Evaluation of e-Health by PSM (Propensity Score Matching) Method

Yuji Akematsu
Graduate School of Economics
Osaka University
Toyonaka, Japan
y_akematsu@yahoo.co.jp

Masatsugu Tsuji
Graduate School of Applied Informatics
University of Hyogo
Kobe, Japan
tsuji@ai.u-hyogo.ac.jp

***Abstract*— The authors have been conducting successive estimations on the effect of e-Health on medical expenditures and outpatient treatment days for chronic diseases using survey data from Nishi-aizu Town, Fukushima Prefecture, Japan. The reason why this town was chosen is that it has been implementing e-Health more than 15 years and is one of the most successful examples. This paper uses several other outcome variables such as medical expenditures and treatment days of outpatient and inpatient, and compares those outcomes among two groups such as 199 treatment (users) of e-Health and 209 control (non-users) selected from residents. In this paper, the propensity score matching (PSM) method, a rigorous analytical method is used to overcome sample selection bias which is contained in data in the process which samples were selected. PSM is a method to choose subjects from two groups with exact similar characteristics except for their use or non-use of e-Health. After eliminating biases, the effect of e-Health on medical expenditures and treatment days was estimated. To obtain robust results, two different matching methods were applied, that is, caliper matching, and Epanechnikov kernel matching. The results demonstrated that the treatment group has lower medical expenditures for chronic diseases than the control group. Using other outcomes enables international comparison of e-Health projects with the same standard. Such comparisons are also presented.**

Key words-e-Health, propensity score matching; sample selection bias; inpatient; outpatient; medical expenditure.

I. INTRODUCTION

The most common method of evaluating the effectiveness of a new drug or clinical intervention is the Randomized Control Trial (RCT), in which subjects are randomly selected and categorized into a treatment and a control group, and the effect is compared between two groups. The most serious problem of RCTs is avoiding bias between the two groups, which is referred to as sample selection bias. Samples are required to be selected randomly without bias and must be as similar as possible between the two groups to obtain an unbiased evaluation. Such unbiased sampling is not always achieved, since there are actually many ways in which the material diverges with regard to users and sample subjects. A suitable method of matching the two groups to obviate such bias is therefore required. Traditional ways of coping with this problem include the matched sampling method or matched-pairs analysis. This method selects subjects in the control group to ensure similar criteria, such as age, sex, or health status, to subjects in the treatment group. In the field of telemedicine, matched each of their treatment subjects with four control subjects having similar demographics and morbidity status ([1] for example). Ambiguity with this method remains, however: what multiple of each treatment subject is sufficient to eliminate bias, and by what degree is bias is actually reduced? Moreover, sampling becomes more difficult with an increase in the criteria; and if the number of criteria must remain small, selection bias will remain.

A more rigorous method of overcoming selection bias is the propensity score matching (PSM) method, which enables the inclusion of as many criteria as necessary. A propensity score related to biased characteristics is first calculated for each individual, and then outcome variables, such as medical expenditures, are compared for individuals whose scores are close. One treatment subject is matched to one control subject who has similar characteristics, reducing sample selection bias. Moreover, the actual decrease in bias after matching can be calculated.

PSM use in medical research has been long and varied. Among studies of clinical interventions, for example, [2] examined the association of ambulatory visits to cardiologists, internists, and family practitioners after discharge for myocardial infarction and mortality. Using PSM to adjust for the demographic, clinical, and hospital characteristics of patients, they successfully ranked treatments among matched patients in terms of a reduction in morality. [3] analyzed whether aspirin is associated with a mortality benefit in patients with coronary disease. While simple univariate analysis found no association between aspirin use and mortality, adjustment by PSM for age, sex, and other characteristics, including risk factors, other medications, and coronary disease did identify a decrease in mortality with aspirin. In drug evaluation, [4] compared conventional and atypical antipsychotic medication for mortality among elderly patients, and used propensity-score adjustments to conclude that the former increased the risk of death.

Our previous paper ([5]) used the PSM method to estimate the effect of e-Health on outpatient medical expenditures and days for treatment and demonstrated that for chronic diseases, e-Health successfully improves these outcomes of its users in comparison with non-users. [5] examined, however, above two outcome variables related to all and chronic diseases, and there are other outcomes we have to compare. The aim of this paper is to expand the previous analysis in such a way that patients are categorized in more detail, that is, we compare medical expenditures and treatment days of inpatient and

 ISBN: 978-1-61208-252-3

outpatient, and so on. Accordingly, this paper can highlight clearly the robustness of the results of our successive estimations, that is, telecare or e-Health has effects on chronic diseases, not necessarily all diseases.

Although treatment-effects studies have been widely used in medicine, only a few studies have examined the effects of telemedicine using PSM. One example is the study of Care Coordination/Home Telehealth (CCHT) conducted by the Veterans Health Administration (VHA) by [6], albeit that their analytical methods of PSM and estimation were less rigorous than those of the present study, with outcome variables restricted to hospital admission and days of hospitalization. To our knowledge, no other study has evaluated the effect of e-Health on medical expenditures using PSM.

II. EHEALTH SYSTEM OF NISHI-AIZU TOWN

A. About Town

Nishi-aizu Town is located in the Northwest corner of Fukushima Prefecture, and is been an important point of transit to reach Niigata Prefecture and Aizu-wakamatsu, a nearby major city. The center of town is in a basin but the main area is surrounded by mountains, which cover 86% of the prefecture's area. The climate is severe in winter and summer, with lots of snow. The population is about 8,000; there are 3,000 households, and the percentage of the elderly (≥ 65 years) was 41.0% in 2010. The main industry is agriculture, and rice is the main product.

B. Health and Medical Situation

As stated earlier, severe winter, especially heavy snow causes elderly people to lack physical exercise. In addition, due to a traditional diet of salty and protein-poor food, the town's death rate was 1.7 times higher than the national average during 1983-87, partly due to high rates of stomach cancer. The number of bedridden elderly people suffering from osteoporosis or arthritis is higher than the national average. In order to cope with these situations, the town office took initiative to establish a "total care system," which is referred to as the "Challenge to 100 Years Old," by unifying health, medical and welfare services. As a part of this project, e-Health was introduced in 1993.

In the town, there are three public clinics, named Nishi-aizu, Murooka and Shingo, which are operated by the National Insurance System, and two private clinics. The total number of medical doctors is four. One full-time physician is employed in the Murooka clinic, while the Shingo clinic has a part-time doctor dispatched from the other two clinics. There are private doctors, a surgeon and a neurologist, but both are more than 70 years old.

C. Introduction of e-Health

In order to prevent chronic diseases such as cerebral infarction and stroke, the town office introduced e-Health in 1994 which is Japan's longest-running e-Health. 300 peripheral devices called "*Urara,*" manufactured by Nasa Corporation, were provided to residents who have symptoms of the above diseases. Each terminal is connected a host computer via PSTN (Public Switched Telephone Network), and health-related data of users, such as blood pressure, pulse, ECG, blood oxygen, weight and temperature are transmitted to a host computer. In 1996 and 1997, an additional 50 terminals each were purchased. These terminals use the CATV network for transmitting data. All costs of operating the system are paid by the town. In 2010, new peripheral device called "*Kouri,*" was introduced in accordance with the network renovation of CATV for optical fiber. Currently all network were transformed to optical fiber.

D. Operation of the e-Health System

The section in charge of e-Health is the town office's Department of Health and Welfare, which consists of seven public health nurses which represents a much larger ratio than in other towns. They check the above health data transmitted by users and if these nurses observe unusual data, they ask medical doctors in clinics to see the patient in question. The health data of each user are summarized in a "Monthly Report," which is sent to a physician in charge. After a public health nurse adds their comments, the report is sent to the user. When the user sees a doctor, he/she is asked to bring the report with him/her.

e-Health is being operated as a part of the town's "Project for Promoting Total Care," and its essence lies in the close collaboration of health, medical and welfare activities. One important example of this collaboration are "Regional Care Meetings," which consist of doctors, nurses, public health nurses, staff of the town office, helpers of elderly people, and living advisers. The total number of participants in each meeting is over 20. Problems and treatments regarding a particular user, such as medical examinations, health advice, and care are discussed in detail. The health data of e-Health plays a role in this meeting. In Nishi-aizu Town, many such examples of exchanging information on residents can be found in the town office.

In addition, the town office organizes users' meetings five times a year in order to enhance motivation to use e-Health, and users exchange their experiences with using the system. These activities promote usage of the system. The introduction of e-Health is not the sole factor promoting regional healthcare; rather, it should establish a framework for the system to assist all related sections and personnel.

III. MATERIALS AND METHODS

A. Selection of sample and data characteristics

The data used in this paper were reported in our previous study ([8]). From a total of 523 users and 3,528 non-users in Nishi-aizu Town, 199 and 209 individuals were selected for each group through a questionnaire survey which asked about individual characteristics and use of e-Health. Healthcare receipts for five years (2002 to 2006) were obtained from the National Health Insurance system and checked. The small number of users meant that the sampling was necessarily biased, as detailed in Table I, which expresses biases by the difference between the averages of the two groups, and uses t-values to indicate the degree of bias for individual variables. Significant biases were identified in "chronic diseases," "age," "number of family" "income," "heart disease," "high blood pressure," "strokes", "ophthalmic diseases," "anal diseases", and in subjective belief in the value of e-Health on health status, termed “Effects 1-4.”

The number of positive replies to the questionnaire item asking whether the subject had chronic diseases or not was substantially higher for the user than the non-user group. Substantial corresponding bias was also seen with regard to the presence of heart disease, high blood pressure, and strokes, and with regard to the number of users treated for these conditions during the sample period. A question on subjective belief in the value of e-Health on health status with respect to four effects showed that users tended to have higher health consciousness than non-users, which is consistent with anecdotal impressions expressed by the town’s public nurses who manage the system.

B. Propensity Score Matching

PSM was initially proposed by [9], [10] [11] and developed by [12]. The procedure is as follows:

(1) First, subjects in the user (treatment) and non-user (control) groups are individually matched with one another so that their propensity scores as calculated according to their attributes become closer. The score is calculated by a probit analysis, which is interpreted as the predicted probability of a probit estimation. The model consists of the user dummy as a dependent variable, while independent variables are those that have a sample selection bias, as shown in Table I.

TABLE I TEST OF SELECTION BIASES

Variable	Non-user	User	t value	
Chronic diseases	0.388	0.466	-3.46	***
Sex	0.568	0.546	0.98	
Age	68.894	71.629	-6.80	***
Education	1.579	1.571	0.21	
Employment	0.532	0.520	0.53	
Number of family members	2.401	2.945	-6.29	***
Income	3.274	2.961	2.61	***
Heart diseases	0.064	0.144	-6.03	***
High blood pressure	0.367	0.469	-4.61	***
Diabetes	0.081	0.087	-0.48	
Stroke	0.045	0.059	-1.45	*
Respiratory diseases	0.129	0.116	0.92	
Cancer	0.068	0.078	-0.86	
Gastropathy	0.157	0.164	-0.40	
Lumbago, Arthritis	0.147	0.159	-0.71	
Ophthalmic diseases	0.211	0.297	-4.43	***
Kidney diseases	0.029	0.021	1.16	
Anal diseases	0.014	0.005	1.95	**
Effect 1: reduced anxiety in day-to-day life	0.962	1.076	-3.15	***
Effect 2: stabilization of illness	0.824	0.977	-5.00	***
Effect 3: enhancement of health consciousness	0.911	0.980	-2.19	**
Effect 4: decrease in medical expenditures	1.026	1.361	-7.75	***
Year 2002	0.243	0.135	5.97	***
Year 2003	0.206	0.191	0.84	
Year 2004	0.206	0.191	0.84	
Year 2005	0.175	0.238	-3.47	***
Year 2006	0.170	0.245	-4.15	***

Note 1: N = 2040 (users = 995, non-users = 1045).
Note 2: Testing was one-tailed.
Note 3: ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

(2) Second, subjects in the treatment and control groups are matched based on propensity score. There are several ways of matching - caliper matching is generally considered better than others, such as nearest neighbor matching, since it can exclude ‘bad’ matches ([7]). This paper utilizes caliper matching, in which a value for the maximum distance of predefined propensity scores is fixed at 0.0001, which the PSM literature describes as sufficiently small. The suitability of the matching can be examined by a balancing test, in which the explanatory variables listed above in the treatment and control groups are compared by a t-test - when a treatment does not meet its best-matched control, re-sampling by the bootstrapping method with 1000 replications is conducted. If there is no statistically significant difference, the matching is concluded.

(3) Finally, the effect of e-Health on outcome variables, which in this paper are medical expenditures and number of days required for treatment, is examined based on matched samples by a t-test (standard error estimation).

IV. RESULTS

Summary statistics for outcome variables, namely medical expenditures and days for treatment, are summarized in Table II.

A. Bias control

PSM thus calculates a propensity score by a probit model in which the dependent variable is the user dummy variable, while independent variables are selected based on whether they contain a selection bias. Whether matching based on the propensity score works is examined by a balancing test is shown in Table III. The column named “% of bias” indicates the percentages of bias contained before and after matching for each variable. For example, “age” has 28.3% bias before matching, which is reduced to 4.4% after matching. Similarly, the column “% of reduced bias” shows the percentage of bias actually reduced by PSM, or 81.9% for age. The reduction in

TABLE II SUMMARY STATISTICS FOR OUTCOME VARIABLES

Variable	Mean	Std. Dev.	Min	Max
Medical expenditure (Outpatient + Inpatient)	20833.30	35027.02	0	469632
Medical expenditure (Outpatient)	16997.22	25083.83	0	469632
Medical expenditure (Inpatient)	3987.99	19277.99	0	242481
Treatment days (Outpatient + Inpatient)	16.32	19.59	0	181
Treatment days (Outpatient)	14.75	15.86	0	144
Treatment days (Inpatient)	1.50	9.06	0	178
Medical expenditure (chronic diseases)	6836.33	10266.33	0	76573
Treatment days (chronic diseases)	6.09	8.37	0	85
Medical expenditure (non chronic diseases)	10160.90	22685.98	0	469632
Treatment days (non chronic diseases)	8.66	12.88	0	144

TABLE III RESULT OF BALANCING TEST

Variables	Treatment	Control	% of bias (Before → After)	% of reduced bias	t-value
Chronic disease	0.466	0.486	15.6 → -4.1	73.8	-0.81
Age	71.629	72.124	28.3 → 4.4	81.9	-1.13
Number of family members	2.945	2.860	26.3 → 4.5	84.4	0.87
Income	2.961	2.968	6.5 → -2	97.5	-0.06
Heart diseases	0.144	0.131	-9.3 → 1.8	83.0	0.79
High blood pressure	0.469	0.466	54.2 → -2.1	96.6	0.14
Stroke	0.059	0.063	30.9 → -1.9	69.5	-0.37
Ophthalmic diseases	0.297	0.275	15.5 → -0.1	74.8	0.97
Anal diseases	0.005	0.003	15.6 → -4.1	80.7	0.55
Effect 1: reduced anxiety in day-to-day life	2.443	2.448	28.3 → 4.4	99.3	-0.08
Effect 2: stabilization of illness	2.548	2.573	26.3 → 4.5	96.2	-0.50
Effect 3: enhancement of health consciousness	2.650	2.635	6.5 → -2	98.1	0.35
Effect 4: decrease in medical expenditures	1.842	1.866	-9.3 → 1.8	93.8	-0.41
Year 2002	0.135	0.136	54.2 → -2.1	99.2	-0.05
Year 2005	0.238	0.238	30.9 → -1.9	99.3	-0.02
Year 2006	0.245	0.254	15.5 → -0.1	88.7	-0.39

Note 1: ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

TABLE IV RESULT OF ESTIMATION BASED ON PSM

	Outcome variables	Matching	Treatment	Control	Difference	S. E.	t value	
(1)	Medical expenditure (Outpatient + Inpatient)	Before	24090.52	18679.51	5411.02	1580.16	3.42	***
		After[a]	19598.07	29947.71	-10349.64	6475.68	-1.60	
		After[b]	24090.52	27385.88	-3295.36	3004.00	-1.10	
(2)	Medical expenditure (Outpatient)	Before	19448.53	15376.33	4072.21	1131.26	3.60	***
		After[a]	19448.53	21898.47	-2449.94	2024.69	-1.21	
		After[b]	16417.11	21692.92	-5275.81	4862.42	-1.09	
(3)	Medical expenditure (Inpatient)	Before	4835.41	3427.64	1407.78	871.62	1.62	*
		After[a]	3282.38	8462.42	-5180.05	2647.19	-1.96	**
		After[b]	4835.41	5606.38	-770.96	1092.70	-0.71	
(4)	Treatment days (Outpatient + Inpatient)	Before	18.39	14.95	3.43	0.88	3.89	***
		After[a]	15.42	23.09	-7.67	3.43	-2.24	**
		After[b]	18.39	20.33	-1.94	1.28	-1.51	
(5)	Treatment days (Outpatient)	Before	16.69	13.46	3.23	0.71	4.53	***
		After[a]	14.14	18.46	-4.32	2.75	-1.57	
		After[b]	16.69	18.04	-1.35	0.88	-1.52	
(6)	Treatment days (Inpatient)	Before	1.60	1.44	0.16	0.41	0.39	
		After[a]	1.17	4.47	-3.31	1.65	-2.00	**
		After[b]	1.60	2.23	-0.63	0.52	-1.22	
(7)	Medical expenditure (Outpatient, chronic diseases)	Before	6888.44	6801.86	86.58	464.47	0.19	
		After[a]	6888.44	9442.27	-2553.82	582.83	-4.38	***
		After[b]	5410.49	9404.12	-3993.63	1781.31	-2.24	**
(8)	Treatment days (Outpatient, chronic diseases)	Before	6.03	6.13	-0.10	0.38	-0.26	
		After[a]	6.03	8.63	-2.60	0.48	-5.47	***
		After[b]	4.80	8.78	-3.97	1.55	-2.56	**
(9)	Medical expenditure (Outpatient, non-chronic diseases)	Before	12560.09	8574.46	3985.63	1022.56	3.90	***
		After[a]	11006.62	12288.79	-1282.17	2662.46	-0.48	
		After[b]	12560.09	12487.07	73.02	1285.91	0.06	
(10)	Treatment days (Outpatient, non-chronic diseases)	Before	10.66	7.33	3.33	0.58	5.76	***
		After[a]	9.34	9.69	-0.35	2.27	-0.15	
		After[b]	10.66	9.40	1.26	0.82	1.54	

Note 1: ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.
Note 2: Cases (1)-(6) are related to all diseases, whereas cases (7)-(10) are chronic diseases.
Note 3: Matching methods are based as follows.
After[a]: Epanechnikov kernel matching
After[b]: Caliper (0.0001) matching.
Note 4: Standard errors of caliper matching are based on the bootstrapping of 1000 replications.
Note 5: Medical expenditure was reduced after matching, as indicated in the column "Difference," and this is measured by "points" of the National Health Insurance system. One point is equivalent to JPY10 (US$0.13).

sample selection bias is thus successful, since no statistically significant variable remains after matching in terms of t-values. In particular, biases related to subjective belief in the value of e-Health on health status shown by “Effects 1-4” are also substantially reduced.

B. Effect of e-Health on medical expenditures and days of treatment for outpatient and inpatient.

This paper uses two outcomes such as medical expenditures and days of treatment, but categorizes patients in different ways, namely, outpatient, inpatient, and outpatient + inpatient. As a result, 10 cases are analyzed, which are listed in Table IV. Our previous paper [5] examined only two cases; (7) and (8), which are related to chronic diseases, the main targets for Nishi-aizu’s e-Health system. Cases (1)-(6) are related to all diseases for comparison with chronic diseases.

In Table IV, the rows named “before” and “after” indicate estimations before and after matching. Two methods of PSM matching are examined, Epanechnikov kernel matching and caliper (0.0001) matching. Table IV shows that both outpatient medical expenditures (7) and outpatient days of treatment (8) for chronic diseases did not significantly differ between users and non-users of telecare before matching, whereas after matching two matching methods showed a significantly negative difference ($p<0.05$), implying that e-Health has an effect on outpatients medical expenditures and days of treatment for chronic diseases. The column “difference” indicates the decrease in the amount of expenditure and number of treatment days. Caliper matching provided the greatest effect, namely JPY 39,936 (US$ 499.20) and 3.97 days per year per user, while Epanechnikov kernel matching produced the smallest, at JPY 25,538 (US$319.23) and 2.60 days.

The above results are already presented in [5], but this analysis shows new results regarding (3), (4) and (6), that is, users have significantly smaller inpatient medical expenditure (3), treatment days (outpatient + inpatient) (4), and inpatient treatment days (6) than those of non-users ($p<0.05$). The amounts of difference are JPY 51,801 (3), 7.67 days (4), and 3.31 days (6), respectively. It should be noted that these results hold only in terms of Epanechnikov kernel matching, and then these do not satisfy robustness. As for the other cases such as (1), (2), (5), (9), and (10), this analysis does not provide any significant results, and further examination is necessary.

The estimation in this paper shows that even if other outcomes are taken as dependent variables, telecare of this town has effect on the reduction of outpatient medical expenditures and days of treatment of chronic diseases.

IV. Discussion

Cases (7) and (8) in Table IV thus demonstrates that e-Health does not contribute to a reduction in medical expenditures for all diseases, but only for chronic diseases ([5] [13] [14] and [15] have the same result), since users’ expenditures for chronic diseases are larger than those of non-users before matching, but significantly smaller after matching.

The estimation results related to cases (4) and (6) for days of treatment, which are statistically significant with Epanechnikov kernel matching, can be used for some interesting international comparisons. Regarding the research results with the Kent Development Pilot in the UK and the CCHT project of the VHA in the US, the former studied the effect of telehealth on the number of inpatient days, general practices (GP), acute care, and others by experimental observation with statistical analysis ([15]). This study compared outcomes at baseline and six month with a focus on patients with COPD, heart disease, and diabetes. The authors concluded that telecare use resulted in a decrease in the number of home visits and GP surgery per participant, Accident and Emergency (A&E) visit of 0.5days, and inpatient treatment days of 1.5days. The latter reported in the same manner as the Kent study, that is, the number of inpatient treatment days was reduced by 25%, and the number of hospital admission by 19% ([16]). Thus other results of international projects were estimated mainly in terms of inpatient treatment days, not expenditures, and all diseases, not only chronic diseases. This paper is aimed to obtain the results which can compare in the same manner. According to our results, the Nishi-aizu project has larger reduction of inpatient treatment days than the Kent project (3.3 vs. 1.5 days). On the other hand, the reduction of bed days of this paper is calculated as approximately 16.12%, which is smaller than that of the VHA project (25%).

Table V also compares the effects obtained by the other estimation methods, such as simple OLS ([13]) and system GMM ([8]), used in our previous papers. The effects of e-Health are underestimated when sample selection biases are not controlled.

TABLE V COMPARISON OF RESULTS USING ALTERNATIVE ESTIMATION METHODS

	OLS[1]	system GMM[2]	PSM
Medical expenditures for chronic diseases	JPY 15,302 (US$ 191.28)	-	JPY 25,538-39,936 (US$ 319.23-499.20)
Days of treatment for chronic diseases	1.6 days	2.0 days	2.6-4.0 days

Note 1: Akematsu and Tsuji [13]
Note 2: Minetaki, Akematsu, and Tsuji [8]

Although PSM offers major benefits in the evaluation of e-Health projects, it has its own limitations. First, it requires a large number of samples, and several previous studies have in fact used samples in the several tens of thousands range. Second, its results are not always robust, which is why our present paper examines two matching methods. These limitations have been described (see [9] and [12] for example), but one limitation specific to e-Health has not. In this paper, PSM successfully demonstrated that the user group had less medical expenditures than the non-user group under the condition that all subjects were closely similar except in their use of e-Health. Our previous study [13] [14] and [17] concluded that these results were due to the difference in health consciousness between the groups. By checking heath data transmitted by the e-Health system and receive health consultation from town's public nurses, users became more concerned with health and had an incentive to change their behavior to be more health-conscious. These findings are not consistent with those of the present analysis, however, which found different expenditures despite a closely similar degree of health consciousness, which could only be due to e-Health use. PSM thus provides little explanation of why and how e-Health leads to these results, and identification of these mechanisms requires the use of other empirical methods together with PSM.

V. Conclusion

By using PSM, this paper successfully controls biases due to the way to collect the sample (sample selection bias) and provides a rigorous demonstration of the effect of an e-Health implementation in a small Japanese town in reducing the number of treatment days as well as medical expenditures. Moreover, this paper uses some other outcomes as dependent variables and their estimation results enable to compare with the outcomes of e-Health projects in the UK and US which have the similar peripheral device and system. According to our in-depth surveys of these projects, there are similarities and differences in these projects, but a common success factor lies in the enthusiasm of nurses, public or visiting nurses who participate in these projects to maintain health of the residents in the community. Further detailed study is required for factors of differences.

Let us discuss on the economic foundation of the project. Nishi-aizu Town does not charge any fee to users. Other projects in the most of counties are the same. Neither this program nor those referenced in the UK and US charge user fees; rather, all are subsidized by the central as well as local government, as indeed are the UK demonstration programs, since they are national pilot projects. However, the ongoing sustainability of e-Health requires a new financial framework. [17] conducted a cost/benefit analysis of Nishi-aizu's e-Health and calculated a B/C (cost-benefit) ratio which was 0.25. The initial costs of the implementation, such as for host computers and peripheral devices, were borne by the central government, however, excluding them form analysis gave a B/C ratio for Town which bore only operational costs, which is 0.91. But this is not sustainable. One possibility for promoting e-Health is reimbursement using public medical insurance. The amount of reimbursement is based on economic effect of e-Health and must be obtained rigorous analysis. Most of countries are not recognized reimbursement for e-Health, which reason is simple; e-Health is not diagnosis but prevention of diseases. The simple e-Health system does reduce medical expenditures of users. The present paper provides important support for the development of evidence-based policies for the diffusion of e-Health.

Acknowledgment

The authors express deep thanks to Mayor of Nishi-aizu Town, Mr. Yamaguchi who admitted us to use the data of National Health Insurance. Thanks are also due to Ms. Satie Nitta, who is a town's public nurse provides useful information on the health situation of residents.

References

[1] S. Sohn, T. Helms, J. Pelleter, et al. "Costs and benefits of personalized health care for patients with chronic heart failure in the care and education program," Telemed e- Health, Vol. 18, pp. 198-204, 2012.

[2] J. Z. Ayanian, M. B. Landrum, E. Guadagnoli, P. Gaccione, "Specialty of ambulatory care physicians and mortality among elderly patients after myocardial infraction," New England Journal of Medicine, Vol. 347, pp. 1678-1686, 2002.

[3] P. A. Gum, M. Thamilarasan, J. Watanabe, E. H. Blackstone, M. S. Lauer, "Aspirin use and all-cause mortality among patients being evaluated for known or suspected coronary artery disease: a propensity analysis," Journal of the American Medical Association, Vol. 286, PP. 1187-1194, 2001.

[4] P. S. Wang, S. Schneeweisse, J. Avorn, M. A. Fischer, H. Mogun, D. H. Solomon, M. A. Brookhart, "Risk of death in elderly users of conventional vs. atypical antipsychotic medications," New England Journal of Medicine, Vol. 353, pp. 2335-2341, 2005.

[5] Y. Akematsu, M. Tsuji, "Measuring the effect of telecare on medical expenditures without bias using the propensity score matching method," Telemedicine and e-Health, 2012, Vol. 18, No. 10, pp. 743-747, 2012.

[6] N. R. Chumbler, M. Garel, H. Qin, et al. "Health services utilization of a care coordination/home-telehealth program for veterans with diabetes: a matched-cohort study," J Ambulatory Care Manage, Vol. 28, pp. 230-240, 2005.

[7] R. H. Dehejia, S. Wahba, "Propensity score-matching methods for nonexperimental causal studies," Review of Economics and Statistics, Vol. 84, pp. 151-161, 2002.

[8] K. Minetaki, Y. Akematsu, M. Tsuji, "Effect of e-Health on the medical expenditures of outpatients with lifestyle-related diseases," Telemed E Health, Vol. 17, pp. 591-595, 2011.

[9] P. R. Rosenbaum, D. B. Rubin, "The central role of the propensity score in observational studies for causal effects," Biometrika, Vol. 70, pp. 41-55, 1983.

[10] P. R. Rosenbaum, D. B. Rubin, "Reducing bias in observational studies using subclassification on the propensity score," Journal of the American Statistical Association, Vol. 79, No. 387, pp. 516-524, 1984.

[11] P. R. Rosenbaum, D. B. Rubin, "Constructing a control group using multivariate matched sampling methods that incorporate the propensity score," The American Statistician, Vol. 39, No. 1, pp. 33-38, 1985.

[12] J. J. Heckman, H. Ichimura, P. Todd, "Matching as an econometric evaluation estimator: evidence from evaluating a job training programme," Review of Economic Studies, Vol. 64, pp. 605-654, 1997.

[13] Y. Akematsu, M. Tsuji, "An empirical analysis of the reduction in medical expenditures by e-health users," J Telemed Telecare, Vol. 15, pp. 109-111, 2009.

[14] Y. Akematsu and M. Tsuji, "An empirical approach to estimating the effect of e-health on medical expenditure," Journal of Telemedicine and Telecare, Vol. 16, pp. 169-71, 2010.

[15] Kent County Council, Promoting and Sustaining Independence in a Community Setting: A Study into the Management of People with Long Term Conditions, 2010

[16] A. Darkins, et al. "Care coordination/home telehealth: The systematic implementation of health informatics, home telehealth, and disease management to support the care of veteran patients with chronic conditions," Telemedicine and e-Health, Vol. 14, pp. 1118-1126, 2008.

[17] M. Tsuji, Y. Akematsu, and F. Taoka, "Empirical analysis of roles and issues of Japanese eHealth systems: Case of Nishi-Aizu Town, Fukushima Prefecture," Journal of eHealth Technology and Application, Vol. 6, pp. 1-8, 2008.

 ISBN: 978-1-61208-252-3