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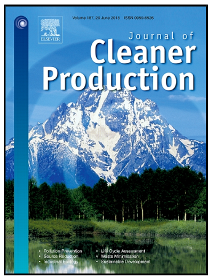

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Smart community evaluation for sustainable development using a combined analytical framework

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Abstract

Current attempts for sustainable-focused smart community evaluation have failed to make significant advancements, and quantitative analysis for sustainable development is still a major challenge in China. In recent years, smart community evaluation (SCE) for sustainable development has attracted considerable attentions. Government decision-makers can make it easier to stimulate household sustainable consumption by conducting SCE. This paper develops a combined analytical framework that will assist in the process of multi-source data integration and uncertain reasoning of SCE. This framework is used to combine quantitative metrics and subjective judgment with evidential reasoning approach, and this frarmework can also take decision makers' risk preferences into consideration using prospect theory. Four urban communities are evaluated by the proposed framework to demonstrate its applicability and effectiveness.

Keywords: Sustainable community development, Prospect theory, Evidential reasoning, Combined

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evaluation

1 Introduction

As the rapid development of economy and the increasing growth of population, problems such as traffic jams and population density in metropolis areas, excessive consumption of non-renewable resources, deteriorating environment and many other social problems have arisen(Chen et al., 2017; Ding et al., 2017; Wang et al., 2017). In order to address these chanllenges, the concepts of "smart planet" and "smart city" have been proposed by IBM (C. et al., 2009). In 2014, the Chinese government issued an urbanization development plan, and declared that the sustainable-focused smart community construction is one of its urban development directions. On April 7th, 2015, the Ministry of Housing and Urban-Rural Development and the Ministry of Science and Technology of the People's Republic of China jointly confirmed a total of 209 smart community pilots which are regarded as an indispensable part of sustainable city development. By the end of 2017, more than 500 cities in China had been constructing smart communities. And during the period of the13th Five-Year Plan for Economic and Social Development of the People's Republic of China, the investment of government on smart communities will exceed 500 billion yuan. Under the effect of policies and market driven impetus, the development of smart communities is faster and faster.

Along with the development of smart communities in China in recent years, there are also a series of problems hindering smart community construction. Facing realities such as different scales of investment, great diversity of participants and various phases of sustainable development, the research on construction mode of smart community and cooperation behavior of different participants are both important for smart community development(Xia et al., 2015). But smart community evaluation (SCE) plays a crucial role in ensuring the effectiveness of its implementation and development. Although the last decade has witnessed a number of results in the research on SCE, there are still many issues to be solved as the multi-source data integration and uncertain reasoning (Chilipirea et al., 2017; Ding et al., 2014; Linlin et al., 2017; Sta, 2017). SCE can allow governments to make more effective funding arrangements, increase the capability of community service and management, and promote the transition from traditional consumption to sustainable household consumption.

Performance evaluation of smart community for sustainable development has been extensively studied by both academia and industry recently, due to their socio-ecological value and the associated research issues(Wang et al., 2017). In France, Toshiba Solutions Corporation has been selected as the leading contractors for a smart community project that has achieved sustainable development by employing multiple sophisticated technologies (Nobutaka et al., 2015). In Aizuwakamatsu Japan, local government is working to build smart communities for providing a high quality of life and security to residents (Tada et al., 2014). In addition, the TERE (technology, environment, resources and the economy) model provides some convenience for exploiting marine resources and construction of smart city in Qingdao, which has been developed for better management and eco-friendly development (Wang et al.) .

Over the past decades, the existing research has made great contributions to the community development, such as reputation mechanism for cooperation(Wang et al., 2017; Xia et al., 2017), multi-dimensional smart community discovery scheme(Kim et al., 2017), and a new government affairs service platform(Lv et al., 2017). While the existing SCE methods still have some limitations, which can be summarized as: (1) It is difficult to find an adaptable methodology to solve the problems of multi-source data integration and uncertain reasoning in SCE. (2) Few works consider the risk preference of decision makers, which has a significant impact on the sustainable-focused evaluation.

In this paper, a prospect theory-based evidential reasoning (PTER) analytical framework is proposed to comprehensively evaluate the smart community for sustainable development. The remainder of this paper is organized as follows: Section 2 reviews some relevant literature. Section 3 introduces a combined indicator system and analyzes the architecture of the developed analytical framework. Section 4 introduces the calculation and modification of prospect value for multi-source data integration. Section 5 presents the assessment combination for SCE, followed by our experiments in Section 6. Section 7 concludes with final remarks and future prospects.

2 Literature review

Smart community is a community that applies IoTs, cloud computing, big data, and other new information technologies to digitize and coordinate community residents' daily lives (Ding et al., 2017; Ianuale et al., 2016; Li et al., 2011). In recent years, smart community evaluation for sustainable development is widely studied to stimulate household sustainable consumption. Ruimin Li developed an evaluation index system for transportation in smart communities (Li et al., 2015). Minako Hara proposed various types of KPIs to evaluate smart cities for sustainable development (Jalaluddin and Malek). However, many evaluation methods cannot make a comprehensive quantitative analysis of smart community for sustainable development (Tushar et al., 2014). Although these findings, to some extent, resolve problems in the evaluation of smart communities, there are still some inadequacies in their application.

Prospect theory was initially proposed by Kahneman and Tversky (1979) in Econometrica, and has been widely used in multi-attribute decision making and evaluation. There are several reasons why prospect theory is one of the most influential theory of decision making in uncertain environment. First, it takes the decision maker's psychological behavior into consideration. Second, prospect theory is always consistent with decision makers facing uncertainty and risks, which remains unexplained by expected utility. In addition, it is more suitable than expected utility theory in many areas, such as economics, organization theory and operations research (Nagarajan and Shechter, 2014). Bromiley proposed a prospect theory model for an entity resource allocation across many risky alternatives (Bromiley, 2009). Nagarajan et al. demonstrated that prospect theory could explain the behavioral deviations in a classical example, the newsvendor problem, using a novel interpretation of the reference point (Long and Nasiry, 2014). Liu et al. developed a linguistic evaluation method based on prospect theory to assess the risk of all alternatives in a decision making problem with interval probability (Jun-Hua et al., 2009). However, the works mentioned above cannot achieve multi-source data integration and uncertain reasoning for multi-attribute evaluation.

The evidential reasoning (ER) approach is an effective methodology for evaluation problems. Jiang et al. applied the ER approach to a weapon system capability assessment problem which is regarded as the beginning of study on military capability quantification (Jiang et al., 2011). Wang et al. made an assessment of environmental impact using the ER approach for the first time (Wang et al., 2006). Recently, public service quality assessments using evidential reasoning, such as a medical quality evaluation model, have been proposed (Kong et al., 2015). However, even for the improvement of ER approach, few researches emphasize the transformation technique with prospect theory focused on risk preference

As discussed before, it is worth noting that few scholars pay attention to the combined analytical framework for sustainable-focused smart community evaluation. To address this problem, we propose a prospect theory-based evidential reasoning (PTER) analytical framework.

3 PTER analytical framework

3.1 Indicator system for SCE

As the sustainable-focused evaluation of smart communities is a program with high complexity and systemization, we must take the character of indicator system into consideration as follows (Yang et al., 2016; Zhang et al., 2016): Firstly, it is necessary for us to make a distinction between mandatory and optional indicators. The mandatory indicators are considered as basic requirements for the construction of smart communities. And the optional ones are some expansibility indicators based on the former, which need to be further improved when mandatory indicators have already been completed. In addition, a huge amount of multi-source heterogeneous data has been produced in SCE by the participants from different organizations.

To support smart community construction, Chinese government has issued a series of construction guidelines for smart communities. According to these guidelines, the sustainable-focused capability of smart communities (named as top-indicators) can be described as guarantee system, infrastructure, community services, and community management. Each top indicator can often be broken into several sub-indicators, which can be further divided into several bottom indicators. A more detailed expression of the developed SCE indicator system can be found in the Appendix Table A1.

3.2 Architecture of the analytical framework

Sustainable-focused SCE is faced with plenty of the problems mentioned above, such as multi-source data integration and uncertain reasoning. To tackle these challenges, our proposed analytical framework will determine the ranking of each community by combining all the indicators in a comprehensive indicator system and study the influence of decision makers' risk preferences on the evaluation results. The evaluation progress of the analytical framework can be divided into two steps, as in Fig. 1.

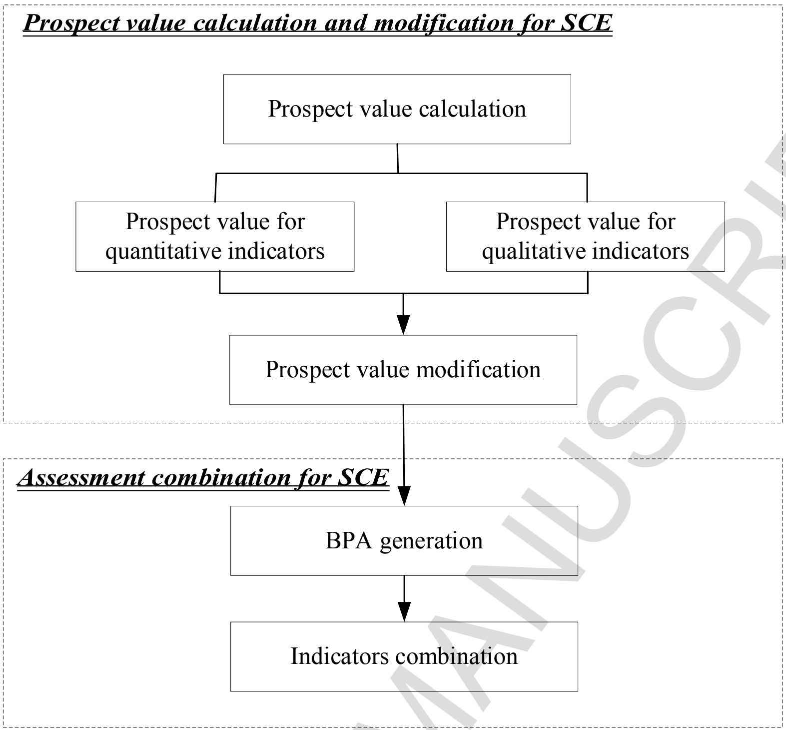


Fig. 1. The architecture of PTER analytical framework

Step 1: With the raw data, we have to do the data pre-processing by distinguishing qualitative indicators from quantitative indicators and then address them separately for prospect value calculation. After the prospect value calculation, a modification is made based on whether an indicator is mandatory or not. The aim of the calculation is to transform the original evaluation information into unified grades.

Step 2: Once the prospect value is obtained, a basic probability assessment can be generated using the rule or utility based transformation technology. Then, the general assessment of each community will be obtained by an ER combination algorithm. Accordingly, we can obtain their order ranking so that it can help decision makers make a rational evaluation for each smart community. More details will be given in Section 4 and Section 5.

4 Prospect value calculation and modification for SCE

As prospect theory is more consistent with decision makers' behavior, it has been widely used in multiple attribute decision making (MADM) problems (Liu et al., 2011). This paper solves the evaluation problem for smart communities from the perspective of prospect value, which considers the risk attitudes of the decision maker.

4.1 Prospect value calculation

4.1.1 Prospect value for quantitative indicators

Suppose $e_i^{'}$ denotes a quantitative indicator, *i* denotes the index of the indicator, $h_{n,i}$ $(\mathrm{n}=1,\cdots,N_i^{'})$ denotes the *n*th possible value of the indicator, $N_i^{'}$ is the number of all possible values, $\beta_{n,i}^{'}$ denotes a belief degree that the indicator has the value $h_{n,i}$. In summary, we can apparently find that the main elements of prospect value include two parts: a value function and a weight function. First, a value function is regarded as a function of variation value and can be calculated by

$$v\left(\Delta x_{n,i}^{'}\right)=\begin{cases}\left(\Delta x_{n,i}^{'}\right)^{\alpha}, & \Delta x_{n,i}^{'}\geq 0\\ -\lambda\left(-\Delta x_{n,i}^{'}\right)^{\alpha}, & \Delta x_{n,i}^{'}<0\end{cases} \tag{1}$$

where α is an exponent parameter representing a coefficient of risk preference (0≦α≦1); λ is the parameter of risk aversion which only exists when $\Delta x_{n,i}^{'}<0$ and it denotes the characteristic that losses are steeper than gains $(\lambda>1)$ as Fig. 2 shows; $\Delta x_{n,i}^{'}$ is the *n*th gain or loss compared to the reference point of the indicator, which can be calculated by

$$\Delta x_{n,i}^{'}=h_{n,i}-\overline{h}_i \tag{2}$$

where $h_{n,i}$ represents the possible value of one quantitative indicator; $\overline{h_i}$ denotes the reference point, which is regarded as the average value of the indicator in many previous studies (Heath et al., 1999), and it is computed as

$$\overline{h}_i = \frac{\sum_1^{O_i^{'}} \sum_1^{N_i^{'}} h_{n,i} \times \beta_{n,i}^{'}}{O_i^{'}} \tag{3}$$

where $O_i^{'}$ denotes the sum of alternatives with respect to the quantitative indicator $e_i^{'}$.

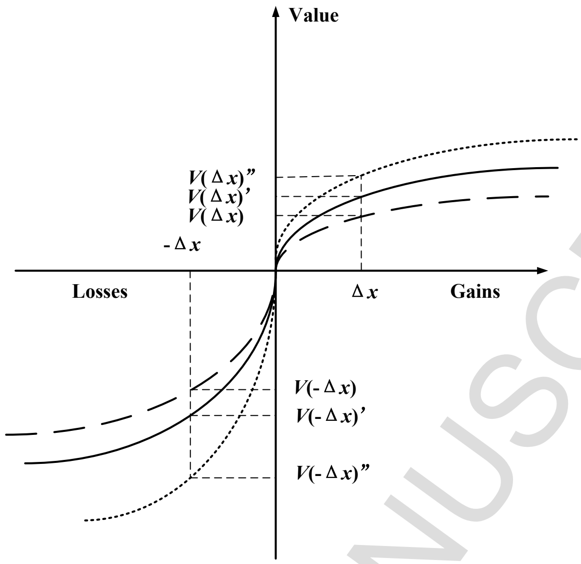


Fig. 2. Three different S-shaped value functions

Second, a decision weight function, which means a choice preference depending on probability $p_{n,i}$, can be computed as follows (Liu et al., 2011):

$$\pi(p_{n,i}) = \frac{p_{n,i}^{\delta}}{(p_{n,i}^{\delta} + (1 - p_{n,i})^{\delta})^{\frac{1}{\delta}}} \tag{4}$$

where $p_{n,i}(0 \leq p_{n,i} \leq 1)$ is equal to the belief degree $\beta_{n,i}^{'}$ of the original evaluation values of indicators in this paper; δ denotes an attitude coefficient toward gains and losses. Based on many experiments by Tversky, the most suitable values of δ reflecting the real experiment results: λ=2.25, when $\Delta x_{n,i}^{'} \geq 0$, δ =0.61; when $\Delta x_{n,i}^{'} < 0$, δ=0.69 (Tversky and Kahneman, 1992).

Lastly, the prospect value of one possible value should be obtained from the value function and weighting function as $V = v(\Delta x_{n,i}^{'})\pi(p_{n,i}) = v(\Delta x_{n,i}^{'})\pi(\beta_{n,i}^{'})$. Combining the results of the two functions to calculate all possible values for each indicator, we can obtain the general prospect value for this indicator to be: $V(e_i^{'}) = \sum_1^{N_i^{'}} v(\Delta x_{n,i}^{'})\pi(p_{n,i}) = \sum_1^{N_i^{'}} v(h_{n,i} - \overline{h}_i)\pi(\beta_{n,i}^{'})$.

4.1.2 Prospect value for qualitative indicators

Suppose $e_i^{''}$ denotes a qualitative indicator, $N_i^{''}$ denotes the number of original evaluation grades, $H_{n,i}$ is an evaluation grade in a basic set H_i for a qualitative indicator, as represented by $H_i = \{H_{1,i}, H_{2,i}, \ldots, H_{N_i^{''},i}\}$, $\beta_{n,i}^{''}$ denotes a belief degree that the indicator is in $H_{n,i}$. And $\Delta x_{n,i}^{''}$ is computed as follows:

$$\Delta x_{n,i}^{''} = H_{n,i} - \overline{H}_i \tag{5}$$

where $\Delta x_{n,i}^{''}$ denotes the nth gain or loss compared to the reference point of the ith indicator; $H_{n,i}$ indicates grade n of indicator $e_i^{''}$ which is in the range of $[H_{n,i}^L, H_{n,i}^U]$; $H_{n,i}^L$ and $H_{n,i}^U$ respectively denote the lower limit and upper limit of the intervals, as $H_{n,i}^L = (n-1)/N$ and $H_{n,i}^U = n/N$ without any preference of the decision maker. $\overline{H}_i$ denotes the average value of one qualitative indicator, which can be calculated by

$$\overline{H}_i = \frac{\sum_1^{O_i^{''}} \sum_1^{N_i^{''}} [H_{n,i}^L, H_{n,i}^U] \times \beta_{n,i}^{''}}{O_i^{''}} \tag{6}$$

where $O_i^{''}$ denotes the sum of alternatives for the qualitative indicator $e_i^{''}$.

The calculation of gain or loss for a quantitative indicator is as shown in Eq. (2) and Eq. (3), otherwise $\Delta x_{n,i}^{''}$ is computed through two interval numbers, $H_{n,i}$ and $\overline{H}_i$ for the qualitative indicators. Since Gaussian distribution is the most common distribution function and the actual data always complies with Gaussian distribution, we assume that $f(x) \sim N(\mu, \sigma^2)$ in the interval $[H_{n,i}^L, H_{n,i}^U]$. The values of μ and σ can be calculated according to the principle of 3σ, as represented by $\mu = (H_{n,i}^L + H_{n,i}^U)/2$, $\sigma = (H_{n,i}^U - H_{n,i}^L)/6$.

It should be noted that the value of $\Delta x_{n,i}^{''}$ is calculated based on six comparison relationships between interval numbers $H_{n,i}$ and $\overline{H}_i$ (Wang et al., 2015). Based on the discussion above, we calculate the general prospect value for a qualitative indicator by integrating all prospect values of assessments by $V\left(e_i^{''}\right)$ =

$\sum_{1}^{N''_i} v\left(\Delta x''_{n,i}\right)\pi\left(p_{n,i}\right) = \sum_{1}^{N''_i} v(\Delta x''_{n,i})\pi(\beta''_{n,i})$.

4.2 Prospect value modification

To assure that general prospect values of different indicators are comparable, the extremum method is used to normalize prospect values. In addition, the normalization method is as follows:

$$V(e_i)^* = \begin{cases} \dfrac{V(e_i) - m_i}{M_i - m_i} & \text{for benefit indicators} \quad (7a) \\ \dfrac{M_i - V(e_i)}{M_i - m_i} & \text{for cost indicators} \quad (7b) \end{cases}$$

where e_i denotes a qualitative or quantitative indicator; $M_i = max\,\{V(e_i)\}$, $m_i = min\,\{V(e_i)\}$, $V(e_i)$ and $V(e_i)^*$ $(0 \leq V(e_i)^* \leq 1)$ respectively denote a general prospect value and the standardized one.

Having the standardized general prospect values in hand, we need to modify them according to whether or not the indicator is mandatory.

As for a mandatory indicator, the modification method is as follows:

$$\tilde{V}(e_l)^* = \begin{cases} V(e_l)^*, & V(e_l)^* \geq 0.5 \\ \eta \times V(e_l)^* & V(e_l)^* < 0.5 \end{cases} \tag{8}$$

where $V(e_l)^*$ and $\tilde{V}(e_l)^*$ respectively denote the original and modified prospect value of a mandatory indicator; η is a correction factor that is used in the case when the indicator does not meet the basic standard $(0 < \eta < 1)$. According to the normalization method, it is obvious that the average of standardized prospect values could be equal to 0.5.

As for an optional indicator, the modification method is calculated by

$$\tilde{V}(e_k)^* = \begin{cases} (1+\mu) \times V(e_k)^* & V(e_k)^* \geq 0.5 \; and \; \forall\, V(e'_l)^* \geq 0.5 \\ V(e_k)^* & V(e_k)^* < 0.5 \text{ and } \forall\, V(e'_l)^* \geq 0.5 \\ (1-\mu) \times V(e_k)^* & \text{otherwise} \end{cases} \tag{9}$$

where e'_l and e_k respectively denote a mandatory indicator and an optional indicator, and the mandatory indicator and the optional indicator both belong to a same upper-indicator; $V(e_l^{'})^*$ and $V(e_k)^*$ are their prospect values, respectively; $\tilde{V}(e_k)^*$ is the modified prospect value of the optional indicator e_k, and μ is adjustment factor which can embody the character of an optional indicator. Based on the property of an optional indicator, there are three different situations in which prospect values are modified: (1) If $V(e_k)^* \geq 0.5$ and $\forall\, V(e_l^{'})^* \geq 0.5$, because both of them are larger than the average value, which indicates the performance of all indicators would be the best in the three situations. Thus, $V(e_k)^*$ can be modified to have a larger value $(1+\mu) \times V(e_k)^*$; (2) If $V(e_k)^* < 0.5$ and $\forall\, V(e_l^{'})^* \geq 0.5$, because all mandatory indicators belonging to a same upper-indicator with the optional indicator are larger than the average value, the performance of the optional indicator might be acceptable and $V(e_k)^*$ can be kept unchanged; (3) If there is a mandatory indicator $V(e_l^{'})^* < 0.5$, the performance is obviously unacceptable even though $V(e_k)^* > 0.5$. Thus, $V(e_k)^*$ can be modified to a smaller value $(1-\mu) \times V(e_k)^*$.

5 Assessment combination for SCE

The evidential reasoning (ER) approach has been applied in many areas, e.g., engineering design, safety assessment, and many other kinds of assessment problems (Jian-Bo and Dong-Ling, 2002). In this section, we introduce the enhanced ER approach for conducting sustainable-focused SCE.

5.1 BPA generation

Only when all the raw data of each indicator is transformed to BPA can the ER approach be applied. Suppose an original assessment of the quantitative or qualitative indicator $S(e_i)$ as follows:

$$S\left(e_i^{'}\right) = \{\left(h_{n,i}, \beta_{n,i}^{'}\right), n = 1,\ldots,N_i^{'}\} \qquad \text{for quantitative indicators} \qquad (10a)$$

or

$$S\left(e_i^{''}\right) = \{\left(H_{n,i}, \beta_{n,i}^{''}\right), n = 1,\ldots,N_i^{''}\} \qquad \text{for qualitative indicators} \qquad (10b)$$

Next, a transformed assessment, $S(e_i)$, for both kinds of indicators would have the following distribution:

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1,\ldots,N\} \tag{11}$$

where H_n is a unified evaluation grade in a general set H; $\beta_{n,i}$ denotes a belief degree ($0 \le \beta_{n,i} \le 1$, $\sum_{n=1}^{N} \beta_{n,i} \le 1$); N denotes the number of transformed grades of e_i, and in general, $N_i^{'}, N_i^{''} \ne N$. In this paper, we suppose that each unified evaluation grade H_n is evenly distributed in the normalized prospect value interval [0, 1], and the normalized prospect values $V(H_n) = (n-1)/(N-1)$. Moreover, $\beta_{n,i}$ can be calculate by

$$\beta_{j,i} = \begin{cases} \dfrac{V(H_{j+1}) - \tilde{V}(e_i)^*}{V(H_{j+1}) - V(H_j)}, 0 \le \tilde{V}(e_i)^* - V(H_j) < \dfrac{V(H_{j+1}) - V(H_j)}{2} \\ \dfrac{\tilde{V}(e_i)^* - V(H_j)}{V(H_{j+1}) - V(H_j)}, \ \tilde{V}(e_i)^* - V(H_j) \ge \dfrac{V(H_{j+1}) - V(H_j)}{2} \end{cases} \tag{12}$$

where $\beta_{j,i}$ is the belief degree assessed to an evaluation grade H_j. The remaining belief degree $\beta_{j+1,i} = 1 - \beta_{j,i}$, and j is computed by

$$j = \begin{cases} \{n | V(H_n) \le \tilde{V}(e_i)^* < V(H_{n+1})\}, n = 1,\ldots,N-2 \\ \{n | V(H_n) \le \tilde{V}(e_i)^* \le V(H_{n+1})\}, \quad n - N - 1 \end{cases} \tag{13}$$

Based on the previous discussion, we can transform the original data for two kinds of indicators into an unified evaluation grade. And we can prove that the prospect value of the original assessment is equal to that of the transformed assessment using the equivalent transformation as shown in Theorem 1.

Theorem 1 (Prospect value-based equivalent transformation of raw data): Suppose a qualitative indicator and a quantitative indicator are respectively assessed by Eq. (10a) and (10b), and the equivalent rule is as described in Eq. (12) and (13). The prospect value of an indicator must be unchanged with transformation by the equivalent transformation.

5.2 Indicators combination

After the assessments of all basic indicators are transformed to BPA, they can be combined by the ER approach (Wang et al., 2006). The indicator e_i is not distinctive in the aggregation and the result of combination does not depend on the sequence of aggregation. Weight acquisition is an important process for assessment, and the weights can be acquired by subjective preference or objective methods with objective information from data. To simplify the PTER analytical framework and avoid the influence of weight on the final combination results, we suppose the indicators are of equal importance. Based on the hierarchy of the indicator system, a community can be evaluated by synthesizing all indicators using the ER approach. According to the prospect value of the unified discernment frame, we calculate the prospect value of each community: $V = V(H_n) \times \beta_n$ and obtain the rankings of different communities.

6 Experiment analysis

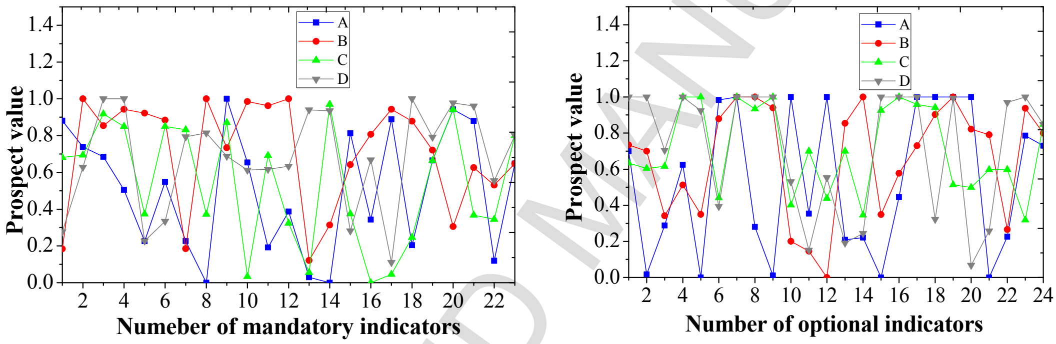
6.1 Data description

To evaluate the performance of the proposed method, we provide an example for assessing actual communities in Hefei city, PR China. The questionnaire survey method was adopted for collecting data gathered from senior community staff (e.g., community director and information collectors of the community) in 20 developed communities. In this experiment, we chose four out of twenty communities for analysis, including the Binghushiji community (community A), the Fangxing community (community B), the Furong community (community C) and the Hebin community (community D). The belief degrees assessed for these four communities are shown in Table A2 of the Appendix.

6.2 Experiment results

We first set the parameter α=0.5 to study the performance of the four communities. Next, we studied the impact of risk attitude on community A and community ranking by changing α from 0.5 to 0.2 and 0.8. In this paper, η and μ are estimated by combining the opinions of six experts in the field of smart community development and taking the average（η=0.8, μ=0.3）.

The performance of all bottom-indicators, including mandatory and optional ones, were evaluated using prospect values, which are the basis for decision making in Fig. 3. It is clear from Fig. 3 that the prospect values of most indicators are good, though several have poor performances. The information provides an important basis for further assessment and ranking of communities. The performance of Fig. 3 (b) conforms to the optional indicators' character of enhancement.



(a) **(b)**

Fig. 3. The general prospect value of indicators are based on the types of indicators for the four communities (mandatory indicators and optional indicators). A, B, C and D represent the four communities.

The prospect values of the indicators can be used to acquire the BPA and then all assessments should be aggregated using the ER approach. The combined belief degrees of the four alternatives and their top-indicators are presented in Fig. 4 and Table 1 respectively. They provide some information for improving smart community construction. The indicators and communities can be evaluated with five grades as $H=\{H_j$, j=1,…,5$\}$={'Worst', 'Poor', 'Average', 'Good', 'Excellent'}. Each community does well with some indicators but is graded poorly in others. In summary, community A should strengthen the construction of infrastructure and community services. In addition, we suggest that communities B and

D invest more money on their guarantee systems for the improvement of community capability. As for the communities with good performance in some top-indicators, they could enhance construction in other top-indicators in order to keep ahead. Next, the prospect values of the four communities are calculated using the equation $V = V(H_n) \times \beta_n$. Therefore, the four communities can be ranked by their prospect values: A $\prec$ B $\prec$ C $\prec$ D, where the symbol "$\succ$" means "is better than".

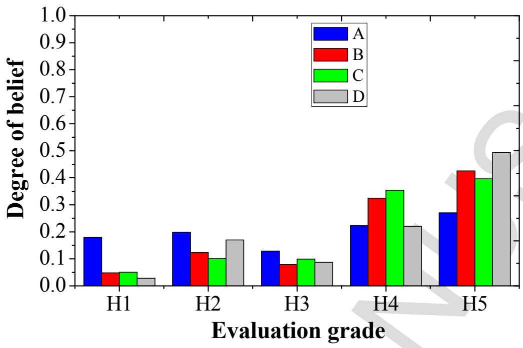


Fig. 4. The combined belief degrees for the four communities are generated by four top-indicators using the ER approach. And A, B, C and D indicate the four communities.

Table 1

The belief degrees assigned to each evaluation grade for the top-indicators of the four communities

Communities	Top-indicators	Belief degrees assessed to each evaluation grade				
		H_1	H_2	H_3	H_4	H_5
A	Guarantee system	0.0242	0.2431	0.2882	0.3801	0.0644
	Infrastructure	0.4102	0.1445	0.1156	0.0975	0.2322
	Community services	0.2106	0.3089	0.0700	0.1108	0.2997
	Community management	0.0879	0.0960	0.0608	0.2973	0.4580
B	Guarantee system	0.0779	0.2336	0	0.1793	0.5092
	Infrastructure	0.0380	0.1273	0.1224	0.2702	0.4421
	Community services	0.0830	0.1231	0.0960	0.2927	0.4052
	Community management	0.0170	0.0492	0.1317	0.5458	0.2563
C	Guarantee system	0	0.0434	0.1057	0.6362	0.2147
	Infrastructure	0.1227	0.1215	0.0783	0.2426	0.4349
	Community services	0.1044	0.1165	0.1522	0.0903	0.5366
	Community management	0	0.1557	0.0938	0.4236	0.3269
D	Guarantee system	0.0079	0.3676	0.1544	0.2173	0.2528
	Infrastructure	0	0	0.1414	0.3684	0.4902

Community services	0.0529	0.2137	0.0398	0.1731	0.5205
Community management	0.0682	0.1500	0.0517	0.1579	0.5722

6.3 Impact of α

Obviously, the parameter α controls the impact of decision makers' risk attitudes in two respects: focusing on one community and ranking the communities. And the bigger values of α is, the more adventurous the decision maker is. For the purpose of studying the influence of parameter α on decision making and evaluation, we conducted a set of experiments for studying the impact of α on four top-indicators of community A and the communities' ranking by changing α from 0.5 to 0.2 and 0.8.

6.3.1 Impact on the evaluation of the Binghushiji community

In our experiments, Fig. 5 and Fig. 6 show the prospect values and combined belief degrees of four top-indicators where parameter α is respectively 0.2, 0.5 and 0.8. In general, the prospect values and combined beliefs assessed to five grades fluctuate as the parameter changes.

The meanings of four top-indicators are as follows: Guarantee system is the fundament of SCC assuring that construction is stable and reliable, such as general design and guarantee condition; Infrastructure denotes a hardware or software facility that guarantees the operation of a smart community and provides public services for community residents; Community services refer to the public services and other material, cultural and life services provided by the government, community committee and third-party service providers; Community management is a series of self-management or administrative management activities in order to maintain the operation of community, promote the development and prosperity of the community. In terms of prospect values, as the parameters increase, the decision maker is getting more and more adventurous, and the prospect values of four top-indicators also increase. This conforms to the assumption of a rational decision maker's behavior.

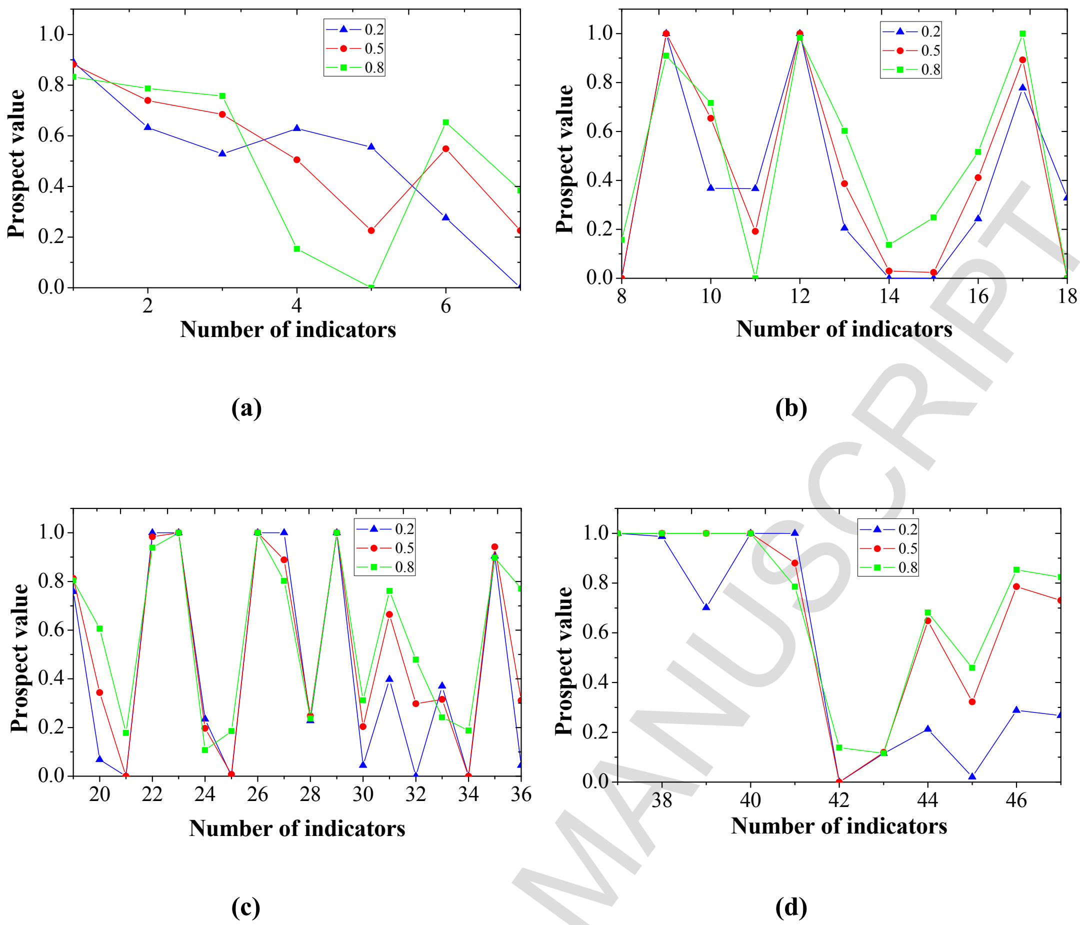


Fig. 5. The general prospect values for bottom-indicators belonging to different top-indicators with different α. The four top-indicators are *Guarantee system* (a), *Infrastructure* (b), *Community services* (c) and *Community management* (d), respectively. The value of α is set to 0.2, 0.5 and 0.8, respectively.

Combined belief degrees fluctuate, as Fig. 6 shows, since combined assessment is generated on the basis of several different prospect values. Moreover, we can easily find that the key points for SCC change with the parameters. In this way, community managers can not only identify poor aspects to improve on but also need to find good aspects to maintain based on the distributed assessments. Furthermore, the ranking scores are useful for allocating government resources to communities.

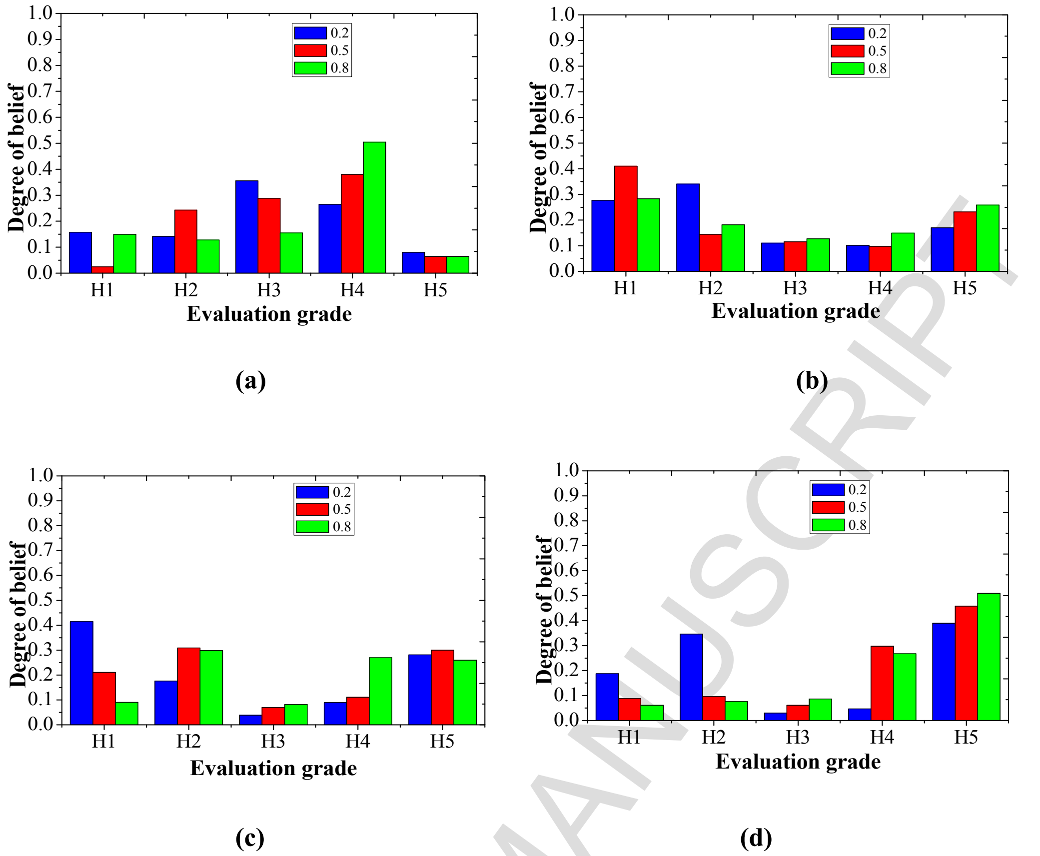


Fig. 6. The combined belief degrees for the four top-indicators belonging to the different top-indicators with different α.

6.3.2 Impact on communities' ranking

Table 6 shows the comparison results of general prospect values for the four alternatives when the α parameter is 0.2, 0.5 and 0.8 respectively. When the parameters are 0.5 and 0.8, the rankings of the four alternatives are respectively: D ≻ B ≻ C ≻ A, B ≻ C ≻ D ≻ A.

As seen in Table 6, increasing the values of α will increase the prospect values of communities. However, the extent of improvement reduces gradually. That decrease is observed because the more adventurous a decision maker is, the smaller the marginal prospect value will be. If a decision maker is more inclined to risk-seeking, the influence of risk attitudes will decrease. To some extent, the results may be consistent with some viewpoints of marginal utility theory. Moreover, it can be concluded from Table 2 that the influence of risk attitude on ranking is much greater when the prospect values are relatively large. For example, the ranking of the communities changes when $V > 0.6$. Because every decision maker pursues risk, the values of the data cannot change their decisions when the values are too small.

Table 2

The influence of decision makers' risk attitude (that is parameter α) on the ranking of communities

Value of α	Community	A	B	C	D
0.2	Prospect value	0.4789	0.6565	0.6909	0.7086
	Ranking	4	3	2	1
0.5	Prospect value	0.5517	0.7391	0.7360	0.7455
	Ranking	4	2	3	1
0.8	Prospect value	0.5940	0.7837	0.7750	0.7653
	Ranking	4	1	2	3

7 Conclusions

In this paper, we propose a combined framework for sustainable-focused smart community evaluation. First, compared with traditional methods, the developed transformation technique employs prospect value to enhance the performance of multi-source data integration. Second, this analytical framework can be applied to evaluation problems without knowing the evaluation criteria in advance. In addition, this study focused on risk preference and demonstrated the impact of that on the smart community evaluation.

Based on the above experiment analysis and conclusions, we derive the following policy implications: first, for the rapid and sustainable development of smart community, we should make more efforts on the construction of mandatory indicators in the present stage. Due to limited resources and funds, it is significant to make appropriate allocation of them on mandatory indicators according to our proposed evaluation indicator system. Thus, construction in order is a good way to not waste resources and funds on meaningless pursuits. Second, evaluation results are affected by risk attitudes of decision maker, so that government should take these into consideration and adjust the main emphasis of smart community construction timely. In addition, we should make full use of the government's guiding role in policy making, and encourage more and more participants to make efforts for smart community construction.

In the real world, it worth to note that combined smart community evaluation always involves incomplete information of indicators. In other words, if the incompleteness of indicators is considered in this paper, that is to say $\tilde{m}_{H,i} \neq 0$, the analytical framework is not applicable. In future work, we are planning to investigate a more feasible approach for ranking smart communities considering the incompleteness of each indicator.

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Appendix

Table A1

The indicator system for smart community evaluation with three-layer evaluation hierarchy

Top-indicators	Sub-indicators	Bottom-indicators	Characters
Guarantee system	General design	General project	L,M
		Implement plan	L,M
	Guarantee condition	Organization framework	L,M
		Per capita investment	T,M
		Reserve of professional	T,M
	Safety, Operation and Maintenance	Information safety	L,M
		Operations management	L,M
Infrastructure	Information service platform	Diversity of service module	L,M
		Residential use coverage	T,M
		Residential satisfaction	T,M
	Network infrastructure	Network bandwidth	T,M
		Wifi coverage	T,O
		CATV coverage	T,M
	Public service facilities	Area of service stations	T,M
		Area of medical stations	T,O
		Area of recreational stations	T,O
	Environment IoT facilities	Area of environment monitoring	T,O
		Number of environment monitor	T,M
Community services	Government services	Information disclosure	L,M
		Diversity of administrative-affairs	L,M
	Special population services	Services for the retired	L,O
		Services for the disabled	L,O
		Services for floating population	L,O
	Security and safety	Area in charge of one police station	T,O
		Capability of conflict mediation	L,O
	Fundamental public services	Satisfaction with employment	T,O
		Satisfaction with elderly home care	T,M
		Frequency of distance education	T,O
		Capability of legal services	L,O
	Life services	Area of convenience service stations	T,M
		Capacity of housekeeping services	L,M
		Satisfaction with catering services	T,O
		Frequency of community interaction	T,O

	Financial services	Integration of one card	L,O
		Diversity of convenience payment	L,M
		Community banks	L,O
Community management	Owner's committee management	Frequency of home-owner's conventions	T,O
		Participation in community management	L,O
	Property management	Capability of store management	L,O
		Satisfaction with express delivery services	T,O
		Satisfaction with sanitation services	T,M
		Informationalized level	L,O
	Object management	Frequency of information collection	T,M
		Capability of social organization	L,M
		Capability of party construction	L,O
	Public management	Capability of law enforcement	L,O
		Capability of emergency management	L,O

Note: L and T respectively denote qualitative and quantitative indicators; M and O respectively denote mandatory and optional indicators.

Table A2

The degrees of belief assigned to each evaluation grade for bottom-indicators of the four communities

Bottom-indicators	Belief degrees assessed to each evaluation grade for each community			
	Community A	**Community B**	**Community C**	**Community D**
General project	{(G,0.4765),(E,0.5235)}	{(W,0.2624),(P,0.7376)}	{(A,0.2752),(G,0.7248)}	{(P,0.8933),(A,0.1067)}
Implement plan	{(A,0.0439),(G,0.9561)}	{(E,1)}	{(A,0.2222),(G,0.7778)}	{(A,0.4867),(G,0.5133)}
Organization framework	{(G,0.2623),(E,0.7377)}	{(G,0.5854),(E,0.4146)}	{(G,0.3275),(E,0.6725)}	{(E,1)}
Per capita investment	{(G,0.9802),(E,0.0198)}	{(G,0.2277),(E,0.7723)}	{(G,0.5996),(E,0.4004)}	{(E,1)}
Reserve of professional	{(W,0.0978),(P,0.9022)}	{(G,0.3116),(E,0.6884)}	{(P,0.5068),(A,0.4932)}	{(W,0.0905),(P,0.9095)}
Information safety	{(A,0.8049),(G,0.1951)}	{(G,0.4648),(E,0.5352)}	{(G,0.6006),(E,0.3994)}	{(P,0.6657),(A,0.3343)}
Operations management	{(W,0.0964),(P,0.9036)}	{(W,0.2595),(P,0.7405)}	{(G,0.6724),(E,0.3276)}	{(G,0.8262),(E,0.1738)}
Diversity of service modules	{(W,1)}	{(E,1)}	{(P,0.5096),(A,0.4904)}	{(G,0.7414),(E,0.2586)}
Residential use coverage	{(E,1)}	{(A,0.6561),(G,0.9349)}	{(G,0.5185),(E,0.4815)}	{(A,0.2462),(G,0.7538)}
Residential satisfaction	{(A,0.3859),(G,0.6141)}	{(G,0.0589),(E,0.9411)}	{(W,0.8643),(P,0.1357)}	{(A,0.5492),(G,0.4508)}
Network bandwidth	{(W,0.2326),(P,0.7674)}	{(G,0.1501),(E,0.8499)}	{(A,0.2349),(G,0.7651)}	{(A,0.5329),(G,0.4671)}
Wifi coverage	{(E,1)}	{(A,0.0638),(G,0.9362)}	{(G,0.3752),(E,0.6248)}	{(E,1)}
CATV coverage	{(P,0.4537),(A,0.5463)}	{(E,1)}	{(P,0.7043),(A,0.2957)}	{(A,0.4665),(G,0.5335)}
Area of service stations	{(W,0.8816),(P,0.1184)}	{(W,0.5144),(P,0.4856)}	{(W,0.7771),(P,0.2229)}	{(G,0.2426),(E,0.7574)}
Area of medical stations	{(W,0.9045),(P,0.0955)}	{(E,1)}	{(G,0.5492),(E,0.4508)}	{(E,1)}
Area of recreational stations	{(P,0.3551),(A,0.6449)}	{(P,0.0490),(A,0.9510)}	{(G,0.4790),(E,0.5210)}	{(A,0.1801),(G,0.8199)}
Area of environment monitoring	{(G,0.4293),(E,0.5707)}	{(A,0.0738),(G,0.9262)}	{(E,1)}	{(E,1)}

Number of environment monitor	{(W,1)}	{(P,0.7438),(A,0.2562)}	{(G,0.1186),(E,0.8814)}	{(G,0.2608),(E,0.7392)}
Information disclosure	{(G,0.7495),(E,0.2505)}	{(A,0.4323),(G,0.5677)}	{(P,0.5020),(A,0.4980)}	{(P,0.8724),(A,0.1276)}
Diversity of administrative-affairs	{(P,0.6261),(A,0.3739)}	{(G,0.7719),(E,0.2281)}	{(W,1)}	{(A,0.3267),(G,0.6733)}
Services for the retired	{(W,1) }	{(W,0.0225),(P,0.9775)}	{(E,1)}	{(G,0.3015),(E,0.6985)}
Services for the disabled	{(G,0.0655),(E,0.9345)}	{(G,0.4860),(E,0.5140)}	{(P,0.7639),(A,0.2361)}	{(P,0.8988),(A,0.1012)}
Services for floating population	{(E,1)}	{(E,1)}	{(E,1)}	{(E,1)}
Area in charge of one police	{(W,0.2147),(P,0.7853)}	{(E,1)}	{(G,0.2662),(E,0.7338)}	{(E,1)}
Capability of conflict mediation	{(W,0.9693),(P,0.0307)}	{(G,0.2400),(E,0.7600)}	{(E,1)}	{(E,1)}
Satisfaction with employment	{(E,1)}	{(W,0.4396),(P,0.5604)}	{(A,0.7057),(G,0.2943)}	{(G,0.9690),(E,0.0310)}
Satisfaction with elderly home care	{(G,0.4456),(E,0.5544)}	{(G,0.2294),(E,0.7706)}	{(W,0.8170),(P,0.1830)}	{(W,0.5607),(P,0.4393)}
Frequency of distance education	{(W,0.0090),(P,0.9910)}	{(W,0.5911),(P,0.4089)}	{(E,1)}	{(W,0.1326),(P,0.8674)}
Capability of legal service	{(E,1)}	{(W,1)}	{(A,0.4938),(G,0.5062)}	{(G,0.8438),(E,0.1562)}
Area of convenience service stations	{(W,0.1868),(P,0.8132)}	{(G,0.4872),(E,0.5128)}	{(W,0.0128),(P,0.9872)}	{(E,1)}
Capacity of housekeeping services	{(A,0.3420),(G,0.6580)}	{(A,0.1145),(G,0.8855)}	{(A,0.3420),(G,0.6580)}	{(G,0.8329),(E,0.1671)}
Satisfaction with catering services	{(P,0.8078),(A,0.1922)}	{(G,0.5845),(E,0.4155)}	{(E,1)}	{(W,0.4657),(P,0.5343)}
Frequency of community interaction	{(P,0.7376),(A,0.2624)}	{(E,1)}	{(P,0.0246),(A,0.9754)}	{(W,0.3171),(P,0.6829)}
Integration of one card	{(W,1)}	{(G,0.0066),(E,0.9934)}	{(G,0.2961),(E,0.7039)}	{(E,1)}
Diversity of convenience payment	{(G,0.2316),(E,0.7684)}	{(G,0.7801),(E,0.2199)}	{(G,0.2316),(E,0.7684)}	{(G,0.0905),(E,0.9095)}
Community bank	{(P,0.7558),(A,0.2442)}	{(G,0.6988),(E,0.3012)}	{(E,1)}	{(E,1)}
Frequency of home-owner’s conventions	{(E,1)}	{(A,0.0799),(G,0.9201)}	{(G,0.1666),(E,0.8334)}	{(E,1)}
Participation in community management	{(E,1)}	{(G,0.3900),(E,0.3100)}	{(G,0.2332),(E,0.7668)}	{(W,0.0993),(P,0.9007)}
Capability of store management	{(E,1)}	{(E,1)}	{(A,0.0682),(G,0.9318)}	{(G,0.0248),(E,0.9752)}
Satisfaction with express delivery services	{(E,1)}	{(G,0.7127),(E,0.2873)}	{(A,0.1512),(G,0.8488)}	{(W,0.8111),(P,0.1889)}
Satisfaction with sanitation services	{(G,0.4787),(E,0.5213)}	{(A,0.4967),(G,0.5033)}	{(P,0.5294),(A,0.4706)}	{(G,0.1555),(E,0.8445)}

Informationalized level	{(W,1)}	{(G,0.8361),(E,0.1639)}	{(G,0.5897),(E,0.4103)}	{(W,0.2774),(P,0.7226)}
Frequency of information collection	{(W,0.5228),(P,0.4772)}	{(A,0.8758),(G,0.1242)}	{(P,0.6204),(A,0.3796)}	{(A,0.7814),(G,0.2186)}
Capability of social organization	{(A,0.4089),(G,0.5911)}	{(A,0.4089),(G,0.5911)}	{(G,0.7989),(E,0.2011)}	{(G,0.7989),(E,0.2011)}
Capability of party construction	{(P,0.7091),(A,0.2909)}	{(W,0.2569),(P,0.7431)}	{(G,0.5815),(E,0.4185)}	{(G,0.1210),(E,0.8790)}
Capability of law enforcement	{(G,0.8567),(E,0.1433)}	{(G,0.2501),(E,0.7499)}	{(P,0.7252),(A,0.2748)}	{(E,1)}
Capability of emergency management	{(A,0.0796),(G,0.9204)}	{(G,0.8013),(E,0.1987)}	{(G,0.6081),(E,0.3919)}	{(G,0.6081),(E,0.3919)}

Proof of Theorem 1. From Eqs. 10(a), 10(b) and 11-13, we have

$$V\left(S\left(e_i^{'}\right)\right) \text{ or } V\left(S\left(e_i^{''}\right)\right) = \tilde{V}\left(e_i\right)^* = \sum_1^N \beta_{n,i} V\left(H_n\right) = \beta_{j,i} V\left(H_j\right) + \beta_{j+1,i} V\left(H_{j+1}\right)$$

$$= \begin{cases} \dfrac{V\left(H_{j+1}\right) - \tilde{V}\left(e_i\right)^*}{V\left(H_{j+1}\right) - V\left(H_j\right)} \times V\left(H_j\right) + \left(1 - \dfrac{V\left(H_{j+1}\right) - \tilde{V}\left(e_i\right)^*}{V\left(H_{j+1}\right) - V\left(H_j\right)}\right) \times V\left(H_{j+1}\right), 0 \le \tilde{V}\left(e_i\right)^* - V\left(H_j\right) < \dfrac{V\left(H_{j+1}\right) - V\left(H_j\right)}{2} \\ \dfrac{\tilde{V}\left(e_i\right)^* - V\left(H_j\right)}{V\left(H_{j+1}\right) - V\left(H_j\right)} \times V\left(H_j\right) + \left(1 - \dfrac{\tilde{V}\left(e_i\right)^* - V\left(H_j\right)}{V\left(H_{j+1}\right) - V\left(H_j\right)}\right) \times V\left(H_{j+1}\right), \tilde{V}\left(e_i\right)^* - V\left(H_j\right) \ge \dfrac{V\left(H_{j+1}\right) - V\left(H_j\right)}{2} \end{cases}$$

$$= V\left(H_{j+1}\right) + V\left(H_j\right) = V(S(e_i))$$

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