DEVELOPMENT OF A FUZZY CONTINGENT VALUATION METHOD TO ASSESS AMENITY: IMPROVEMENT OF A NEIGHBORHOOD STREET

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Abstract
This study attempts to explore the sources of respondents' uncertainty regarding their willingness to pay (WTP) in CVM (Contingent Valuation Method). To capture the uncertainty in respondents' responses, the concept of certainty level for dichotomous choice response is introduced in CVM survey. Furthermore, an alternative approach based on fuzzy logic (i.e. fuzzy-CVM approach) is newly developed to incorporate the uncertainty into the WTP estimates. The approach can tackle the irreversible effects of WTP and WNTP (willingness not to pay). Moreover this paper addresses how to estimate the upper and lower values of WTP. Throughout an empirical analysis in Japan, it is shown that the respondents' WNTP is more sensitive to both bid amount and confidence level than the WTP. It is concluded that the Fuzzy-CVM can improve the reliability of the conventional CVM.

Keywords: Contingent valuation method; Willingness to pay/willingness not to pay; Fuzzy logic; Uncertainty; Heterogeneity
Topic Area: E1 Assessment and Appraisal Methods

1. Introduction
Contingent valuation method (CVM) is one of the most widely used methods for assessing environmental goods, such as non-market goods and public goods. This approach simply asks survey respondents how much they are willing to pay (WTP) for hypothetical (hence the term "contingent") increments or decrements in the availability of the environmental goods. However, CVM has been criticized by many researchers, because of its nature on less reliability, validity and heterogeneity. These problems inherent in CVM are related to the difference between the observed responses of WTP and the unobserved "true" value. Since there is no judgment standard of the error (i.e. with the broad sense of the word) included in the stated WTP, a problem is complicated. That is, the result in the market for judging the accuracy of an evaluation value does not exist. Many researches have made efforts to solve the problems which true value cannot be obtained. Mitchell and Carson (1989) give us an important idea regards on the error of WTP as follows.

Let us quote their statement at the beginning. $TWTP_j$ (true willingness to pay) which the j-th person to the public goods of a certain specific level has can be expressed as follows.

$$TWTP_j = f(X, \alpha) \tag{1}$$

where, X expresses the attribute matrix of the j-th person, such as an attitude for income or environment, and α expresses the vector of an unknown parameter. However, it is impossible to observe this $TWTP_j$. Instead, researchers can use $SWTP_j$ (stated willingness to pay) which the respondent specified. $SWTP_j$ can be expressed as follows.

$$SWTP_j = h\left[f(X,\alpha), g_1(W,\beta), g_2(R,\varphi), g_3(Z,\delta)\right] \tag{2}$$

where, $g_1(W,\beta)$ is the process of a probability error, and is expressed as the function of the matrix of variable W and the parameter β which is not observed. The term closely concerns with "reliability" which implies variation from $TWTP_j$. $g_2(R,\varphi)$ is the process of a systematic error and is expressed as the function of the matrix of Variable R and unknown parameter φ vector. This indicates "validity", that is the degree of bias from $TWTP_j$. is the function which shows how much actually observed. And the function of $g_3(Z,\delta)$ deeply concerns with "heterogeneity" that means no answer or the problem of sample selection, and it influences the representativeness of the $SWTP_j$ over sample respondents on the population distribution.

In addition, we assume that fuzziness causes another part of the error in CVM as well. It is plausible that people's responses essentially consist of uncertainty portions. Especially, $SWTP_j$ for the improvement of public goods includes much fuzziness in their responses, since respondents may make decisions under imperfect information that the project is not undertaken yet. Thereby, the influence of fuzziness on people's $SWTP_j$ might be non-negligible. Nevertheless, the fuzziness latent in $SWTP_j$ has not sufficiently been expressed by the existing literatures.

In this study, we develop a new evaluation methodology, which can enhance the reliability of WTP estimate by improving both survey and evaluation methods in order to take into consideration the "fuzziness" in connection with a questionnaire respondent's consciousness, judgment of WTP and etc. Moreover, this study aims at proposing a technique computable in the form which had the width of the estimated WTP which are the upper and lower values of WTP. We discuss how to calculate WTP with width which can be useful for project evaluation. Another main contribution of this study is to suggest important refinements to consider difference between WTP and willingness not to pay (WNTP). Fuzzy membership function allows us to tackle the asymmetry between WTP and WNTP.

2. Literature review of CVM approaches considering uncertainty

Since Weibrod (1964) has originally introduced the concept of uncertainty inherent in WTP responses, many efforts have continuously made to deal with the uncertainty such as option value approach (e.g. Cicchetti and Freeman, 1971; Schmalensee, 1972; Freeman, 1984a) and quasi-option value approach (e.g. Arrow and Fisher, 1974; Henry, 1974; Freeman, 1984b). Sequentially, the importance of incorporating uncertainty is corroborated in the study of Champ et al. (1996). Individuals in their research were asked how certain they intended to actually pay using a ten point scale, where ten is very certain and one is very uncertain. Based on this rating exercise, they predicted a WTP estimate of 12\$, quite similar to the true WTP (9\$). This provides a piece of strong evidence in favor of incorporating respondent uncertainty into CVM response analysis. Ready et al. (1995) also developed a similar type of WTP question where the respondent express the strength of WTP on six semantic scales; definitely yes, probably yes, maybe yes, maybe no, probably no and definitely no to a given single bid amount. They found that the estimated value of WTP by incorporating uncertainty tended to be raised than that by ignoring it, for instance by forcing respondents to answer yes or no in a standard dichotomous choice CVM question.

On the other hand, Loomis and Ekstrand (1998) examined the sources and patterns of respondents' uncertainty regarding their WTP and presented alternative approaches to incorporating the uncertainty into the estimation of the logit model. The question was formed out of the single-bounded dichotomous choice. The respondents were asked to fulfill the post–decisional certainty level for the prior dichotomous response with a scale of 1 (not certain) to 10 (very certain). The result of their study showed that extreme recoding of "yes/no" responses reduced the explanatory power of the estimated WTP models of logit type, reduced the WTP estimates and frequently resulted in negative median of WTP.

Contrary to the survey methods, very little drastic modeling approaches have been proposed to handle the uncertainty so far as the authors know. Determinants of respondents' uncertainty might consist of the bid level and prior knowledge and/or familiarity with the corresponding resources. Furthermore, there could be significantly higher uncertainty on the acceptable (i.e. "yes") responses than on the unacceptable ("no") ones. Even the above-mentioned studies focused on the uncertainty, their estimation schemes did not exceed the traditional modeling approaches. As Hanemann and Kristrom (1995) argued, however, the fuzzy approach can provide an alternative to the random utility maximization model based on dichotomous choice CVM responses. A resent work has applied fuzzy numbers in order to consider the different types of uncertainty due to fuzziness, imprecision, and ambiguity (Kooten and Krcmar, 2000). This study attempts to extend the fuzzy approach to relieve the remaining problems in terms of survey and analysis methods.

3. A proposal of fuzzy-CVM

The CVM survey first describes the environmental goods under hypothetical conditions to respondents and then directly asks their WTP. Many respondents may however face difficulties in valuing the environmental goods, either because they are not familiar with it or because they are not used to answer such kind of questions. Even if the respondents are completely familiar with the environmental goods, they are probably not confident to judge the tradeoff between the environmental goods and monetary value. Moreover, unlike actual market goods, the environmental goods cannot be clearly described in crisp language. Because of these matters, the respondents' WTP might be uncertain. To obtain the reliable WTP estimates, it is therefore necessary to take this kind of uncertainty into account. However, the conventional WTP survey (e.g. Bishop and Heberlein, 1979) simply asks the respondents to answer "yes/no" questions by leaving the respondents' different degree of certainty out of consideration.

To deal with the above-mentioned issues, an approach named "Fuzzy-CVM" is newly proposed in this study. Fuzzy-CVM consists of two steps; survey and analysis of WTP as in Figure 1. At the first step, a WTP rating exercise with five-point certainty level of responses is employed, in which the respondents are asked to report how confident about their dichotomous choice responses by scaling 0 (not confident) to 5 (very confident), after answering the double bounded WTP questions. Those who are not familiar with the environmental goods could state well-founded values so that their responses may be very certain and can probably match their actual WTP closely and vice versa.

In the second step, fuzzy logic is adopted to incorporate the uncertainty existing in the respondents' stated WTP, since the logic is a powerful tool for representing the vagueness, imprecision, subjectivity, and ambiguity of human being's stated preference as previously mentioned. We suggest a methodological procedure of fuzzy logic to represent the double-bounded choice responses with certainty levels. Moreover, we consider the heterogeneity of individuals' decision rules for WTP. Thus, the fuzzy-CVM approach can easily incorporate the heterogeneity by assuming different fuzzy inference and rule weights. The survey and the analysis methods of Fuzzy-CVM will be introduced in a case study of a neighborhood street improvement in the rest of this chapter.

Survey step

- Socio-economic characteristics (including income)
- Attitude for a future change
- Confidence level in dichotomous choice response with double bounded

Analysis step

Input: Attitude for a future change, Bid amount

Rule: Fuzzy logic model

1) Fuzzifier
2) Fuzzy Rule Base
3) Fuzzy inference
4) Defuzzification

Output: Possibility of WTP

Figure 1 Survey and analysis steps of Fuzzy-CVM Approach

3.1 Fuzzy-CVM survey

3.1.1 Study area and street improvement project

The object of this study is a neighborhood street located in the town center of Kisuki, Japan. The total distance of the corresponding street is about 600m. Residents living in Kisuki habitually use this street for shopping, commuting, and other trip purposes. Various stores such as superstores, flower shops and shoe stores look out on the street. However the street has no sidewalk, so that the conflicts between pedestrians and cars often appear on this street. This causes the recent decline of the safety for bike users and pedestrians, the driving conditions and consequently the life quality of residents. An improvement project for the amenity of the street seems to improve the life quality of the residents as well as to induce visitors in this area. The project includes the improvements of parking places and sidewalk of the street. In addition, it is planned to change the current two-way passing road to one way. Figure 2 shows the street conditions before the implement of the project.

Figure 2 Conditions before Street Improvement Project

3.1.2 Survey and social experiment

A CVM survey was undertaken to elicit the respondents' WTP for the improvement project of the street from October 27 to November 9, 2002. The street users who were both of the inhabitants in the town and visitors from the outside were requested to cooperate the face-to-face interview at a street-side booth. During the survey period, a social experiment was carried out to encourage the residents and visitors to undergo the street improvement plan actually. Figure 3 outlines the street environment during the social experiment.

At the beginning of the interview, the respondents were asked to carefully watch a computer graphic (CG) screen, which showed the future images of the street improvement project as shown in Figure 4 for around 5 minutes. After showing the CG screen, interviewers explained the whole project to the respondents in detail, and then respondents were asked to state their willingness to given bid amounts and attitudes for the street improvement project. It was expected that the social experiment and the CG could reduce a portion of CVM errors such as information bias and embedding bias. The information bias may occur by the difficulty to appropriately explain the survey subject of CVM, and the embedding bias may happen by the indistinct survey range and levels of corresponding environment improvement project.

Figure 3 Street Environment During the Social Experiment

Figure 4 A Computer Graphic Image Used in Interview

Since all respondents of our CVM survey actually experienced the street improvement plan through the social experiment and/or virtually experienced it through the CG, the respondents should well recognize the actual benefit of the project. Therefore, the scope test to check the magnitude of the above biases was omitted in our case study.

The respondents answered their attitudes for the street improvement project as well as WTP. Table 1 shows the questionnaire sheet, in which they rated their attitudes for each question by 5 point scale from 0 (certainly yes) to 5 (certainly no).

To investigate the respondents' WTP values with the uncertainty, specially designed double bounded choice questions were presented to the respondents in accordance with their confidence levels by scaling ten rates, -5 (certainly willingness not to pay) to 5 (certainly willingness to pay) as in Figure 5. In the CVM survey, we designed two different payment methods for the residents and the visitors; pay by tax and pay by parking fee, respectively. The payment of tax is applied for the residents, since the street environment will be recognized as a public property for them and it is directly related with their daily life. The payment of parking fee is applied for the visitors, since they will visit the street area for shopping or sight seeing. Therefore, the important thing for the visitors is the attractiveness of the street, and they can recognize that the purpose of the project is to improve the attractiveness of the street.

Table 1 Questionnaire Sheet to Survey Respondents' Attitude for the Street Environment Project

	Certainly Yes				Certainly No
1) Car speed decreases	1	2	3	4	5
2) Roadside parking cars reduce	1	2	3	4	5
3) The safety of pedestrians and bike users is improved	1	2	3	4	5
4) The street becomes well-appointed of barrier-free	1	2	3	4	5
5) The space for pedestrians and bike users is improved	1	2	3	4	5
6) The street becomes as a space for communicating	1	2	3	4	5
7) The number of visitors increases	1	2	3	4	5
8) Parking facilities become more convenient	1	2	3	4	5
9) The landscape is improved	1	2	3	4	5

Question

…If your tax increases ¥200 per month for the implement of the street environment improvement plan, indicate your opinion with confidence levels for this improvement plan….

	Certainly WNTP				↔					Certainly WTP
Certainty level	-5	-4	-3	-2	-1	1	2	3	4	5

Figure 5 WTP/WNTP Question with Certainty Levels

3.2 The fuzzy-CVM analysis

3.2.1 Methodological framework for the fuzzy-CVM approach

In this section, we propose a methodology of fuzzy inference to estimate the WTP under uncertainty. The fuzzy logic scheme is comprised of four principal components: fuzzifier, fuzzy rule base, fuzzy inference, and defuzzification. The fuzzifier has an effect of transforming the observed crisp values of attributes into suitable linguistic values. The fuzzy rule base represents the relationship between the respondents' perceptions for corresponding environmental goods and their willingness to pay. The fuzzy inference is the kernel of an inference process, and it has the capability of simulating the respondent' decision-making process by performing fuzzy reasoning to achieve a desired control strategy. The fuzzy reasoning allows flexible rules of interpretations and adjustments. That is, even if the input does not match exactly the standard one required by the rule, the fuzzy reasoning supports the application of the current input against each rule and the derivation of the appropriate outcome. The defuzzification is utilized to yield a crisp value decision from an inferred fuzzy linguistic value set that is estimated by the fuzzy inference process.

(a) Fuzzifier

The fuzzy membership functions are crucial in fuzzy set calculus. Triangular membership functions are employed to represent the respondents' uncertainty in CVM. The shape of triangular membership functions corresponds with the normal distribution in probability theory. For the antecedent term, the respondents' perceptions for the bid amounts and the attitudes for the street improvement plan are employed as explanatory variables, and for the consequent term, the degree of respondents' WTP or WNTP for bid amounts is employed as a dependent variable.

Respondents' perceptions for bid amounts = {VC, C, M, E, VE}
= {Very Cheap, Cheap, Moderate, Expensive, Very Expensive}
Respondents' attitudes for the future image = {VB, B, M, G, VG}
= {Very Bad, Bad, Moderate, Good, Very Good}
Degree of respondents' willingness to pay or not to pay= {CN, PN, M, PY, CY}
= {Certainly Not, Probably Not, Moderate, Probably Yes, Certainly Yes}

(b) Fuzzy rule bases

Fuzzy IF-THEN rules are applied to model the decision process of respondents. The general rule form is

$$R^k\text{: } IF\ x\ is\ A_k,\ THEN\ z\ is\ C_k,\ k=1,\ldots,K \tag{3}$$

Where x and z are linguistic variables representing the input variables and the control variable respectively. A_k and C_k are the linguistic predicates of the linguistic variables x and z in the universes of discourse U and W, respectively. k is the number of rule. The antecedent term, "x is A_k", represents the respondents' perception for corresponding environmental subjects and bid amounts. The consequent term, "z is C_k", describes the possibility of respondents' WTP.

Twenty fuzzy inference rules in total are established as in Table 2, and all rules will be fired in parallel (all weight of rules equal to 1.0). However, it is important to consider the heterogeneity of individuals' decision rules. For instance, some individuals might be willing to pay by considering both the bid amount and future image, but others might consider only either bid amount or future image. Since it is difficult to consider the heterogeneity of all individuals' decision rules, the heterogeneity among groups will be considered in this chapter. We assumed that in our sample data, there exist three decision groups. The first group is assumed to consider both bid amount and future image in their decision process, so that the weights of bid amount and attitude are almost same. The second group is assumed to consider only future image and ignore bid amount. For the second group, the weight of future image is higher than that of bid amount. The third one is assumed to consider only bid amount and ignore future image, and the weight of bid amount is higher than that of future image.

(c) Fuzzy Inference and Defuzzification

In general input values, x will have a certain amount of overlap, $\mu_{Ak}(x)$, with several linguistic predicates, A_k. Every rule k is fired and results in an output $\mu_{C'k}(z)$.

$$\text{Min: } \mu_{Ck}(z) = \min[\mu_{Ak}(x), \mu_{Ck}(z)],\ \forall x, z \in U, W \tag{4}$$

The aggregation scheme to combine C^* should reflect the nature of the problem under consideration and the interpretation of the fuzzy sets involved (Lin and Lee, 1996). In this study, a general aggregation scheme is employed:

$$\text{Max: } \mu_{C^*}(\mathrm{z}) = \max_{1\le k\le K} \mu_{C_k^*}(\mathrm{z}) \quad \forall z \in \mathrm{W} \tag{5}$$

The Centroid of Area (COA) method has been generally used as a defuzzification method to extract a crisp value that represents the possibility distribution of an inferred fuzzy linguistic value set.

$$\text{COA: } \mathrm{P} = \sum_{z\in Z} \mathrm{z}\cdot\mu_{C^*}(z) \Big/ \sum_{z\in Z}\mu_{C^*}(z) \tag{6}$$

Table 2 Initial Fuzzy Inference Rules and Rule Weights

	Rules			Initial weights
Bid amount	Rule 1)	If bid amount is VC,	then willingness to pay is CY	1.0
	Rule 2)	If bid amount is C,	then willingness to pay is PY	
	Rule 3)	If bid amount is M,	then willingness to pay is M	
	Rule 4)	If bid amount is E,	then willingness to pay is PN	
	Rule 5)	If bid amount is VE,	then willingness to pay is CN	
Attitude	Rule 6)	If attitude for car use is VG,	then willingness to pay is CY	1.0
	Rule 7)	If attitude for car use is G,	then willingness to pay is PY	
	Rule 8)	If attitude for car use is M,	then willingness to pay is M	
	Rule 9)	If attitude for car use is B,	then willingness to pay is PN	
	Rule 10)	If attitude for car use is VB,	then willingness to pay is CN	
	Rule 11)	If attitude for passengers is VG,	then willingness to pay is CY	1.0
	Rule 12)	If attitude for passengers is G,	then willingness to pay is PY	
	Rule 13)	If attitude for passengers is M,	then willingness to pay is M	
	Rule 14)	If attitude for passengers is B,	then willingness to pay is PN	
	Rule 15)	If attitude for passengers is VB,	then willingness to pay is CN	
	Rule 16)	If attitude for life quality is VG,	then willingness to pay is CY	1.0
	Rule 17)	If attitude for life quality is G,	then willingness to pay is PY	
	Rule 18)	If attitude for life quality is M,	then willingness to pay is M	
	Rule 19)	If attitude for life quality is B,	then willingness to pay is PN	
	Rule 20)	If attitude for life quality is VB,	then willingness to pay is CN	

where, P is the possibility of willingness to pay.

3.2.2 Fuzzy logic for double bounded choice question

The fuzzy question of double bounded choice is that the respondents are asked to rate options on appropriate confidence scales if they would pay X1$ for a condition of some attributes. A second bid amount is then offered to the respondent in accordance. If the respondent agree to the first X1$ amount then the amount is raised to X2$, while if the respondent disagree to pay the initial X1$ amount then the follow up X3$ amount would be lowered. The implicit assumption with this type of approach is that the respondent's answers to both of the payment questions are driven by one underlying true WTP value. If this assumption is true, the second question increases the information about the true WTP contained in the answer because it creates a tighter interval around the true WTP than that defined by response to the first bid only (X1$), as in the single bounded choice approach. Even the question format of double bounded choice is widely used and the logit/probit type model is adopted in CVM approach, the analytical methodology adopting fuzzy inference process has not been proposed yet. In this section, we suggest a fuzzy inference process for double bounded choice question.

The general fuzzy inference process is applied to analyze the possibility of respondent's willingness to pay for the first bid amount. For the second bid amount, the information of the first response is used to establish the fuzzy membership function of consequent term as can be seen in Figure 6. The figure shows the fuzzy membership functions of consequent term for the second bid amount, in the case of the possibility of WTP for the first bid amount is equal to 3.

Let us the possibility of respondent's willingness to pay for the first bid amount δ. The fuzzy membership functions of consequent term can be established as follows.

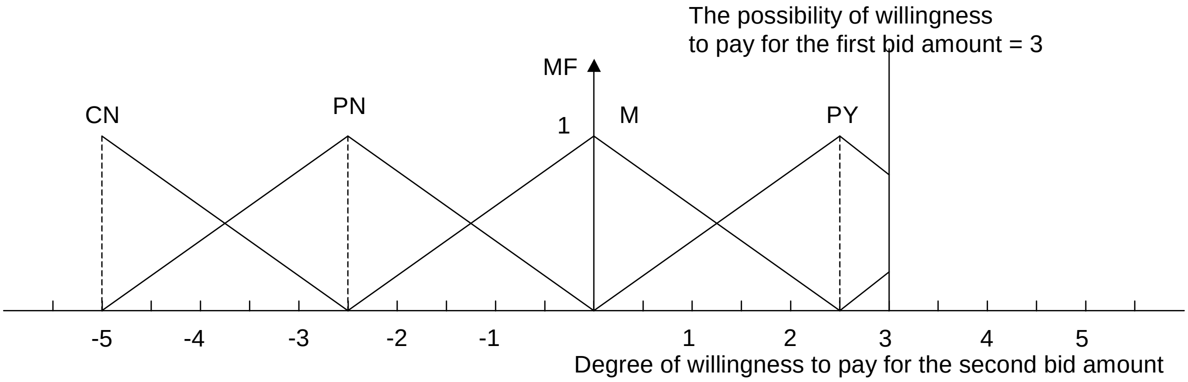


Figure 6 An Example of Membership Functions of WTP for the Second Bid Amount

1) In the case of "Yes" response for the first bid amount,

$$\mu_{C''k}(z) = \begin{Bmatrix} \mu_{\mathrm{Ck}}(z), & \text{if } z \le \delta \\ 0 & , \text{ if } z > \delta \end{Bmatrix}, \quad \forall \delta, z \in W \tag{7}$$

2) In the case of "No" response for the first bid amount,

$$\mu_{C''k}(z) = \begin{Bmatrix} \mu_{\mathrm{Ck}}(z), & \text{if } z \ge \delta \\ 0 & , \text{ if } z < \delta \end{Bmatrix}, \quad \forall \delta, z \in W \tag{8}$$

Using the equations (7) and (8), the equation (4) can be written in equation (9).

$$\text{Min: } \mu_{Ck}(z) = \min[\mu_{Ak}(x), \mu_{C''k}(z)], \quad \forall x, z \in U, W \tag{9}$$

Equation (9) is used to estimate the possibility of respondent's willingness to pay for the second bid amount.

3.2.3 Heterogeneity of decision rules

The heterogeneity of decision-making rules for WTP is dealt with in this study. In the traditional modeling approaches for CVM such as logit or probit models based on probability theory, it is not simple to consider the heterogeneity of individuals' decision rules (e.g. Sugie et al., 1999). On the other hand, the suggested fuzzy-CVM approach can easily incorporate the heterogeneity by assuming different rule weights that is initially set up to 1.0 as in Table 2. Figure 7 shows a modeling framework for incorporating the different decision rules for WTP. We suggest a sequential estimation procedure as follows.

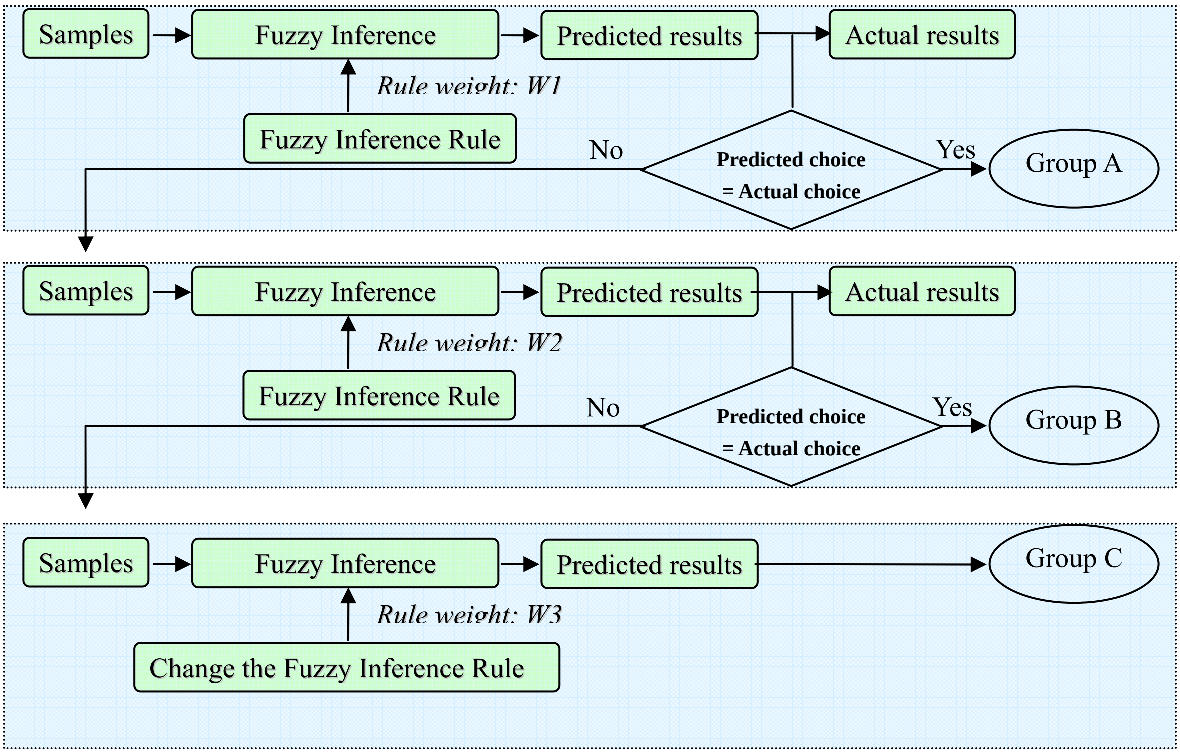


Figure 7 A Methodological Procedure of Fuzzy Inference to Consider Individuals' Different Decision Rule

In the first stage, we assume initial weight values, usually set up 1 for all fuzzy inference rules. As changing the weights of each fuzzy inference rules, the estimation based on fuzzy inference process are continued until the maximum goodness of fit (GOF) index is obtained. In the second stage, the same procedures of the first stage are continued only using the incorrectly predicted samples of the first stage. After achieve the maximum GOF index in the second stage, we change the fuzzy inference rules for the incorrectly predicted in the second stage. The respondents of the third stage are considered to have extreme decision rules for WTP. For instance, they consider only one factor for their decision or they are very insensitive for all variables. Therefore, we estimate the fuzzy inference model for these respondents as changing the fuzzy inference rules as well as the rule weight.

4. Estimation results

We compare the proposed fuzzy-CVM approach with the traditional CVM approach to verify the effectiveness of the suggested fuzzy-CVM approach. The two CVM approaches have several differences: (1) the traditional CVM approach is developed based on probability theory, while the fuzzy-CVM approach is based on fuzzy set theory; (2) The traditional CVM approach ignores the respondents' uncertainty of their WTP responses, while the fuzzy-CVM approach incorporates the uncertainty in the model; (3) The traditional CVM approach uses the extremely recording data, that is, the data recorded to one if the WTP response is "yes" and zero if "no", while the fuzzy-CVM approach uses continuous recording data scaled from -5 (certainly no) to 5 (certainly yes) certainty levels of the WTP.

4.1 The factors of respondents' attitudes

The respondents' attitudes for the street improvement project can affect their WTP. The respondents in our case study answered their attitudes for 9 questions. In this study, factor analysis is executed to avoid the multicollinearity among the variables of questions and to find representative latent variables. As a result of the factor analysis in Figure 8, three representative latent variables are elicited; the first factor is related with the respondents' attitudes for car use, the second factor is for waling environment, and the last factor is for the life quality of the street. The factor scores for these three latent variables will be used as explanatory variables in the following analysis.

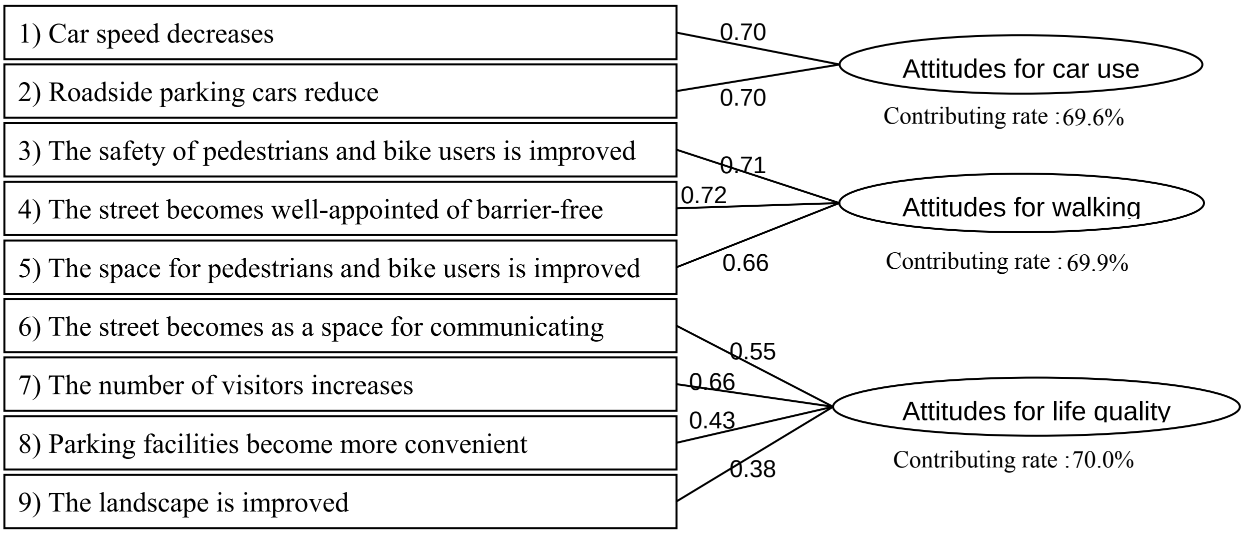


Figure 8 Result of Factor Analysis

4.2 Estimation results of the traditional CVM approach

In the traditional CVM approaches, logit model is usually applied for modeling the respondents' WTP based on the extreme recording data (i.e. yes/no). Logit models in our case study are extended into the double bounded dichotomous choices for the residents and the visitors, respectively. The rating scales of 10 points were transformed into dichotomy based on their signs (i.e. WTP or WNTP) prior to estimating the binary choice model of logit type.

The estimation results are summarized in Table 3. All estimated parameters show reasonable signs except income variable for the visitors, but the income parameter is not statistically significant. The parameters of bid amount for the residents and the visitors are significant at 99% confidence levels. This shows that the bid amount strongly affects the respondents' WTP. In addition, the attitude for the future life quality is a significant factor dominating the residents' WTP. The mean (median) values of the WTP are calculated 177yen (355yen) and 138yen (243yen) for the residents and the visitors, respectively.

Table 3 Estimation Result of Logit Models with Double Bounded Dichotomous Choice

	Residents		Visitors	
Explanatory variables	Coefficient	t-statistic	Coefficient	t-statistic
Constant	1.893	1.721	2.614	0.951
Bid amount (100 Yen)	-0.340	-5.778	-0.780	-5.004
Income (1,000,000 Yen)	-0.022	-0.235	0.242	1.780
Gender dummy (Man=1)	0.770	1.636	0.900	1.533
Age	-0.009	-0.631	0.019	0.789
Drive license dummy (Have=1)	-1.237	-2.139	-3.055	-3.187
Walk dummy	0.596	1.321	1.994	1.715
Attitude for car	0.569	1.676	-0.453	-0.993
Attitude for passengers	0.384	0.796	0.257	0.656
Attitude for life quality	0.922	2.380	0.424	0.931
Number of samples		123		65
Adjusted rho-square		0.315		0.233
%-right		62.6%		61.5%
Mean WTP		177 Yen		243 Yen
Median WTP		355 Yen		136 Yen

Note) Walk dummy is equal to one when more than one household member frequently use the street by work

4.3 Estimation results of the fuzzy-CVM approach

4.3.1 The estimation results of the optimal membership functions

As previously mentioned, the membership functions work to treat the uncertainty in the fuzzy-CVM approach, so that it is important to calibrate the optimal functions. In our case study, we calibrate the membership functions by changing the width and central point of triangular membership functions. The heterogeneity of the respondents' decision rules is also considered by introducing different weights of fuzzy rules.

4.3.2 The estimation results of the rule weights

The estimated weights of rule are summarized in Table 4. In our case study, the respondents are divided into three respondent groups having same decision rules for WTP but different between groups. It is worthy to note that we changed the fuzzy inference rules related with the bid amount in Table 2 into new ones in the bottom of Table 4 to adjust the respondents in group C, while the rules for the respondents' attitude are not changed. It is known that the respondents of group C are not sensitivity and are willingness not to pay without considering the bid amount.

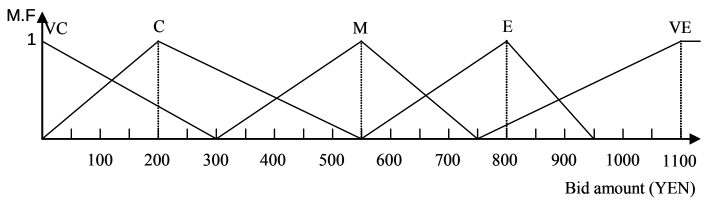
From the estimation results of rule weights, we can define the characteristics of each group. The group A residents who have relatively higher weight are sensitive to the bid amount and the attitudes for car use and walking in their WTP but they are not strongly affected by the attitude for life quality on the street. On the other hand, the residents of group B are significantly affected by the all attitudes. It is difficult to compare the weight parameters of group C and those of group A and B, because different fuzzy inference rules are applied for group C. It can be noted that the bid amount is important factor for the residents' WTP in group C, but the effect of the bid amount is limited whether they are certainly or probably willingness not to pay. The visitors of group A are more sensitive to only the bid amount, while the visitors of group B simultaneously consider the bid amount and the attitude of passengers. The visitors of group C have similar characteristics with the residents of group C.

Table 4 Estimation Results of Rule Weights

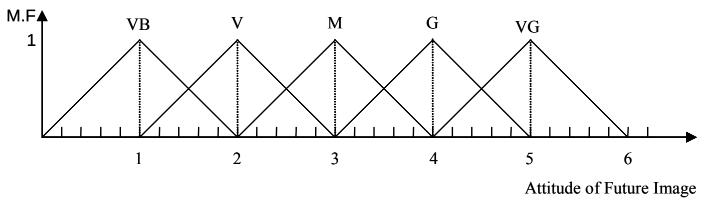
	Rule Weight		
Residents	Group A	Group B	Group C
Bid amount	0.30	0.04	0.50
Attitude for car use	0.30	0.30	0.05
Attitude for walking	0.30	0.22	0.3
Attitude for life quality	0.10	0.44	0.15
Percent of respondents	22%	48%	30%
Visitors	Group A	Group B	Group C
Bid amount	0.94	0.5	0.97
Attitude for car use	0.02	0.05	0.01
Attitude for passengers	0.02	0.4	0.01
Attitude for life quality	0.02	0.05	0.01
Percent of respondents	34%	18%	48%

Revised Fuzzy Inference Rules for Group C

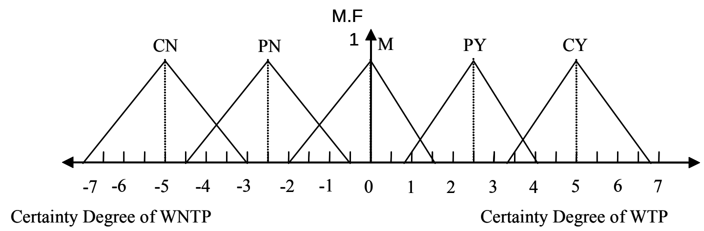
Rule 1) If bid amount is VC,	then willingness to pay is M
Rule 2) If bid amount is C,	then willingness to pay is PN



(a) Optimal Membership Functions for the Perceived Perceptions of Bid Amounts



(b) Optimal Membership Functions for the Attitudes of the Future Image Amounts

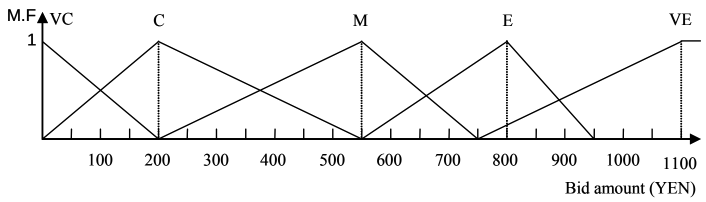


(c) Optimal Membership Functions for the Certainty Degree of W(N)TP

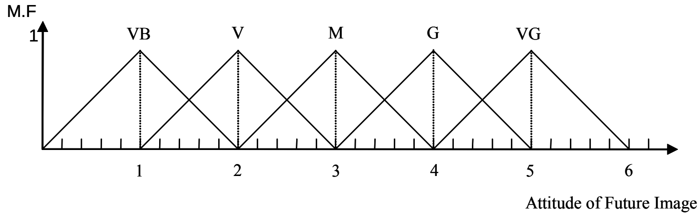
Figure 9 Optimal Membership Functions for the Residents

4.3.3 The estimation results of mean WTP

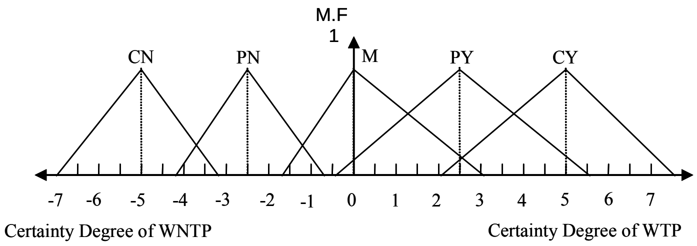
The mean WTP in fuzzy-CVM approach is calculated by weighted average of the possibility distribution of WTP in Figures 11 and 12. In addition, the median WTP in fuzzy-CVM approach is identical to the bid amount when the possibility of WTP equals to zero. The values of mean WTP are calculated to 726yen and 185yen for the residents and the visitors, respectively. Certainty levels is relatively stable against the changes in the bid amount in the results of residents, consequently the residents might not regard as important the bid amount rather than the future image. The visitors have much lower mean WTP than the residents.



(a) Optimal Membership Functions for the Perceived Perceptions of Bid Amounts



(b) Optimal Membership Functions for the Attitudes of the Future Image Amounts



(c) Optimal Membership Functions for the Certainty Degree of W(N)TP

Figure 10 Optimal Membership Functions for the Visitors

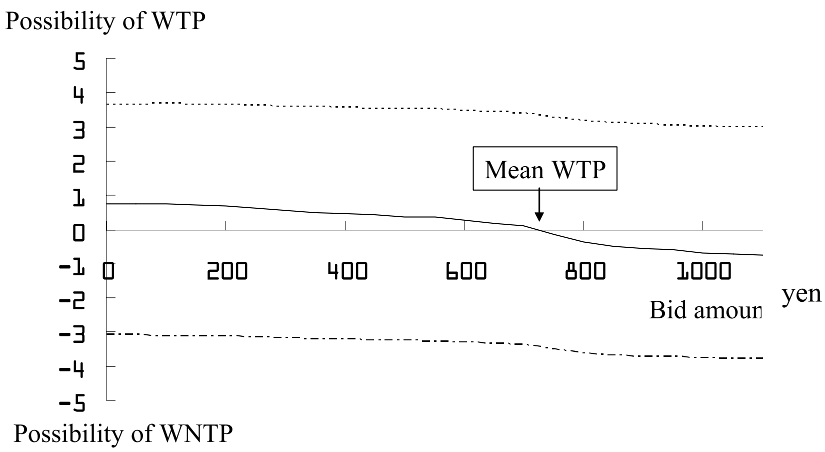


Figure 11 Cumulated Possibility of W(N)TP for Residents

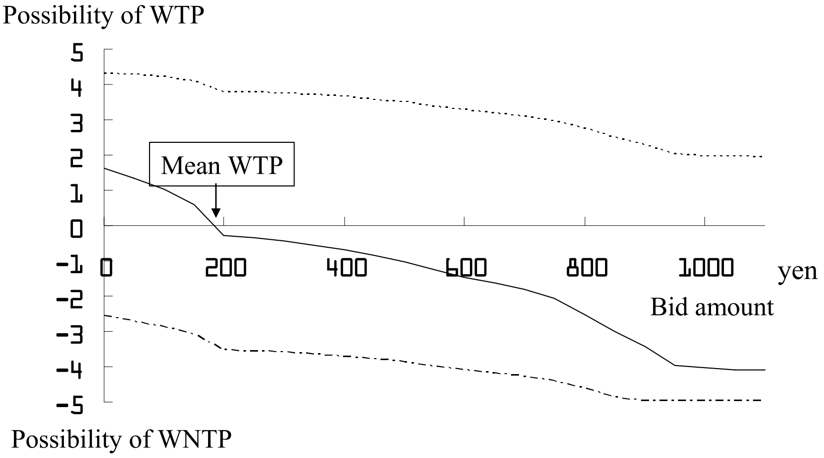


Figure 12 Cumulated Possibility of W(N)TP for Visitors

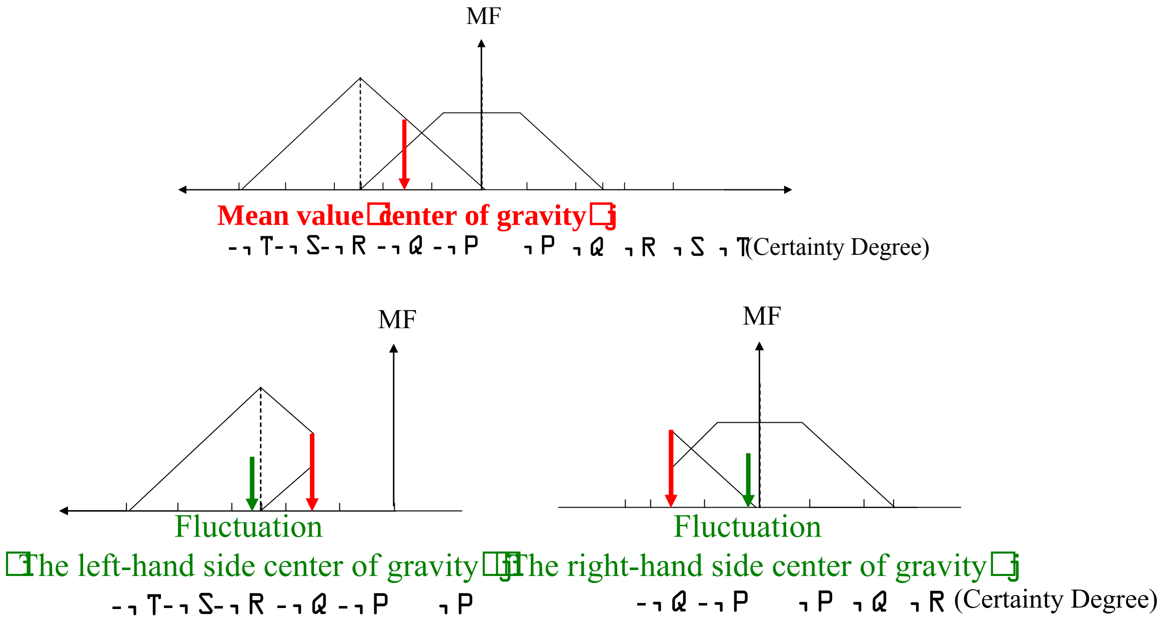


Figure 13 Calculation methods of average, upper and lower values

In Fuzzy-CVM, it is possible to compute WTP in the arbitrary possibilities. A calculation method of the upper and lower values of WTP estimates with the range of 50% possibility is illustrated in Figure 13. The upper and lower values obtained by this method shows figures 11 and 12, it turns out how WTP includes fuzziness.

4.4 Comparison of the estimation results of fuzzy-CVM and logit models

Table 5 summaries the comparison of the mean WTPs obtained by the logit and fuzzy-CVM approaches. The predicted mean WTP of fuzzy-CVM approach is higher than that of logit model in both cases of residents and visitors. One reason is due to the extremely recording data (dichotomous choice) in the logit model. This extremely recording data should lead to information loss by ignoring the respondents' uncertainty of WTP responses. Another reason is that the goodness of fit index of the logit model is lower than that of the fuzzy-CVM model as see in Table 6. It is obvious that Fuzzy-CVM model is superior to the logit model in terms of the index, indicating percentages that the actual choices are coincide with the predicted choices by the models.

Table 5 Comparison of Mean WTP Values of the Logit and Fuzzy-CVM Approaches

	Logit Model Mean WTP	Fuzzy-CVM Mean WTP
Residents	177 Yen	726 Yen
Visitors	136 Yen	185Yesn

Table 6 Comparison of Goodness of Fit

		Predicted choice			
		Logit Model		Fuzzy-CVM	
Residents		Yes	No	Yes	No
Actual choice	Yes	**33%**	15%	**47%**	1%
	No	14%	**38%**	17%	**35%**
Visitors		Yes	No	Yes	No
Actual choice	Yes	**11%**	23%	**29%**	5%
	No	11%	**55%**	4%	**62%**

5. Conclusions

Respondents' uncertainty for their WTP is focused in this study. The sources of the respondents' uncertainty are the difficulty of valuing the environmental goods, the uncertain trade off between the environmental goods and monetary value, and the imprecise information of linguistic expression. We applied the fuzzy theory which is the most appropriate theory for dealing with the respondents' uncertainty. While many literatures in CVM have widely used a dichotomous choice response (Yes/No), this extreme recording data is difficult to consider the uncertainty of respondents' WTP and reduces the accuracy of predicted WTP. Therefore, we newly developed a fuzzy-CVM

Survey method with the rating scale of certainty level which requires the respondents to express the strength of WTP on numerical scales against respondents' dichotomous choice to incorporate the uncertainty in the model.

A fuzzy-CVM analysis is also proposed to incorporate the uncertainty of respondents in WTP estimates effectively. The effectiveness of the suggested fuzzy-CVM approach is vilified by comparing with the conventional modeling approach (logit model). A methodological procedure for the fuzzy-CVM is proposed to estimate the double bounded choice question by using fuzzy inference. In addition, different fuzzy rules and weights are applied to incorporate the heterogeneity of decision rules. It was found that the suggested methodology can enhance the applicability of fuzzy model in CVM.

Even the fuzzy-CVM approach shows higher explanatory power than the conventional model, the estimation procedure of fuzzy techniques is still difficult and somewhat ad hoc (for instance, finding optimal membership functions and rule weight). To overcome these difficulties, soft computing method combining fuzzy logic and neural algorithm is necessary to be introduced in fuzzy-CVM approach.

Acknowledgement

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