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Analysis of Young People's Attitudes toward Mutual Aid Support System in Local Community Using Sensitivity Analysis of Bayesian Network

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Abstract

We have shown the concept of an information-sharing system to support vulnerable road users living in the suburban slope residential areas where public transport is scarce. Then we also have constructed a web service to support their daily life named MASS. The role of MASS is to facilitate the encounter between local community people and to provide the opportunity of resource sharing for solving the difficulties in daily life by mutual assistance. To effectively solve the problems of vulnerable road users, mainly older people with MASS, young people's active participation is essential because most of the resources of skills will be provided by young people. Therefore, to discuss our system's continuity as a general service, the previous research has conducted an attitude survey on young people's awareness of resource sharing in their local community and analyzed it with Bayesian networks. From the analysis, the previous research has shown the relationship between the factors, which are not clarified so far, and obtained results that support several hypotheses. However, the previous research has analyzed only the results of evaluating MASS from a subjective view and has not dealt with the survey results of evaluating MASS from an objective viewpoint. Furthermore, each explanatory variable's strength concerning the objective variable (each one's evaluation about MASS) was not sufficiently clear. This study aims to analyze the sensitivity of each explanatory variable for the objective variable in the constructed model of Bayesian networks and perform inference using the model. From the experiment, we were able to clarify the strength of each explanatory variable quantitatively.

Keywords: vulnerable road users, resource-sharing, mutual assistance, local community activation, Bayesian network, sensitivity analysis.

1 Introduction

Some of the main bedroom communities of Hiroshima City, a major city in Japan, are located at the slopes of mountains surrounding Hiroshima City. In some suburban residential areas, municipal public transport services are currently insufficient for the daily short-distance movements of vulnerable road users, mainly older people [1][2]. Based on

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the survey results, we had shown the concept of a transport support model for the vulnerable road users living in the suburban residential estates, where public transport is scarce. We have also designed and developed a prototype of a Web service called MASS (Mutual Assistance Support System) [3]-[5]. MASS can provide efficient transportation means for vulnerable road users and municipalities by utilizing other resident's help, which is realized by the mechanism of sharing economy [6][7]. Besides, we had improved this prototype to a skill-sharing service to support vulnerable road user's daily life [8]. With MASS, for example, a resident, who will move to his/her destination with one's mobility, such as a private car, can help troubled another resident (mainly older people) simultaneously as his/her original purpose. We expect that MASS's mutual assistance will enhance local people's relationship building and the regeneration of the local community. We can position MASS as the system ahead of skill-sharing services for solving regional problems by regional resources like goodtiming [1] frequently addressed in recent years [2].

Many sharing services have been successful results thanks to the active participation of young people [9]-[12]. In addition, most of the resources in MASS are likely to be provided by young people [13]. Therefore, to make MASS to penetrate the local community more, young people's active use is considered indispensable. Based on the assumption, to discuss the continuity of our system as a general commercial service, the previous research has conducted an attitude survey on young people's awareness of resource sharing in their local community and analyzed it [14][15].

The previous research [14] has focused on Quantification Method Type II and unveiled a trend of the youth consciousness about skill sharing in their local community. However, the previous work could not verify hypotheses and acquire knowledge, which determines the evaluation of MASS. We assumed that the cause making the impression mechanism about MASS hard to understand is dependencies between explanatory variables. We thought that grasping a structure where factors as explanatory variables have relationships with each other would be presumably helpful to understand the mechanism of young people's judgment for MASS. Based on the assumption, the previous research has focused on Bayesian networks [16]-[24], and analyzed young people's awareness for MASS[15]. The previous research has shown the relationship between the factors and obtained results supporting several hypotheses. However, the previous research has analyzed only the results of evaluating MASS from a subjective view and has not dealt with the survey results of evaluating MASS from an objective viewpoint. Furthermore, each explanatory variable's strength concerning the objective variable (MASS evaluation) was not sufficiently clear.

Therefore, this study analyzes each explanatory variable's sensitivity for the objective variable in the constructed Bayesian network model and performs inference using it. The sensitivity analysis results allowed us to visualize the magnitude of the explanatory variables' effect on the objective variables. This paper conducted a sensitivity analysis for two types of data; the one is that whose objective variable is a subjective assessment, the other is that the objective variable is an objective assessment. The analysis results for the former supported the possibility found in the previous research [15]; young people may accept MASS as a general CtoC service when getting other people's resources and has a large psychological resistance engaging with others when providing own resource. Similarly, the analysis results for the latter suggested what the young people were thinking. Concretely, the result indicated that MASS should be used in conjunction with public services instead

[1] http://goodtiming.jp/
[2] https://www.shareshikoku.com/

of replacing them. The result also showed that MASS would penetrate community people without a strong desire to revitalize the community.

2 Mutual Assistance Support System

Figure 1 shows the concept of MASS [4]-[15]. The core service of MASS is to enhance encounters between local community people, which is realized by sharing personal information that was not previously evident such as each one's skills and troubles, and to lead to solving a troubled resident's problem in daily life. Especially for the elderly, there are many difficulties in their daily lives. General public services alone have not been able to support the elderly adequately. Therefore, MASS aims to solve such difficulty through social media mechanisms.

MASS provides two primary services. The one is the time-dependent skills/troubles information sharing to coordinate each user's resources and requirements. The other is the negotiation support with a thread-based BBS to facilitate the realization of mutual assistance.

Most vulnerable road users' troubles might be on their daily short distance travel, but the requests are not limited to these. Therefore, MASS can accept various kinds of troubles, such as gardening, dog-walking, and electric appliance maintenance. Using MASS, for example, a troubled person, who has no daily transport means but wants to go out, can find a person, who lives near this troubled person, and will be able to bring the troubled person along together with his/her out. Although mutual aid is basically a volunteer activity, a helper can obtain decent wages as a donation. The user's system usage fee will cover the operational costs.

Here shows the flow of resource sharing with MASS briefly. Firstly, a resident in need of someone's help called "Client" posts a request to MASS. For example, a resident, who wants to go out but does not have transport means or needs assistance for the conveyance of daily necessities, inputs the detail to MASS. Secondly, if another user, called "Server", who is willing to accept another resident's help, checks the details of another resident's request, such as conditions and personal information. When the Server judges it acceptable, the Client can contact the Server using the direct message function (thread-based BBS). After the negotiation with the direct message function, these residents will actually meet and solve the problem if they reach an agreement. According to such a procedure, MASS will promote the rationalization and the efficiency of transporting people and goods. Furthermore, since MASS encourages each resident's meetings, MASS is expected to contribute to revitalizing a local community.

3 Bayesian Network

Bayesian network is a graphical model that approximates the simultaneous distribution of discrete probability distributions by an acyclic directed graph network structure with random variables as nodes, and conditional probability parameter sets [16][17]. Bayesian network is said to be a form of representation of human knowledge in terms of probability [18]. Bayesian network is said to systematically handle the uncertainty of phenomena that is difficult with traditional deterministic methods of reasoning by interjecting probability into reasoning [19].

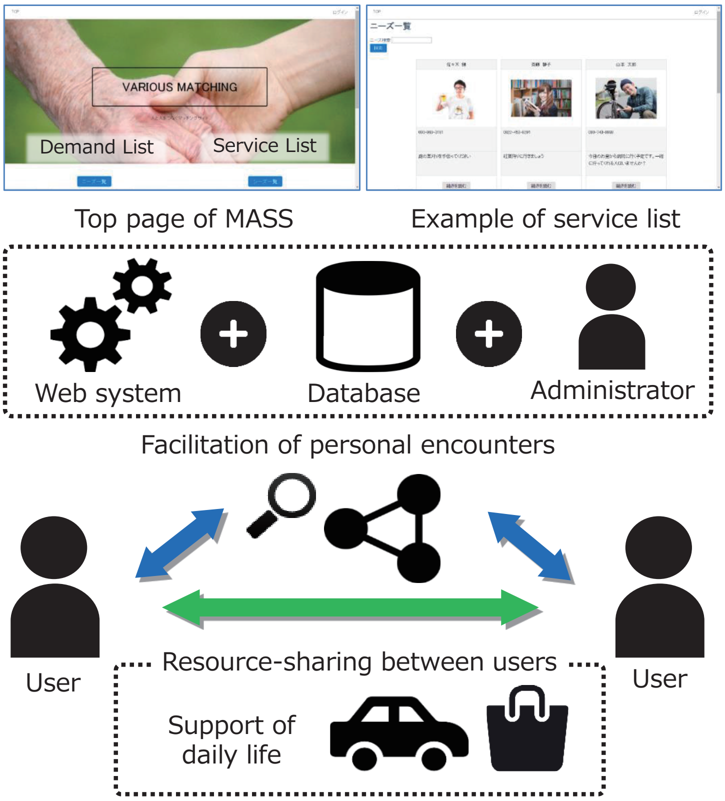

Figure 1: The concept of MASS

In Bayesian network, events are represented by nodes and causal relations by links. A directed link connects each node, and the link from node X_1 to node X_2 implies that X_2 is in a relationship that is directly affected by X_1. That is, it means that there is a causal relationship between the directions of the links. Each node has a value of 1 if the corresponding event occurs and 0 if no event occurs. Dependencies are represented by $X_1 \rightarrow X_3$ or $X_2 \rightarrow X_3$, which means that X_3 is valued by conditional probabilities that depend on the values of X_1 and X_2. A conditional probability table based on cross-tabulation is created between nodes connected by links and is calculated as a prior probability. When a link such as $X_1 \rightarrow X_3$ exists, X_1 is called the parent node, and X_3 is called the child node. A node without a parent node is determined by its own occurrence probability $P(X_1)$. On the other hand, since X_3 has two parent nodes, X_1 and X_2, its occurrence probability is determined according to the conditional probability $P(X_3|X_1,X_2)$. Once it is confirmed that some parameters have occurred, the posterior probability is computed. For example, if only X_3 is observed, we set the observation to $X_3 = 1$. This kind of operation is called the setting of evidence. After the setting of evidence, the posterior probabilities of X_1 and X_2, which are the parent nodes of X_3, are obtained by using Bayesian estimation. The probability calculation to set the evidence and infer the cause from the result is called probabilistic inference. By obtaining the variation in the probability value of an event through sensitivity analysis, it can be used for decision-making, such as estimating the event that causes the event.

In this study, we considered Bayesian network reasonable to unveil the factors and these structures leading to the evaluation of MASS. Hereafter shows the reasons why we have assumed Bayesian network effective described below. From the result of previous research, we have found a possibility of existing some causal relationships between the attributes. That is, the experimental results of the previous researches suggested that each youth's evaluation results about MASS might depend on the basic attributes and psychological reasons of respondents [15]. For example, if the respondent is introversive, his/her motivation for contributing to the region will worsen. As our previous work has already shown, the mechanism of determining the evaluation of MASS is complex, so there is likely a relationship between factors as explanatory variables. In other words, the value of the objective would be determined variable after many factors have influenced each other. Such a structure can be thought of as a complex network. The regression analysis generally used by studies on social science can reveal the relationship between objective variables and explanatory variables but cannot clarify the relationship between explanatory variables. On the other hand, Bayesian network can visualize the relationship between the objective variable and the explanatory variable and also the relationship between the factors as explanatory variables at the same time. Focusing on these characteristics, we thought that Bayesian network could describe various factors related to the impression on MASS as one network. We hope to elucidate the structure of the factors leading to the final assessment and better describe the mechanism of regional resource sharing impressions for the Bayesian network. Therefore, we have determined Bayesian network to apply to the questionnaire result, which investigated the sharing system's consciousness for the support of the vulnerable road users, and analyzed what kind of characteristics young people's answers had, what they expected for, and how they evaluated MASS. This paper reports the latest analysis results using Bayesian network in our researches through these processes.

4 Experimental Result

4.1 Condition of Analysis

We conducted an attitude survey on young people's awareness of sharing their resources with their local community. We employed 88 Hiroshima residents from 20 to 24 years old as examinees and obtained the questionnaire's awareness data. Each response of the questionnaire was on the 4-grade Likert scale (strongly agree, weakly agree, weakly disagree, strongly disagree); 4 is the maximum (positive), and 1 is the minimum (negative). This paper binarized the responses. Specifically, we analyzed the Bayesian network data after transforming positive responses (3 and 4) as 1 and negative responses (1 and 2) as 0. First, the examinees listened to about 10 minutes of presentation on MASS. After the instruction, they operated the prototype freely of MASS for sufficient time while receiving its explanation to operate from an experimenter. Finally, each examinee responded to each item on the questionnaire. In the questionnaire, we firstly confirmed whether the examinees sufficiently understood the concept of MASS to check the reliability of the responses. As a result, we confirmed that all examinees understood the concept of MASS adequately. After this confirmation, we assumed all responses reliable and used them in our analysis. The items of the questionnaire are as follows.

Evaluation of MASS

- Q_1: When MASS is actually launched, do you want to use it as a user providing your resource?
- Q_2: When MASS is actually launched, do you want to use it as a user getting another one's resource?

Q_1 and Q_2 are evaluations as to whether the examinees actually wanted to use MASS.

We identified the reasons that led to the responses in Q_1 and Q_2 by a checkbox. We prepared several reasons, both positive and negative. Examinees responded by checking off some reasons we provided. Positive reasons (P_1-P_4) and negative reasons (N_1-N_4) are as follows.

Positive reasons

- P_1: I am interested in a new service.
- P_2: I want to get rewards.
- P_3: I want to make a new connection with people in our local community.
- P_4: I want to contribute to our local community.

Negative reasons

- N_1: I am nervous (scared) to engage with unknown others.
- N_2: I do not want to disclose personal information.
- N_3: I do not go out much.
- N_4: I am not interested in making money in such this way.

Concerning Q_2, Positive reasons (P_5-P_7) and negative reasons (N_5-N_8) we prepared are as follows.

Positive reasons

- P_5: I want to join the interaction with local people.
- P_6: I want to reduce waste/to save money.
- P_7: I feel MASS useful.

Negative reasons

- N_5: I am not interested in our local community.
- N_6: I feel MASS is useful, but it is uneasy to interact with unknown people.
- N_7: I do not need another's help because I can do my own thing myself.
- N_8: I am worried about some kinds of accidents/troubles.

Next, We asked the examinees whether MASS will be used in society, which required them to answer from an objective standpoint, not from their subjectivity. We gave the following two questions to the examinees.

- Q_3: Do you think that local residents will use MASS to share their resources to support the daily life of vulnerable road users, such as housework, gardening, maintenance of household appliances, repairing furniture, pet care, the assistance of shopping, and short-distance ride-sharing for commuting or shopping? Give your opinion from an objective standpoint.
- Q_4: Do you think sharing resources by local people's mutual aid ideal instead of relying on public services?

Q_3 is an item to objectively assess whether the examinees felt MASS was good as a general business or not. Q_4 is an item to investigate individuals' opinions on the effectiveness of the use of mutual aid to improve public services.

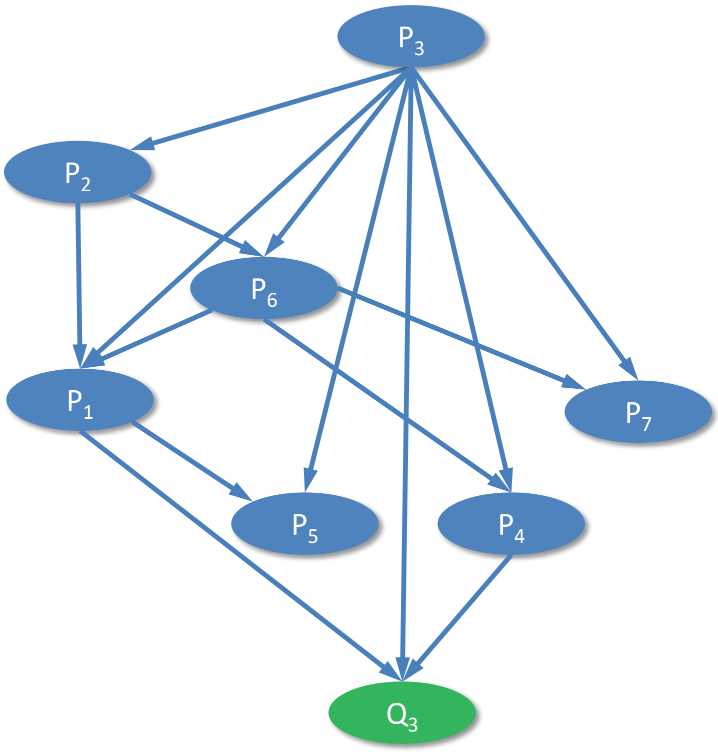

Figure 2: The constructed network model consisting only of nodes that have connections to the mode of the objective variable Q_3

4.2 Structure of Bayesian Networks

We constructed four Bayesian networks. The model with objective variable Q_1 had P_1 to P_4, N_1 to N_4 as explanatory variables, and the model of Q_2 had P_5 to P_7, N_5 to N_7 as explanatory variables respectively. The models of objective variables Q_3 or Q_4 had P_1 - P_7, N_1 - N_8 as explanatory variables. For all models, the nodes Q_1 to Q_4 had no children. We inputted the questionnaire result as learning data and constructed four models automatically using the information reference amount by AIC as the threshold value. Greedy Search built the model. The termination condition of the search was assumed to be the case where the average value of cross-tabulation became the threshold value of 0.01 or less. There would be a causal relationship among the same reasons, but causalities between different types of reasons, like the relationship between positive-negative reasons, are unrealistic. Therefore, we restricted the causal relationship between positive and negative reasons while constructing four models.

The constructed model with objective variable Q_3 is as shown in Figure 2, and the model of Q_4 is as shown in Figure 3. For the structures of the model Q_1 and Q_2, see Ref. [15]. Both the models of Q_3 and Q_4 were separated into two networks. One part of the constructed model was connected to the node of the objective variable, and all nodes except the objective variable were positive reasons. The other part consisted only of nodes related to negative reasons. The structure of the parts was consistent between Q_3 and Q_4 as shown in Figure 4.

Figure 2 shows that the three factors P_1 "interest about a new service", P_3 "making

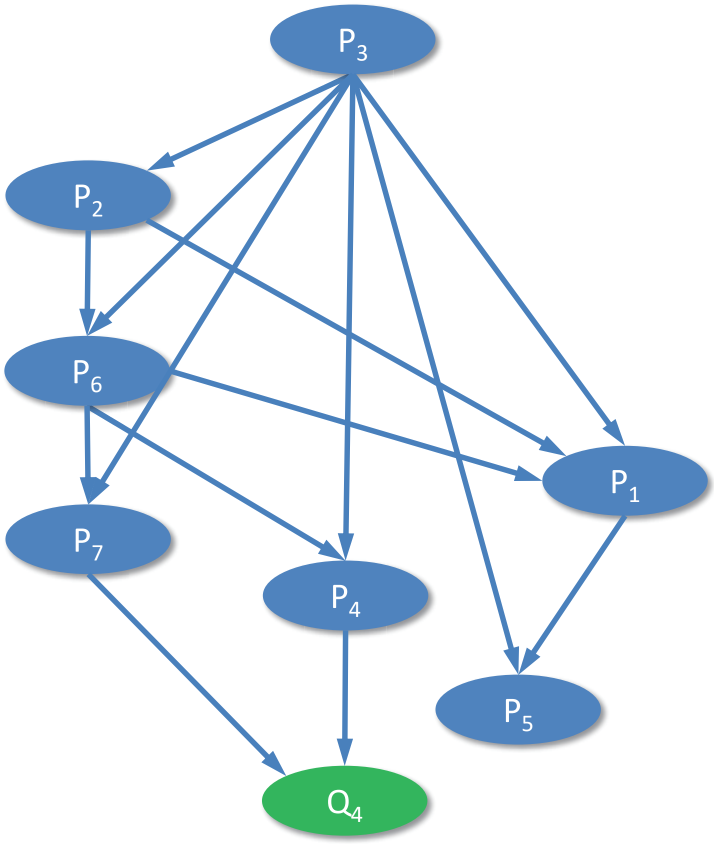

Figure 3: The constructed network model consisting only of nodes that have connections to the mode of the objective variable Q_4

a new connection with people in the local community" and P_4 "contribution to the local community" are directly related to the evaluation of Q_3. From the structure shown in Figure 2, it is likely that the young people evaluated that if they were willing to contribute to the community (P_4) and were receptive to new technology (P_1), they would be accepted by the general public. In particular, it is worth noting that the motivation to create new relationships in the community (P_3) is causally related to all the other nodes in the structure. Figure 3 shows that the importance of convenience (P_7) and the desire to contribute to the community (P_4) were directly related to the evaluation of the objective variable. Figure 3 also shows that P_3 has many causal relationships as in Figure 2, suggesting that P_3 was an important factor in determining the objective variable.

We also touch a little on the structure of the negative factor shown in Figure 4. This network does not affect the determination of the objective variable, but the structure itself has many implications. The factor of not wanting to give out personal information (N_2) placed the highest position. This structure suggests that young people were reluctant to give out their personal information even in the community. The psychological mechanisms of young people, such as not wanting to earn money by giving out personal information ($N_2 \rightarrow N_4$) and not wanting strangers to know their personal information ($N_2 \rightarrow N_6$), can be inferred from the structure of Figure 4. We can also see that young people did not go out because they did not want to get involved with other people ($N_1 \rightarrow N_3$). $N_7 \rightarrow N_3$ can be

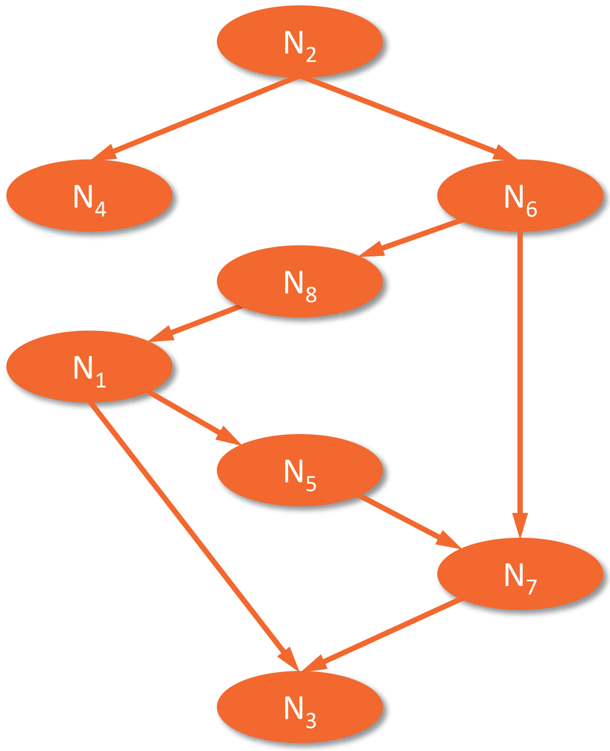

Figure 4: The constructed network model consisting only of nodes that are not connected to the nodes of the objective variables Q_3 and Q_4

read as "I don't go out because I don't need help from others". It is certainly a meaningful effort to analyze the factors in detail from this structure itself. On the other hand, such an approach is not the main purpose of this paper. So, the detailed analysis of this network will be the subject of future work.

The causal relationships among explanatory variables have been clarified. Based on this structure, we can make various arguments. In addition to the structure, understanding the impact on the target variable will surely enable more accurate discussion. Therefore, in this paper, we focus on sensitivity analysis.

4.3 Sensitivity Analysis

This paper performed sensitivity analysis and inference using P_1 - P_4 and N_1 - N_1 for Q_1, P_5 - P_7 and N_5 - N_8 for Q_2, and P_1 - P_7 and N_1 - N_8 for Q_3 and Q_4 as explanatory variables respectively. Sensitivity analysis is a method for quantitatively calculating each factor's influence in a model in which an event occurs from multiple factors. Usually, when a change is made to a factor, the change in the result is evaluated by various indicators. Examples of the application of sensitivity analysis include, for example, the extent to which changes in retail prices affect earnings and what factors pose a risk to earnings. There are two main purposes of doing sensitivity analysis: first, to find variables that have a high impact on the objective variable, and second, to analyze the role cases that give the best (or worst) results for the objective variable. This paper conducted the sensitivity analysis by the inference with specified explanatory variables and calculated the posterior probability of the objective

Table 1: Values of $P(\mathrm{Q}_1 = 1)$ depending on the evidence

Rank	P_1	P_2	P_3	P_1	N_1	N_2	N_3	N_4	Prob.
1	-	1	-	-	-	-	-	-	0.89
2	-	-	-	-	0	-	-	-	0.81
3	1	-	-	-	-	-	-	-	0.77
4	-	-	-	1	-	-	-	-	0.77
5	-	-	1	-	-	-	-	-	0.76
6	-	-	-	-	-	-	-	0	0.61
7	-	-	-	-	-	-	0	-	0.59
8	-	-	-	-	-	0	-	-	0.57
9	-	-	-	-	-	-	-	-	0.55
10	-	-	-	0	-	-	-	-	0.48
11	0	-	-	-	-	-	-	-	0.47
12	-	-	-	-	-	1	-	-	0.44
13	-	-	0	-	-	-	-	-	0.41
14	-	0	-	-	-	-	-	-	0.38
15	-	-	-	-	-	-	1	-	0.30
16	-	-	-	-	-	-	-	1	0.20
17	-	-	-	-	1	-	-	-	0.10
	0.30	0.50	0.36	0.28	-	-	-	-	
					0.71	0.12	0.29	0.41	

variable. We obtained the amount of mutual information and the difference in probabilities when the values of the objective variable is 0 and discussed.

Table 1 shows the results of the sensitivity analysis of the model in Q_1, where Prob. refers to the probability of $P(\mathrm{Q}_1 = 1 \mid \boldsymbol{E}), \boldsymbol{E} = \{\mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3, \mathrm{P}_4, \mathrm{N}_1, \mathrm{N}_2, \mathrm{N}_3, \mathrm{N}_4\}$ and the numbers in each cell refer to the value of evidence set for each explanatory variable. In Table 1, the results are summarized in order of the highest $P(\mathrm{Q}_1 = 1 \mid \boldsymbol{E})$. The number at the bottom of the table is a number to quantify the magnitude of the impact of the explanatory variables. It is obtained by subtracting the value of $P(\mathrm{Q}_1 = 1 \mid \boldsymbol{E})$ when each explanatory variable is 1 from the value of $P(\mathrm{Q}_1 = 1 \mid \boldsymbol{E})$ when it is 0. For example, in the case of P_1, $P(\mathrm{Q}_1 = 1 \mid \mathrm{P}_1 = 1)$=0.77 and $P(\mathrm{Q}_1 = 1 \mid \mathrm{P}_1 = 0)$=0.47, so we obtain 0.30 as the impact about the objective variable. By looking at these values, we can see the extent to which each explanatory variable positively or negatively affects the positive answers from Q_1 to Q_4.

Figure 5 is a visualization result of the values obtained according to the procedure shown in Table 1. From Figure 5, we can intuitively grasp the sensitivity of the model's explanatory variables with Q_1 as the objective variable. As mentioned above, for more detail on the structure of this model, please refer to the literature [15]. The previous research has suggested that contribution to and interaction with the community is only an indirect factor and that young people expect rewards rather than a contribution to the community [15]. Also, from the structure of N_1, the previous research suggested that it may be a significant psychological burden for young people to engage with unfamiliar people when providing services. Thus, we subjectively found the impact of the effect of P_2 and N_1, but the details of their respective strengths were unclear. In this regard, as shown in Figure 5,

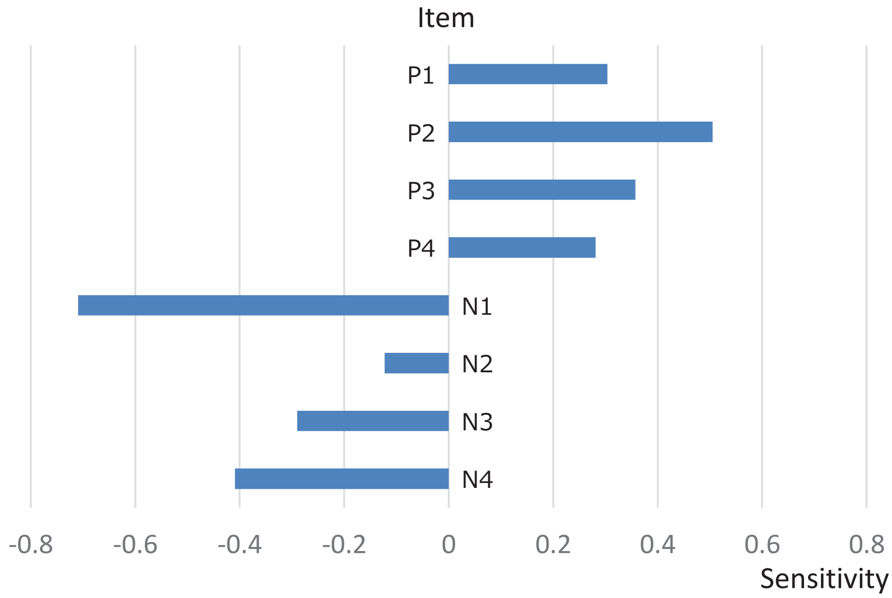

Figure 5: Sensitivity of each explanatory variable to Q_1

Table 2: Discriminating accuracy when Q_1 is the objective variable

	Observation		
Prediction	0	1	Accuracy
0	38	0	100.0 %
1	4	46	92.0 %

we were able to clarify the strength of each of them quantitatively and found that N_2, in particular, had a huge impact.

Figure 6 visualizes the sensitivity of the explanatory variables to Q_2 in the same way as Figure 5. The previous research showed that the two reasons "MASS is convenient" and "MASS can save money" are related directly to the evaluation of Q_2 [15]. However, the influence of these two points was unclear because it was not quantitative. On this point, the influence of Figure 6 can be newly clarified, especially P_7, which is found to be twice as large as P_6.

We verified the degree of correctness predicted by each of the models. The validation data are the same as the training data, and Table 2 and Table 3 show the model's validation

Table 3: Discriminating accuracy when Q_2 is the objective variable

	Observation		
Prediction	0	1	Accuracy
0	44	0	100.0 %
1	0	44	100.0 %

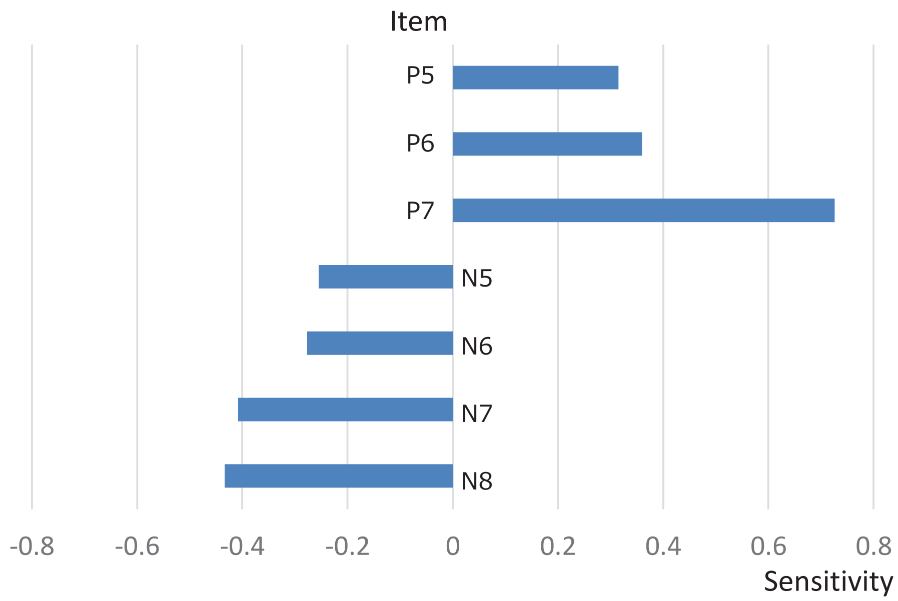

Figure 6: Sensitivity of each explanatory variable to Q_2

results. Since the model's prediction accuracy is high, it seems that relatively clear rules determine the evaluation of MASS. Simultaneously, the result implies that it is easy to divide the examinees into two groups based on the explanatory variables. The combination of explanatory variables can be assumed equal to the examinees' attributes. Then, it is understandable that young people are polarized in their thinking: people who are positive for sharing their resources and those that are not.

Figure 7 and Figure 8 visualize the sensitivity of the explanatory variables to Q_3 and Q_4 respectively. In Figure 7, although P_4 was directly connected to the target variable, it is clear that its impact on the target variable was small. On the other hand, Figure 7 shows the high sensitivity of P_1. Considering the network structure, this result suggests that the relationship $P_3 \to P_2 \to P_1$ had a strong impact on the objective variable. Here, $P_3 \to P_2$ can

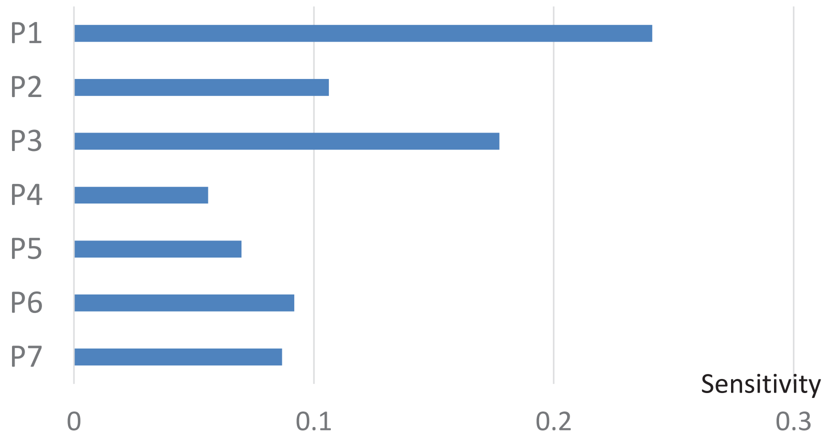

Figure 7: Sensitivity of each explanatory variable to Q_3

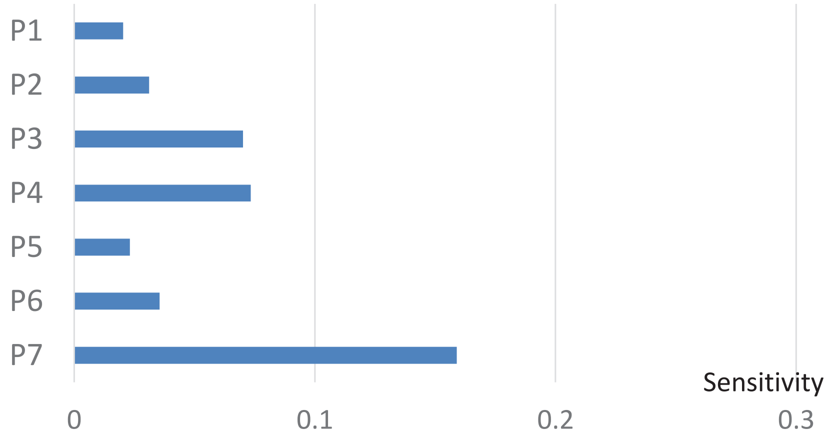

Figure 8: Sensitivity of each explanatory variable to Q_4

be understood as "proactivity in earning rewards with a new service". Similarly, $P_2 \rightarrow P_1$ can be understood as "Intention to expand contacts in the community while earning". From Figure 8, we can confirm the strength of P_7. Also, we can see from Figure 8 that the relationship between P_3 and P_7 and P_3 and P_4 had a strong influence on the decision of the objective variable. $P_3 \rightarrow P_7$ can be understood as "MASS is useful for making new connections", while $P_3 \rightarrow P_4$ can be understood as "I want to contribute to the community by making new connections". We can say that young people with these attitudes tended to evaluate resource sharing as an ideal public service.

Table 4 and Table 5 show the validation results of these models. It is interesting to note that only the prediction accuracy of $Q_3 = 0$ was low. This result suggests that there were no clear rules in the subjects' reasoning with $Q_3 = 1$, while there were no clear rules in the subjects' reasoning with $Q_3 = 0$. Specifically, about half of the subjects might not want to use it but thought ordinary people would accept it. Based on such a view, we can imagine that many people would be willing to provide their resources around the examinees. Therefore, it may be useful for MASS to offer different functions and public relations strategies to these people than other skill-sharing systems aimed primarily at young people. Table 5 suggests that some people thought negatively of MASS as an alternative to public service, even though they had the typical rule determining $Q_4 = 1$. In other words, some examinees thought they were good but found it difficult to replace public services. Based on the high impact of P_7, they probably imagined someone who had difficulty using the system or did not want to contact other people. Perhaps the ideal form of MASS for public service needs to satisfy two things. First, people do not have to manipulate the system. Next, there is no need to connect directly with others. In this case, it may be best to mediate between existing transport companies and housekeeping services, with these companies managing and providing the resources.

5 Conclusion

This paper conducted the sensitivity analysis of Bayesian network to unveil the impact of each explanatory variable for the objective variable in the constructed model and perform inference using the models. From the experimental results, we were able to clarify the

Table 4: Discriminating accuracy when Q_3 is the objective variable

	Observation		
Prediction	0	1	Accuracy
0	30	16	65.2 %
1	6	36	85.7 %

Table 5: Discriminating accuracy when Q_4 is the objective variable

	Observation		
Prediction	0	1	Accuracy
0	0	0	0.0 %
1	14	74	84.1 %

strength of each explanatory variable quantitatively.

First, the results of sensitivity analysis presented important information for a deeper discussion based on the findings of previous research [15]. Concretely, we first found that engaging with others had a huge impact on providing one's resources. Also, when getting other person's resources, we newly clarified that the usefulness of MASS is about twice as large as the effectiveness for saving money. From the verification of constructed models, we found that young people might be polarized in their thinking: people who are positive for sharing their resources and those that are not.

Next, this paper newly showed two new Bayesian network models; the one is the structure of the decision on the general acceptance of MASS, and the other is the structure of resource sharing as a public service. From the structures of these networks, we confirmed the possibility that young people evaluated that if they were willing to contribute to the community and were receptive to new technology, they would be accepted by the general public. Similarly, the importance of convenience and the desire to contribute to the community were directly related to the evaluation of resource sharing as a public service. In addition to these, we showed the strength of all explanatory variables with the sensitivity analysis. By quantitatively showing the impact of all explanatory variables, we were able to examine the psychological mechanisms of young people more accurately.

We used the constructed model to perform inference and obtained some knowledge. From the result, we could hypothesize that people who are willing to provide their resources around young people tend to evaluate MASS as generally acceptable. Besides, we found that some people thought negatively of MASS as an alternative to public service. Based on the result, we could conclude that one of the best ways of MASS might be to mediate between existing transport companies and housekeeping services, with these companies managing and providing the resources.

This paper showed the structure of only the negative factors. This network did not affect the determination of the objective variable, but we found that the structure itself had many implications. This paper did not discuss the meanings along with the structure enough. Then, the detailed analysis of this network will be the subject of future work.

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