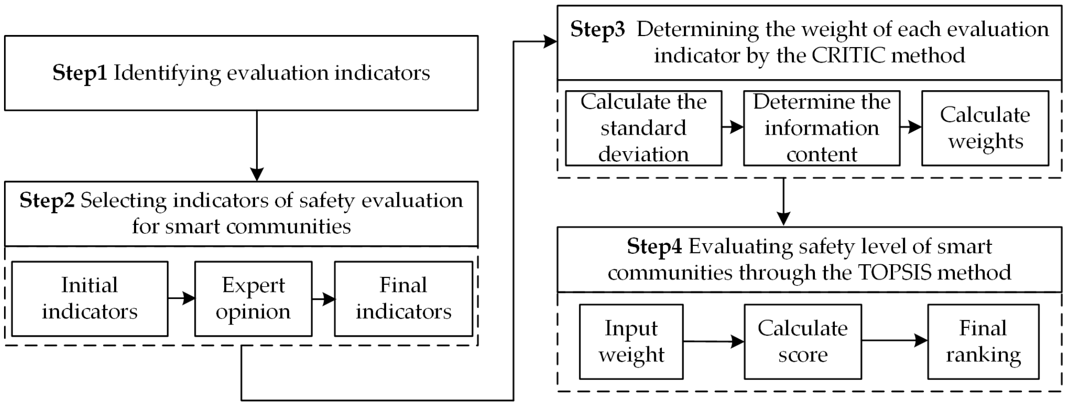

Figure 1. Flow chart for evaluating smart community safety.

Step 1: Identifying initial indicator system of safety evaluation for the smart community.

Step 2: Selecting indicators of safety evaluation for smart communities through expert interviews.

Step 3: Determining the weight of each evaluation indicator by the CRITIC method.

Step 4: Evaluating the safety level of the smart community through the TOPSIS method.

3.1. Selecting Indicators of Safety Evaluation for Smart Sommunities

Identifying evaluation indicators is the basis for evaluating the safety level of the smart community [47], and it is crucial to choose indicators of smart community safety in an all-round and multi-angle manner. Therefore, establishing a smart community safety evaluation indicator system requires considering a wide range of factors and following certain principles to make the indicator system systematic and accurate [48]. Based on the systematic literature review (SLR) method (as illustrated in Figure 2), a preliminary indicator system of the safety assessment of smart communities is established, as illustrated in Table 1. The evaluation indicator system includes 7 dimensions and 33 indicators.

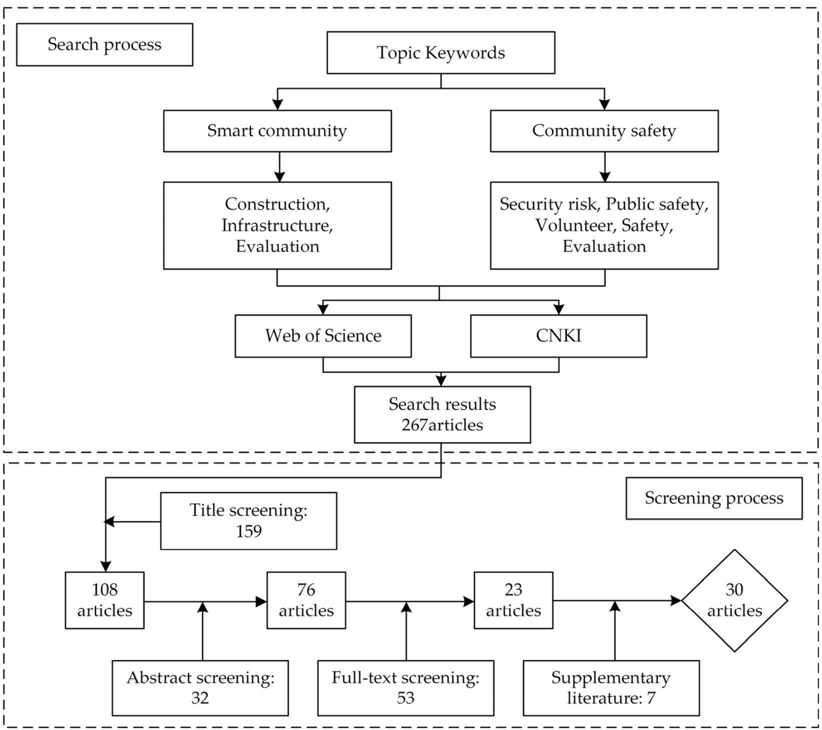

Figure 2. Flow chart for the process of SLR.

Table 1. The initial indicator system of safety evaluation for smart communities.

Dimension	Indicators	Source
Safeguard mechanism	Organizational safeguard, capital safeguard, institutional safeguard, talent safeguard, operation safeguard	[20,24,27,49–51]
Platform safety	Information safety safeguard, platform data safety, platform access safety	[21,51–57]
Emergency plans	Developing emergency plan, emergency plan revision, emergency plan effect, emergency exercise, public participation, disaster risk map	[22,23,51,58–60]
Community public safety	Accident and injury reporting, special population management, police–civilian linkage, public health events processing, violations of residence management	[4,50,51,61–67]
Smart infrastructure	Life channel facilities monitoring, smart safety facilities (smart personnel monitoring facilities, object monitoring facilities, inflammable and explosive dangerous goods management, integrated system of smart safety), public facilities monitoring, smart environment monitoring, smart firefighting facilities, community medical ambulance station	[19,21,51,68–74]
Emergency measures	Emergency duty, accident warning system, emergency shelter guidelines, emergency supplies reserve, emergency linkage mechanism	[21,22,51,64,71,75–77]
Safety propaganda and education	Emergency safety propaganda and education, community administrator training, characteristic propaganda and education	[22,23,78–80]

Safety evaluation indicators of smart communities are mainly generated from the literature and evaluation guidelines related to community safety and smart communities. The evaluation indicators should be optimized to better reflect the status quo for community safety development. Then, experts who participated in the development of the smart community and community safety were selected. Experts have rich knowledge and experience in smart community safety. A total of 26 scholars and experts in the research and development of smart community safety were interviewed in June and July 2022. Detailed profiles of the valid interview experts are shown in Supplementary File S5. Expert interviews were conducted to discuss the importance of a preliminary indicator system for the smart community, and the indicator system was adjusted according to expert suggestions. Ultimately, 7 dimensions and 32 indicators were selected in the evaluation indicator system, which is illustrated in Table 2. A detailed explanation of evaluation indicators is shown in Supplementary File S1.

Table 2. The final indicator system of safety evaluation for smart communities.

Dimension	Indicators	Effect	Code
Safeguard mechanism (SM)	Organizational safeguard	Positive	SE11
	Capital safeguard	Positive	SE12
	Institutional safeguard	Positive	SE13
	Talent safeguard	Positive	SE14
	Operation safeguard	Positive	SE15
Platform safety (PS)	Information safety safeguard	Positive	SE21
	Platform data safety	Positive	SE22
	Platform access safety	Positive	SE23
Execution of emergency plans (EP)	Emergency plan implementing	Positive	SE31
	Emergency exercise	Positive	SE32

Table 2. *Cont.*

Dimension	Indicators	Effect	Code
Community public safety (CPS)	Abnormal events recording	Positive	SE41
	Special population management	Positive	SE42
	Multi-sectoral linkage	Positive	SE43
	Public health events processing	Positive	SE44
	Management and control of key parts	Positive	SE45
	Building monitoring	Positive	SE46
Smart infrastructure (SI)	Life channel facilities monitoring	Positive	SE51
	Smart personnel monitoring facilities	Positive	SE52
	Smart object monitoring facilities	Positive	SE53
	Integrated system of smart safety	Positive	SE54
	Public facilities monitoring	Positive	SE55
	Smart environment monitoring	Positive	SE56
	Smart firefighting facilities	Positive	SE57
Emergency measure (EM)	Emergency duty	Positive	SE61
	Emergency warning	Positive	SE62
	Emergency rescue alarm	Positive	SE63
	Emergency shelter guidelines	Positive	SE64
	Emergency supplies reserve	Positive	SE65
	Emergency command and dispatch	Positive	SE66
	Disaster risk map	Positive	SE67
Safety propaganda and education (SPE)	Propaganda and education of emergency safety	Positive	SE71
	Training of community administrators	Positive	SE72

3.2. Determining the Weight of Each Evaluation Indicator through the CRITIC Method

It is a complex task to prioritize one criterion over the others due to the nature of subjectivity when a decision-making problem has multiple responses [47]. To avoid this, the CRITIC method was developed by Diakoulaki, Mavrotas, etc. [81]. As one of the objective evaluation methods, the CRITIC method assigns an indicator weight according to the information of the indicators and the correlations between them [81–83]. The weight obtained by this method includes the contrast intensity of each indicator and the conflict between the evaluation indicators [84], and the calculated metric weight is more objective and accurate, which makes it better than the entropy weight method [82]. In recent years, this method has been applied in different fields of research, including operations, economic management, and performance evaluation [85–87]. Considering that there is a certain correlation between evaluation indicators of smart community safety, the weight of each assessment indicator for smart community safety was determined using the CRITIC method. The following are the specific steps in the CRITIC process:

(1) The evaluated variable data are normalized according to the following equation:

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

where x_{ij} is the score for evaluation indicators by experts, x'_{ij} means the normalized score for x_{ij}, $man(x_{ij})$ is the maximum score of x_{ij}, and $\min(x_{ij})$ is the minimum score of x_{ij}.

(2) The standard deviations of the evaluation indicators are determined.

$$\overline{x}_j = \frac{1}{n}\sum_{i=1}^{n} x'_{ij} \quad (2)$$

$$\sigma_j = \sqrt{\frac{\sum_{j=1}^{n}(x_{pj}\overline{x}_j)^2}{n}} \quad (3)$$

where $\overline{x}_j$ means the *j-th* indicator score of smart community safety, σ_j represents the standard deviation for each safety assessment indicator, n represents the number of experts, and x_{pj} indicates the normalization value of the *j-th* evaluation indicator.

(3) Correlation coefficients can reflect the strength of the relationship between two variables. The correlation coefficient is determined using the equation below:

$$r_{ij} = \frac{\sum(x_i\overline{x}_i)(x_j\overline{x}_j)}{\sqrt{\sum(x_i\overline{x}_i)^2\sum(x_j\overline{x}_j)^2}} \tag{4}$$

where r_{ij} indicates the correlation coefficient between evaluation indicators, x_i means the *i-th* indicator score of smart community safety, x_j represents the *j-th* indicator score for smart community safety, and $\overline{x}_i$ indicates the score for the *i-th* evaluation indicator.

(4) The conflict between indicators is determined by:

$$y_j = \sum_{i=1}^{n}(1 - r_{ij}) \tag{5}$$

where y_j indicates the conflict between the evaluation indicators.

(5) The information content of the indicator is calculated by:

$$C_j = \sigma_j \sum_{i=1}^{n}(1 - r_{ij}) = \sigma_j y_j \tag{6}$$

where C_j represents the content of information in the *j*-th criterion.

(6) To determine the indicator weight of the *j*-th criterion, we use:

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{7}$$

where W_j is the indicator weight of smart community safety.

3.3. Evaluating Safety Level of Smart Communities through the TOPSIS Method

Hwang and Yoon originally developed the well-known major classical multiple attribute decision making (MADM) [47]. The TOPSIS method attempts to select the alternative that has the shortest distance to the positive ideal solution and the largest distance to the negative ideal solution [88,89]. Specifically, the positive ideal solution maximizes the benefit criterion and minimizes the cost criterion, and the negative ideal solution maximizes the cost criterion and minimizes the benefit criterion [89–92]. TOPSIS can provide a ranking of alternatives using the attribute information, and attribute preferences are not required to be independent [93,94]. It is applied in this study to assess, rank, and compare smart community safety levels with the above criteria and indicators. The TOPSIS method is described in the following manner.

(1) The standardization for all indicators is determined by:

$$\overline{d}_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^2}} \; (1 \le i \le m,\ 1 \le j \le n) \tag{8}$$

where d_{ij} is the value of each indicator for the safety assessment of smart communities, and $\overline{d}_{ij}$ means the standardized value of d_{ij}.

(2) Then, the weighted value for normalized indications is calculated with:

$$\rho_{ij} = W_j\overline{d}_{ij} \tag{9}$$

where ρ_{ij} means the weight value of standardization indications used to assess smart community safety, and W_j represents each indicator weight of the smart community through Section 3.2.

(3) The positive and negative ideal solutions (l^+) and (l^-) are calculated:

$$l^+ = \left\{ \left(\max_{1 \le i \le m} \rho_{ij} | j \in j^+ \right), \left(\min_{1 \le i \le m} \rho_{ij} | j \in j^- \right) \right\} = \left(\rho_1^+, \rho_2^+, \rho_3^+, \cdots, \rho_n^+ \right) \tag{10}$$

$$l^- = \left\{ \left(\min_{1 \le i \le m} \rho_{ij} | j \in j^+ \right), \left(\max_{1 \le i \le m} \rho_{ij} | j \in j^- \right) \right\} = \left(\rho_1^-, \rho_2^-, \rho_3^-, \cdots, \rho_n^- \right) \tag{11}$$

where J^+ means the maximum value of ρ_{ij}, and J^- is the minimum value of ρ_{ij}.

(4) The distance of the evaluation alternative i from the positive ideal solutions S^+ is calculated:

$$S^+ = \sqrt{\sum_{j=1}^{n} \left(\rho_{ij} - l^+ \right)^2}, 1 \le i \le m, 1 \le j \le n \tag{12}$$

Further, the distance of the evaluation alternative i from the negative ideal solutions S^- is calculated:

$$S^- = \sqrt{\sum_{j=1}^{n} \left(\rho_{ij} - l^- \right)^2}, 1 \le i \le m, 1 \le j \le n \tag{13}$$

(5) The proximity coefficient is calculated:

$$C_i = \frac{S^-}{S^+ + S^-},\ 0 \le C_i \le 1, 1 \le i \le m \tag{14}$$

where C_i is the proximity coefficient of the level for smart community safety, and m is the number of smart communities.

(6) The safety levels of the smart community are ranked.

According to C_i (I = 1, 2, . . . , m), the ranking results of two aspects can be obtained: (1) The final score and ranking of each dimension for smart community projects can be determined. (2) In addition, the total score and ranking for the smart community projects can be calculated.

4. Case Study

4.1. Study Area

Shenzhen, a city in Guangdong Province, is located in southern China. The investigation site was chosen for a number of reasons. First, extensive experience has been accumulated since Shenzhen became a pilot city for smart community implementation. Second, as one of the most economically developed cities in China, Shenzhen has a strong economy to provide financial support for the safety development of smart communities [95]. Third, these smart communities were developed earlier in Shenzhen, and the data for the safety assessment of the smart community are easily collected. On this basis, five smart communities in Shenzhen were determined as sample collection sites according to the interview with 26 experts in the smart community, including Yucun community (N1), Baolong community (N2), Fuguang community (N3), Huilongpu community (N4), and Nanyuan community (N5). The locations of these smart communities are shown in Figure 3. Table 2 shows the information on the experts who were interviewed.

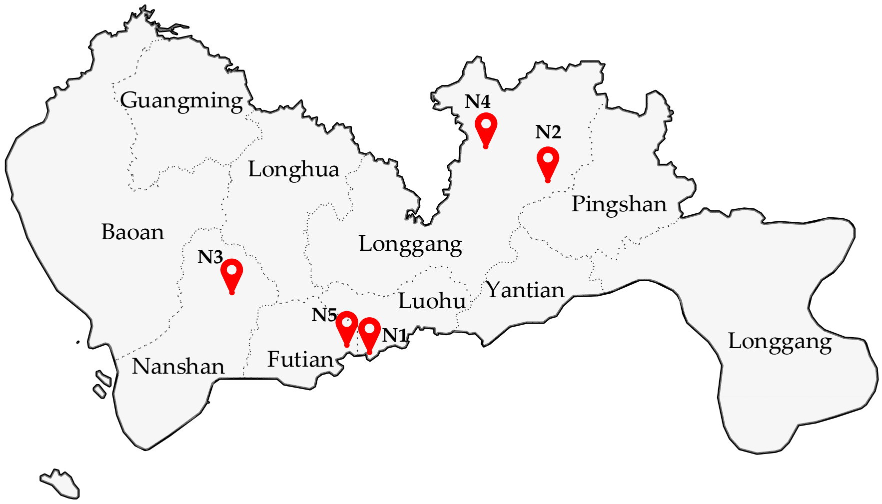

Figure 3. Location map of the five smart communities selected. Note: N1–N5 represent the five smart communities selected.

4.2. Data Collection

The expert interview was used to collect the weighted data of each safety evaluation indicator for the smart community. It was organized online in June and July 2022 through VOOV Meeting. Each expert was interviewed for at least one hour, and the same interview questions were used. A total of 26 experts were asked to score the importance of smart community safety indicators from 1 to 5. Then, the collected data were used to determine the weight of each assessment indicator for smart community safety. (A detailed outline of the interview questions can be found in Supplementary File S2) Detailed information on the experts who were interviewed is provided in Supplementary File S5. The confidence level (Cronbach α) of the importance of the 32 indicators was 0.949, which indicates that the data collected were highly reliable. Experts who participated in the development of the smart community and community safety were selected, which shows that they have a wealth of experience and knowledge for the safety development of the smart community. Through expert interviews, the data for the safety assessment indicators of the smart community were gained, which provided the basis for calculating the indicator weight through the CRITIC method.

In addition, objective scoring criteria were used to determine the indicator values for the safety evaluation of smart communities. A detailed overview of the objective scoring criteria of evaluation indicators can be seen in Supplementary File S3. According to the scoring criteria of indicators, the scoring data of the five smart communities were obtained directly from government websites and news coverage. Additionally, Supporting Materials on the five surveyed smart communities were collected by interviewing community administrators, and the corresponding safety assessment indicator values of each smart community were determined, which provided basic data to compute the overall score of smart community safety through the TOPSIS method.

5. Result

5.1. The Result of Each Safety Evaluation Indicator Weight through the CRITIC Method

Each evaluation indicator was scored by expert interview, and the weights of evaluation indicators were computed by Equations (1)–(7) of the CRITIC method. In this paper, the indicator scoring data given by 26 experts was used to determine the weights for assessment indicators. The confidence level (Cronbach's α) of the importance of the 32 indicators was 0.949, which indicates that the data collected were highly reliable. Then, the weight for each assessment indicator was calculated through Equations (1)–(7). The weighted values of all safety assessment indicators are illustrated in Table 3. The SI dimension weight value is the highest, followed by the CPS dimension weight value. This shows that the

SI dimension and the CPS dimension are the focus of the safety development of smart communities. Moreover, the three highest weights were the SE46, the SE53, and the SE55, and the three lowest were the SE64, the SE51, and the SE67.

Table 3. The result of each indicator weight for safety evaluation in smart communities.

Dimension	Weights	Indicators	Code	Weights
Safeguard mechanism (SM)	0.1596	Organizational safeguard	SE11	0.0315
		Capital safeguard	SE12	0.0390
		Institutional safeguard	SE13	0.0338
		Talent safeguard	SE14	0.0260
		Operation safeguard	SE15	0.0293
Platform safety (PS)	0.0938	Information safety safeguard	SE21	0.0329
		Platform data safety	SE22	0.0327
		Platform access safety	SE23	0.0282
Execution of emergency plans (EP)	0.0650	Emergency plan implementing	SE31	0.0319
		Emergency exercise	SE32	0.0331
Community public safety (CPS)	0.1960	Abnormal events recording	SE41	0.0261
		Special population management	SE42	0.0313
		Multi-sectoral linkage	SE43	0.0322
		Public health events processing	SE44	0.0289
		Management and control of key parts	SE45	0.0321
		Building monitoring	SE46	0.0454
Smart infrastructure (SI)	0.2307	Life channel facilities monitoring	SE51	0.0233
		Smart personnel monitoring facilities	SE52	0.0296
		Smart object monitoring facilities	SE53	0.0426
		Integrated system of smart safety	SE54	0.0243
		Public facilities monitoring	SE55	0.0430
		Smart environment monitoring	SE56	0.0334
		Smart firefighting facilities	SE57	0.0345
Emergency measure (EM)	0.1786	Emergency duty	SE61	0.0265
		Emergency warning	SE62	0.0279
		Emergency rescue alarm	SE63	0.0260
		Emergency shelter guidelines	SE64	0.0214
		Emergency supplies reserve	SE65	0.0253
		Emergency command and dispatch	SE66	0.0276
		Disaster risk map	SE67	0.0239
Safety propaganda and education (SPE)	0.0760	Propaganda and education of emergency safety	SE71	0.0392
		Training of community administrators	SE72	0.0368

5.2. Result of Safety Evaluation for Smart Communities through the TOPSIS Method

Expert opinions and existing literature were used to establish the scoring criteria for evaluation indicators. The scoring data for smart communities were obtained according to these criteria, which is the basis for calculating the total score of the smart community based on the TOPSIS method. In order to ensure the objectivity of the scoring data for each assessment indicator, smart communities were required to provide objective data and Supporting Materials. According to the weight for each assessment indicator (as illustrated in Table 3), the performances and rankings of the five smart communities selected were determined through Equations (8)–(14). The proximity coefficient of each smart community was calculated through Equation (14) of the TOPSIS method. Then, the safety levels for the smart community were ranked. The calculation results are illustrated in Table 4. At the same time, to deeply analyze the total rankings of the five smart communities, the proximity coefficients and rankings of five smart communities in seven dimensions were also determined through the TOPSIS method, as shown in Table 5, and the rankings of the five smart communities on each indicator are shown in Supplementary File S4.

Table 4. The proximity coefficients and ranking of smart communities.

Community	S^+	S^-	C_i	Rank
N1	0.031	0.170	0.845	1
N2	0.108	0.098	0.475	2
N3	0.127	0.082	0.392	3
N4	0.140	0.064	0.312	5
N5	0.140	0.085	0.379	4

Note: S^+ and S^- are, respectively, the distances between the respective security levels of the smart community and the positive and negative ideal solutions. N1–N5 represent the five smart communities selected.

Table 5. The results of ranking for smart communities in seven dimensions.

Dimension \ Community	Type	N1	N2	N3	N4	N5
SM	C_i	0.586	0.532	0.162	0.385	0.584
	Rank	1	3	5	4	2
PS	C_i	1.000	0.678	0.151	0.562	0.372
	Rank	1	2	5	3	4
EP	C_i	1.000	0.642	0.438	0.245	0.601
	Rank	1	2	4	5	3
CPS	C_i	1.000	0.418	0.421	0.190	0.245
	Rank	1	3	2	5	4
SI	C_i	1.000	0.466	0.518	0.259	0.302
	Rank	1	3	2	5	4
EM	C_i	1.000	0.418	0.405	0.333	0.413
	Rank	1	2	4	5	3
SPE	C_i	1.000	0.233	0.233	0.285	0.715
	Rank	1	5	4	3	2

Note: C_i is the proximity coefficient of the level for smart community safety. N1–N5 represent the five smart communities selected.

As shown in Table 4, the five smart community's safety levels were ranked from high to low as N1 > N2 > N3 > N5 > N4. The results indicated that the highest overall score of five sample projects was 0.845, and the lowest overall score was 0.312. The average score of the five sample projects was 0.481. The performance score ranged from 0 to 1. Thus, considering the value range of the final total score, the total score can be divided into five levels, including five stars (0.8~1), four stars (0.6~0.8), three stars (0.4~0.6), two stars (0.2~0.4), and one star (0~0.2). Then, it can be concluded that the safety level of the smart communities was five stars for N1, three stars for N2, and two stars for N3, N4, and N5. Although N2, N3, N4, and N5 did not reach the overall requirements for high-star communities, these four communities fared well in some dimensions. For instance, the PS, the EP, and the EM of N2 ranked second among the five smart communities. The results showed that no community was at a one-star level, which means that the five smart communities had achieved good results in terms of safety development.

According to Table 5, the Yucun community (N1) had the highest ranking among all dimensions, and the overall safety development level was the highest. When it came to the SM dimension and the PS dimension, the Fuguang community (N3) had the worst performance. The Huilongpu community (N4) performed poorly in four aspects: the EP, the CPS, the SI, and the EM. The Baolong community (N2) had the worst performance in the SPE. The N1 community achieved the highest ranking in all dimensions, and this makes its overall ranking the highest, which is consistent with the results in Table 4. All dimensions of N4 were generally ranked low, which makes it the worst performance among the five communities, which is consistent with results of the Table 4. In addition, the average score of the EP dimension was the highest score, followed by the PS dimension. The results show that the five communities have made great progress in the EP dimension and the PS dimension.

6. Discussion

6.1. Differences in Weights of Safety Evaluation Indicators for Smart Communities

The results showed that there were significant differences in the weights of the safety indicators in the smart communities. On the one hand, the SE46 indicator (building monitoring) had the highest indicator weight, followed by the S53 indicator (smart object monitoring facilities) and the SE55 (public facilities monitoring). The safety status of buildings and the normal operation of public facilities directly affect the lives of residents in smart communities [69]. At the same time, real-time monitoring of various objects in communities is conducive to reducing community safety accidents [70]. The SE46 belongs to the CPS (community public safety) dimension, and the SE53 and SE55 belong to the SI (smart infrastructure) dimension. The "Community Public Safety" and "Smart Infrastructure" are essential components of safety development for smart communities. Therefore, a higher weight was conferred to the SE46, the SE 53, and the SE55 indicators. On the other hand, the weight of the SE51 (life channel facilities monitoring), the SE64 (emergency shelter guidelines), and the SE67 (disaster risk map) indicators was lower than that of other indicators. The reason for this may be that the risk factors in the smart community are constantly changing, which affects the accuracy of the SE51, the SE64, and the SE67 [19]. Moreover, the realization of functions for these indicators depends on the normal operation of the smart safety infrastructure. Therefore, the SE51, the SE64, and the SE67 indicators received lower weights.

The weight sensitivity was calculated to better analyze the influence of the weight for the results of smart community safety. The five indicators with a high weight sensitivity were selected in each smart community. Figure 4 shows the results of the weight sensitivity analysis. As a result, the SE54 (integrated system of smart safety) appeared in the images of each community, which shows that the weight change in the SE54 will have a great effect on the evaluation results of the safety level of smart communities. The SE13 (institutional safeguard), the SE46 (building monitoring), and the SE67 (disaster risk map) appeared more frequently, which shows that the change in these indicators' weights could cause a change in the scores of multiple smart communities. Specifically, the SE46 had the highest indicator weight, and the SE67 and the SE54 had a lower indicator weight. The weight changes in these three indicators are concerned. According to the results of each community, the scores of some communities gradually increase, and those of some communities gradually decrease when the indicator weight increases. For example, with the increase in the weight of the SE54 indicator, the scores of the N1 and the N3 communities gradually increase, whereas those of communities N2, N4, and N5 gradually decrease. The reason for this is that the scores of the N2, N4, and N5 communities are lower than the scores of the N1 and N3 communities in the data of the five communities. Therefore, community administrators should pay attention to the development of the SE54 to achieve a better performance. Through weight sensitivity analysis, decisionmakers can understand how a change in indicator weight impacts the decision-making results, and this can help decisionmakers to formulate suitable strategies for the safety development of smart communities [96].

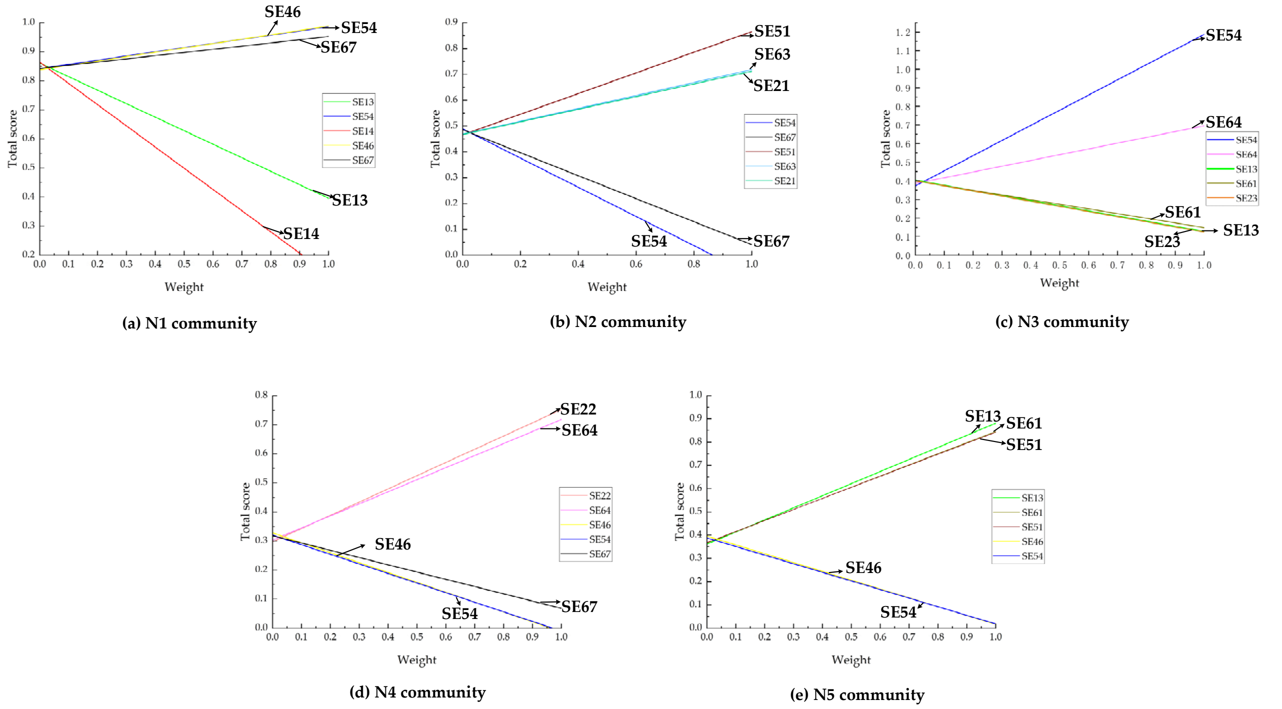

Figure 4. Results of the weight sensitivity analysis. Note: N1–N5 represent the five smart communities selected. The (**a**–**e**) represent five indicators with high weight sensitivity in N1–N5 smart communities.

6.2. Differences in Overall Safety Level of Smart Communities

There was a significant difference in the overall score between the sample smart communities. In detail, N1 was the best-performing community among the five samples. According to Table 5, N1 ranked well in the PS, the EP, the CPS, etc. The reason for this may be that the "smart Yucun system" and a "smart community management platform" have been established in N1, and these can enable community administrators to obtain the community safety status in real time [97]. The N1 community had a poor score in SM compared with the other six aspects. The reason for this is that the talent safeguard (SE14) and the institutional safeguard (SE13) had lower scores, so they did not attract anticipation in terms of safety development for smart communities. N4 had the worst level in the safety evaluation. This evaluation result was influenced by all dimensions, which may be due to the development background, geographical location, personnel distribution, and other aspects of this community [15]. For instance, because N4 is an old community, it has difficulties in smart updating of the community, and it takes longer to upgrade the community. This shows that the safety development of these communities is unbalanced, and each community needs its own plan to improve the safety level according to the community's shortcomings.

These evaluation results can also provide policy decisionmakers with a reference for safety development, because the safety level of each smart community can be discovered in the assessment results. For instance, N3 had a better performance in terms of the CPS dimension and the SI dimension, but it had a poorer performance in terms of the SM dimension and the PS dimension. This result can provide decisionmakers with a direction for safety development. Community administrators should focus on those aspects with poor performances, and they can organize detailed surveys to improve the safety development for smart communities.

6.3. Priority for Renewal Strategy of the Smart Community

To propose better suggestions for smart communities, the scores of the smart community were further compared. According to the research on the development of smart communities, smart community implementation can be discussed from two aspects: management and technology [13]. As for management, the policy foundation for the technological development of the community is provided by the community management, including the safeguard mechanism, community culture, safety education, and so on [98,99]. In terms of technology, advanced technical means are used to ensure community safety, which is mainly reflected in community smart infrastructure, emergency protection, and public safety monitoring [100,101]. Thus, the smart community safety level was divided into two parts: the managerial safety level and the technological safety level. The managerial safety level was calculated by the SM, the PS, the EP, and the SPE, and the technological safety level came from the SI, the CPS, and the EM. Thus, a decision matrix was established, as shown in Figure 5.

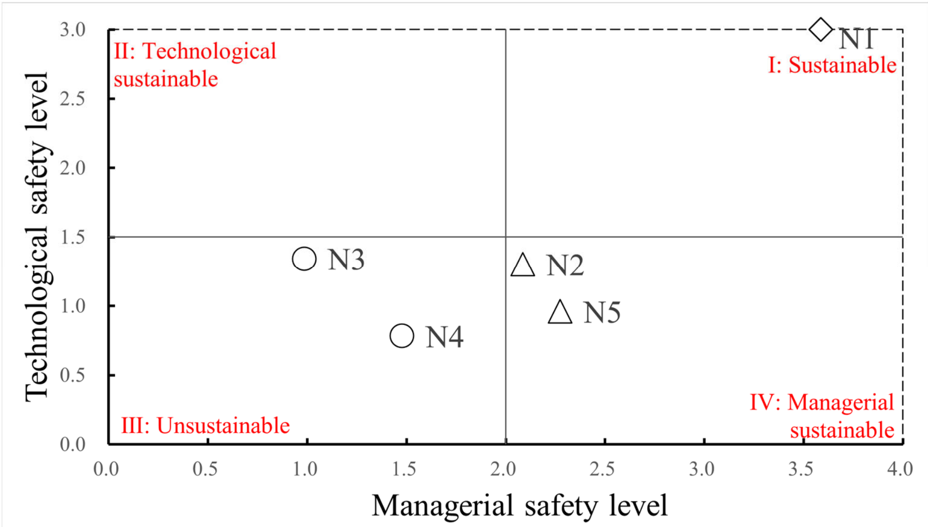

Figure 5. Decision matrix of smart community safety level. N1–N5 represent the five smart communities. The rhombus represents a sustainable smart community, the circle represents an unsustainable smart community, and the triangle represents a sustainable smart community in management.

As demonstrated in Figure 5, no smart communities were in quadrant II. One smart community was classified into quadrant I, which indicated a high level in both management and technology aspects. This smart community could be given a high safety level and designated as a sustainable smart community. As a result, N1 can be relevant for the safety development of other communities. However, N1 did not reach the highest standard in the SM. Combined with survey data, the results indicated a weakness in talent training for N1. In our communications with community administrators, it was revealed that due to a lack of volunteers with professional knowledge of community safety development, the safety score of the community was negatively affected. Volunteer teams with professional knowledge can directly or indirectly reduce the occurrence of community safety accidents [24,50,102]. Therefore, this community should pay attention to community talent training.

Two smart communities belonged to quadrant IV. These smart communities were better in the management level but relatively worse in technology conditions. According to the scoring data and interviews with community administrators, one reason for this is that these two communities are older. Generally, old communities have been unable to keep up with the development practice of the times [95], a situation that is characterized by outdated safety facilities, poor living conditions, no parking space planning, and little public area, which in turn affects community safety levels [103,104]. In order to solve these problems, the old community facilities were updated, and more advanced safety infrastructure was adopted, measures that gained residents' acceptance. For example, Baisha Community in Xianning City has built smart safety infrastructure through smart upgrading of the community, including a smart monitoring system and smart access control system, which has improved the safety and convenience of the community and the satisfaction of community residents [105]. Safety infrastructure is critical to the life safety of community residents [106]. The normal operation of safety infrastructure directly affects the overall safety level of the community [107–109]. In the long run, the buildings and facilities of these communities can be investigated in depth to discover other detailed problems. New strategies may include continually upgrading building monitoring and increasing safety infrastructure to improve community safety.

N3 and N4 were two smart communities with low levels, as they are illustrated in quadrant II. This shows that continuous development may be a long-term development strategy for these smart communities. While N3 performed well in the CPS and the SI, ranking second among all communities, the overall safety level was not high due to the poor level of other aspects. N4 presented the lowest safety level among these five communities. According to the survey data, these communities have a large gap compared with other communities in the PS, the EP, the EM, and the SPE due to the historical background of community development. The reason for this may be that the improvement of volunteer teams, safety education, and safety infrastructure has been neglected in community development. All-around safety updating has a positive effect on improving the safety level of the community, which can reduce loss to the community when safety accidents occur [110–112]. In addition, residents are the direct or indirect beneficiaries of the promotion of community safety [104]. Thus, the comprehensive improvement of community safety combined with residents' needs can better promote the smart community safety level.

6.4. Suggestions for Promoting the Safety Level of the Smart Community

Considering the above research results, some tactics and suggestions for improving the safety level of smart communities can be obtained for decisionmakers.

First, a higher safety level of smart communities needs the participation of all stakeholders in the public sector and social capital. The participation of social capital in community safety platforms and infrastructure construction should be encouraged, and government financial pressure can be reduced. Private enterprises should be encouraged to invest in the safety development of smart communities through modern financial models such as public–private partnerships, ensuring that smart community safety development has capital safeguards [113].

Second, regarding the specific content of smart community safety implementation, it is crucial for the government and community responsibility groups to actively summarize the highlights and problems of community safety. According to the data gathered from the five smart communities studied in this paper, each smart community has its highlights and problems in the safety development process of smart community safety. When building a smart and safe community, the successful experience of other community safety development projects can be used for reference. Furthermore, focusing on the community's problems will boost safety levels in the community [114]. In the construction of infrastructure, partnerships with technology companies have to be strengthened in order for technical updates to be performed and infrastructure monitoring facilities to be maintained on a timely basis. In addition, community talent training, especially of a volunteer team, should be strengthened [24,115]. At the same time, stronger training and education programs should be implemented for community staff and volunteers to ensure the correct use of smart facilities and to give the community a constant level of safety [55].

Finally, due to the differences in the history, people, and cultural development of different communities, a promotion plan for smart community safety should be combined with the actual situation. Before carrying out community safety implementation, it is necessary to fully investigate the details of the community, which will help to determine essential residents' needs and the actual status quo of different smart communities in a timely manner [116]. Furthermore, citizens are users of smart community safety, so it is necessary to consider the needs of residents when planning and delivering smart community safety [117]. Hence, it is suggested that a detailed implementation plan for smart community safety could be developed by considering various influencing factors comprehensively [118]. In addition, multiprogram management measures should be provided according to different and local needs.

7. Conclusions

Decisionmakers who make decisions about the safety development of smart communities need to develop a relatively unified evaluation method in order to evaluate the safety level of smart communities, a topic that is rarely addressed in existing research. This study develops an evaluation model of smart community safety and then explores the development levels of five smart communities. This study has several key findings. First, an indicator system of safety evaluation for smart communities was developed, and an assessment framework for the safety level of smart communities was proposed based on the CRITIC-TOPSIS method. Second, according to the indicator weight, SE46 had the highest weight, and SE64 had the lowest weight. Third, the assessment results indicated that N1 had the highest score, whereas N4 had the lowest score, so improving all dimensions of N4 may be especially important. In addition, more attention should be given to those lower ranking dimensions, for example, the SPE dimension of N2 and the SM and PS dimensions of N3. These findings not only develop an innovative evaluation model of smart community safety; they also enrich the knowledge of smart community safety. In practice, the safety level of the smart community can be evaluated through the evaluation framework proposed in this paper, and the safety development of the smart community can be improved based on the evaluation results. However, this research has two limitations. First, there was a relatively small sample size in this study. Second, the evaluation model based on the CRTIC-TOPSIS method is a static model, but in real life, the implementation of smart community safety is a dynamic process, so dynamic and complex models should be developed to analyze longitudinal variables.

Future studies need to be carried out to validate the applicability of the evaluation model in other communities of China or countries with datasets of larger scale. Moreover, as smart communities develop, their safety levels may change, and regular evaluations are recommended for comparisons to promote sustainable development.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings13020476/s1. File S1: Detailed information about the evaluation indicator system of smart community safety; File S2: Questionnaire about assessment of smart community safety; File S3: Detailed evaluation criteria for each indicator of smart community safety; File S4: The rankings of the five smart communities on each indicator; File S5: Detailed profiles of valid interview experts.

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Abbreviations

SM	SAFEGUARD MECHANISM
PS	PLATFORM SAFETY
EP	EXECUTION OF EMERGENCY PLANS
CPS	COMMUNITY PUBLIC SAFETY
SI	SMART INFRASTRUCTURE
EM	EMERGENCY MEASURE
SPE	SAFETY PROPAGANDA AND EDUCATION

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