Performance evaluation index formulae

		(Classified as)	
		CNL deterioration	CNL stable or improved
Actual	CNL deterioration	TP	FN
	CNL stable or improved	FP	TN
Sensitivity		$\frac{TP}{TP+FN}$	
Specificity		$\frac{TN}{TN+FP}$	

21

The evaluation results on precision, recall, F1, and overall accuracy of CART and Random Forest model.

Evaluation	CART	Random Forest
Sensitivity	0.7396	0.7973
Specificity	0.5841	0.5742
AUC	0.6973	0.7279

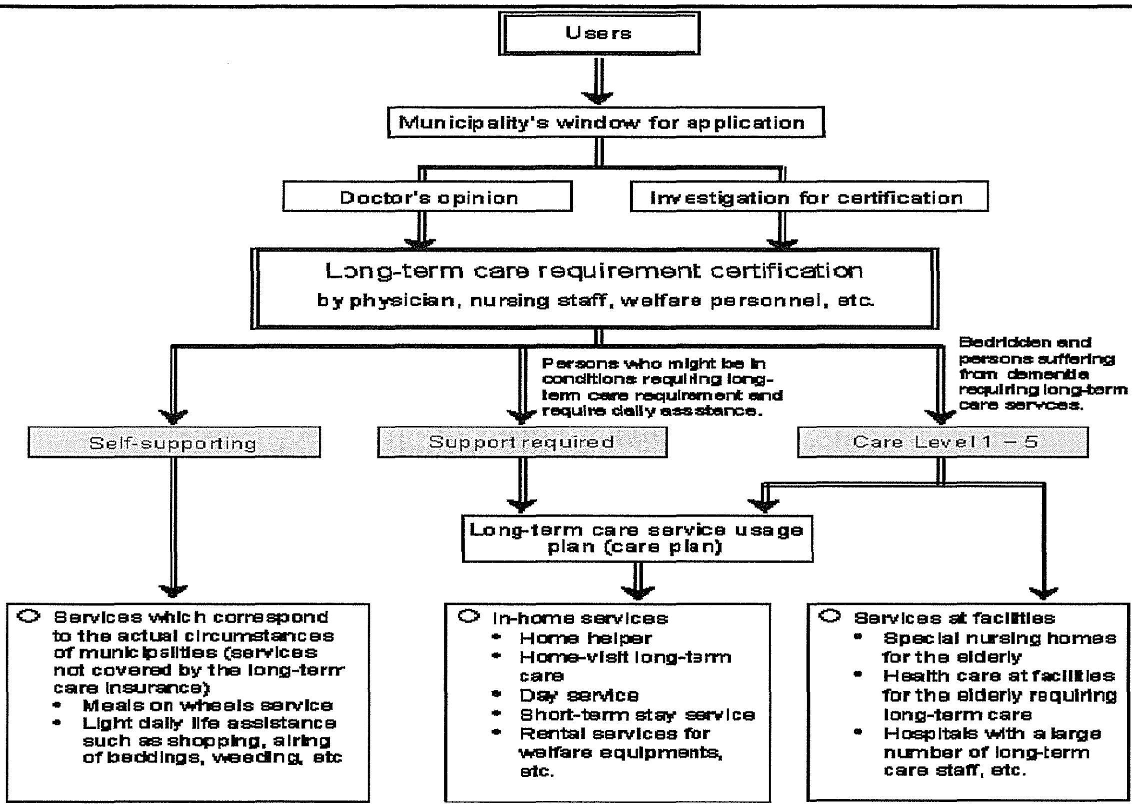
22

Conclusion

- The variables actually used in tree construction are age, baseline care needs level, facility care service, home care service, medical area, new dementia diagnosis, other service, and sex (listed by weighting).
- According to our analysis of 6,876 long-term care service insured in Japan, both systems predict the adequacy of deterioration around 0.7 is reliable.
- The decision support systems incorporating learning-based classification approaches can serve as a supplementary tool due to the superior performance in predicting adequacy.

Thank you for your listening.

Procedures for the use of service



25

Ministry of Health, Labour and Welfare Home Page. Long-term Care Insurance in Japan; http://www.mhlw.go.jp/english/topics/elderly/care/2.html Accessed May 14, 2015.

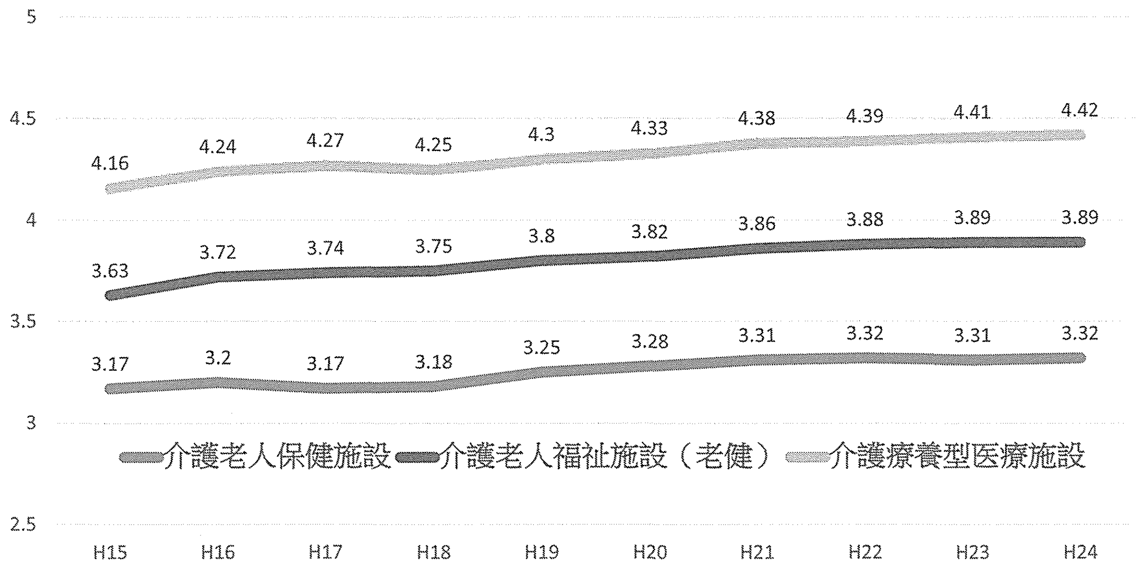
Benefit limit standard amounts for in-home services

Level	Benefit limit standard amounts (units/month)
Support requiring level 1	4,970
Support requiring level 2	10,400
Care-Needs Level 1	16,580
Care-Needs Level 2	19,480
Care-Needs Level 3	26,750
Care-Needs Level 4	30,600
Care-Needs Level 5	35,830

Ministry of Health, Labour and Welfare. Long-Term Care, Health and Welfare Services for the Elderly;
. http://www.mhlw.go.jp/english/wp/wp-hw6/dl/10e.pdf Accessed May 14, 2015.

26

Average Care-Needs Level of Facility Care Service Users

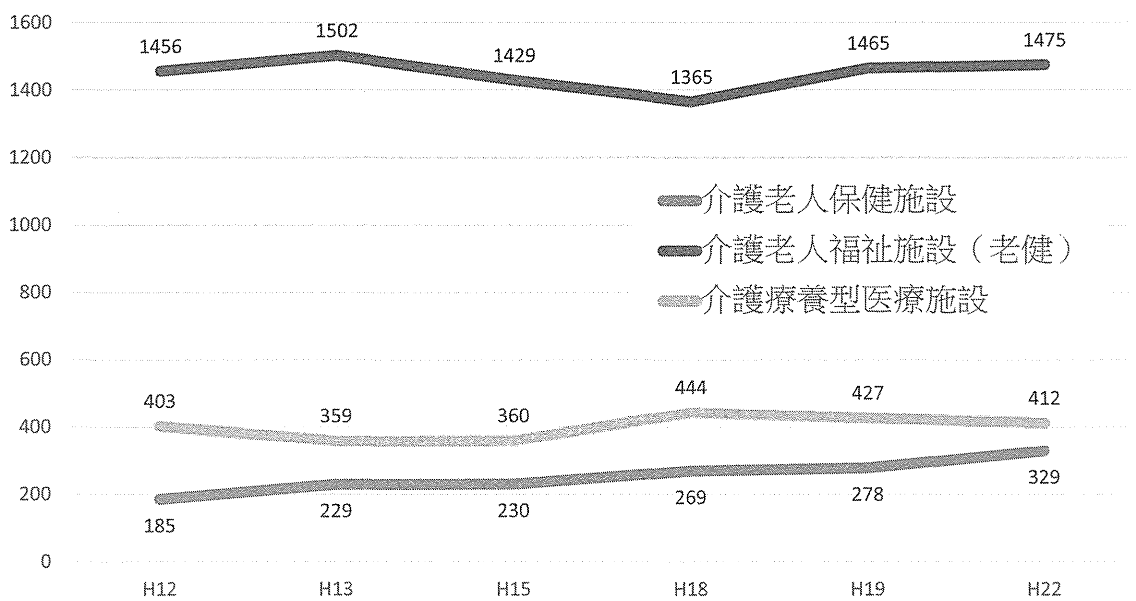


$$\text{平均要介護度} = \frac{\text{在所者の要介護度合計}}{\text{要介護度1～5の在所者数の合計}}$$

Ministry of Health, Labour and Welfare. Survey of Institutions and Establishments for Long-term Care

27

Average Length of Stay by Facility Type



Ministry of Health, Labour and Welfare. Survey of Institutions and Establishments for Long-term Care

28

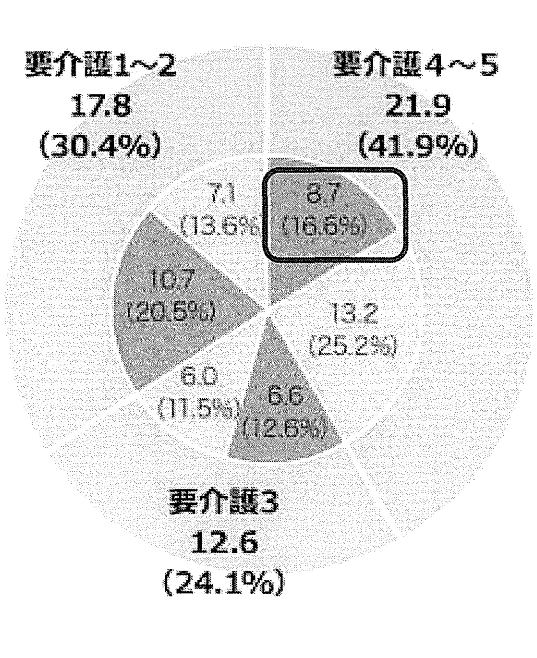
健康寿命の計算

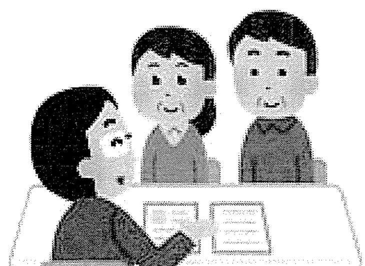
- 健康な状態を、日常生活動作が自立していることと規定する。介護保険の要介護度の要介護２～5を不健康（要介護）な状態とし、それ以外を健康（自立）な状態とする。

平成24年度厚生労働科学研究費補助金（循環器疾患・糖尿病等生活習慣病対策総合研究事業）による「健康寿命における将来予測と生活習慣病対策の費用対効果に関する研究班」（2012）健康寿命の算定方法の指針。From http://toukei.umin.jp/kenkoujyumyou/syuyou/kenkoujyumyou_shishin.pdf Accessed 25 May 2015

29

特別養護老人ホームの入所申し込み者の割合





単位：万人 ■在宅の方 在宅以外の方

＊要介護1～2の人数には、要支援などで入所申込みをされている方の人数を含む。
＊1,000人未満四捨五入のため、合計に一致しないものがある。

出典：厚生労働省 H26.03

30

特養老人ホーム新規利用の要介護度

要介護度	利用者数((万人)	割合(%)
1	0.4	2.8
2	1.2	8.7
3	3.6	26.1
4	5.1	37.0
5	3.5	25.4

31

出所：厚生労働省「2012年介護給付費実態調査」

Application of Machine Learning in Predicting Risk Factors of Care Needs Level Deterioration among Elderly with Dementia

Huei-Ru Lin
Department of Healthcare Economics and Quality Management, Kyoto University
Yoshida Konoe-cho, Sakyo-ku, Kyoto, 606-8501, JAPAN
Doctoral Candidate
lin.hueiru.72c@st.kyoto-u.ac.jp

Chia-Lun Lo
Institute of Healthcare Information Management, National Chung Cheng University, Chiayi 62102, Taiwan
Lecturer
allen1o@gmail.com

Tetsuya Otsubo
Department of Healthcare Economics and Quality Management, Kyoto University
Yoshida Konoe-cho, Sakyo-ku, Kyoto, 606-8501, JAPAN
Assistant Professor
otsubot-kyoto@umin.ac.jp

Yuichi Imanaka
Department of Healthcare Economics and Quality Management, Kyoto University
Yoshida Konoe-cho, Sakyo-ku, Kyoto, 606-8501, JAPAN
Professor
imanaka-y@umin.ac.jp

Abstract— **Japan has one of the highest life expectancies in the world, resulting in various needs of the elderly population that require fulfilment, including long-term care needs.**
Furthermore, there is a rapid increase in the demand for long-term care services in older individuals with dementia.

Previous studies have demonstrated that dementia is an independent predictor of medical and long-term care utilization and expenditure. However, little is known about the influence of the types of long-term care services on care-needs level deterioration among insured elderly dementia patients.

The purpose of this study was to determine risk factors that are associated with care needs level deterioration among elderly dementia patients in Japan.
We developed and pruned a supervised learning approach using nonparametric Classification and Regression Tree (CART) and Random Forest, an algorithm of machine learning, to create risk factors for care needs level deterioration.

The supervised learning approach, which including CART and RF algorithms for care needs level deterioration included baseline care needs level, home care service, facility care service, sex, new dementia diagnosis, community-based care service, other service, medical area, and age group with an area under the curve (AUC)of 0.6973 and 0.7279 of CART and random forest, respectively.

Keywords— **Long-Term Care, Care Needs Level, Dementia, CART, Random Forest, Supervised learning approach, RF algorithms**

1. INTRODUCTION

Japan has one of the highest life expectancy in the world[1]. Therefore, the needs of long-term care service is required to be fulfilled in a rapidly aging society. The government in Japan is also forced to face the inevitable challenge and implemented the Long-Term Care Insurance (LTCI) in year 2000 for citizens who are above 65-year old or people who are above 40-year old in needs of long-term care services[2]. Besides, the surveys conducted by the Ministry of Health, Labour and Welfare of Japan have shown that long-term care services were most employed by patients with cerebrovascular disease, but the demand of long-term care services in dementia elders increases most rapidly[3-5]As prevalence of dementia rises sharply with age, the number of persons with dementia will have increased from 2.8 million to 4.7 million in the near future in Japan[6].

Previous studies reported that dementia is the crucial factor for influencing the medical and long-term care expenditure and utilization [7, 8].The impact of dementia on aging society is an inevitable challenge. Nevertheless, Japanese Prime Minister Sinzo Abe claimed that early diagnosis and intervention is the key to an Integrated Community Care System for dementia patients[9].

Furthermore, there are some researches focusing on the care-needs level (CNL) shift related to long-term care (LTC) service use [10-13].Regarding to dementia influence on CNL shift, Lin, Otsubo, and Imanaka pointed that dementia diagnosis is related to the higher odds ratio of CNL deterioration, especially the new dementia diagnosis[13]. However, most studies conducted logistic/multiple regression to clarify the relationship between risk factors and CNL shift. To our knowledge, there is still no research determine CNL deterioration by supervised learning approach (CART and RandomForest (RF) algorithms were selected in this study).Tree based algorithms could not only explore the risk factors but identify the order that which factor would be higher ranked.

To sum up, the aim of this study is to predict the deterioration of dementia insured of long-term care insurance system by supervised learning approach, which including CART and RF algorithms.

2. Materials and Methods

2.1. Data Preparation

In this study, we selected complete records from the long term care insurance database who had applied for long-term care service and also were the insured of national healthcare insurance aged above 65 years in 2010 in Kyoto prefecture.

We set the changes of care-needs level into 2 categories: stable or improved and deteriorated. The changes of care-need level were calculated by subtracting the baseline care-needs level in June 2010. If the changes were minus or equal to 0, it will be identified as stable or improved, otherwise it will be identified as deteriorated

Classification model in this study was built by several variables as predictors, including age, sex, medical area, baseline care needs level, new dementia diagnosis, and type of service use (including facility care service, home care service, community-based care service, and other service).

This study collects, filters, and pre-processes clinical data of all samples. First, we excluded subjects who had not used long-term care service during our research duration from June 2010 to June 2011. Second, if the subjects had been certified as care needs level 5 in June 2010 and could not be identified as death (deterioration) or improvement during the research period would also be excluded. Because of the subjects who were certified as care-need level 5 could be identified as sustained or improved but could not be classified as deteriorated otherwise we know the subjects dead.

The care need level certification of LTCI was determined by the municipalities of Kyoto government. The long-term care approval board investigated the mental and physical condition of insured person and made a screening judgment based on a gate keeper.

Since the utilization of service use of support-required would be very different from those classified as having care needs levels 1 to 5, beneficiaries at support-required levels were excluded from analysis.

Furthermore, as dementia was defined according to the ICD-10 by the National Healthcare Insurance data, insured users who were not qualified as insured in would be excluded, too.

After employing these exclusion criteria and pre-processing steps, the study sample and variables of dataset are shown in Table 1.

TABLE 1
Summary Statistics of Variables

Variables	Range	N (%)
Sex	Male	1,696 (24.7%)
	Female	5,180 (75.3%)
Age Group	65-74	422 (6.1%)
	75-84	2,725 (39.6%)
	>85	3,729 (54.2%)
Medical Area	Tango	463 (6.7%)
	Cyutan	617 (9.0%)
	Nantan	448 (6.5%)
	KyotoOtokuni	4,230 (61.5%)
	Yamashirokita	886 (12.9%)
	Yamashirominami	232 (3.4%)
Baseline Care Needs Level	1	949 (13.8%)
	2	1,110 (16.1%)
	3	1,911(27.8%)
	4	1,638(23.8%)
	5	1,268(18.4%)
New Dementia Diagnosis	Yes	719 (10.5%)
	No	6,157(89.5%)
Facility Care Service	Used	1,904 (27.7%)
	Unused	4,972(72.3%)
Home Care Service	Used	4,709 (68.5%)
	Unused	2,167 (31.5%)
Community-Based Care	Used	798(11.6%)

Variables	Range	N (%)
Service	Unused	6,078(88.4%)
Other Service	Used	5,547 (80.7%)
	Unused	1,329(19.3%)
CNL deterioration	Yes	3,438 (50%)
	No	3,438(50%)

2.2. Experimental Design for Classification Model

The Classification and Regression Tree (CART) procedure was used to build a classification model on care needs level deterioration. CART is a recursive partitioning procedure aim at splitting the data into distinct partitions base on the most important exposure variables determined by the procedure. A split on a partition is carried out to maximize the purity, that is, the dominance of one class, of its descendant partitions. In this study, the purity of a partition is measured by the **Gini impurity**, which equals $1 - p_1^2 - p_2^2$ where p_1 and p_2 are the proportions of classes 1 and 2 respectively. The model is named as a tree model as the partitions can be arranged in a tree-like structure. The CART was fitted using package *rpart* of R, with a complexity parameter and minimum number of partition size of 0.001 and 20, respectively.

We also fitted CART model with complexity parameter determined by the 1-SE rule (a standard, accepted method for complexity parameter determination).

Besides, the random forest model using package *randomForest* of R with 500 trees. Random forests is extension of CART models by supervised learning approach, which including CART and RF algorithms to improve prediction accuracy.

2.3. Measurement

As the imbalance dataset has been recognized as a crucial problem in machine learning and data mining, there are many solutions which have been proposed to deal with this problem including data sampling[14]. Therefore, the CART was fitted using datasets with care needs level deterioration to stable or improved insured with case-to-control ratio 1:1 (n=6,876).

To assess the classification power of the supervised learning approach, this study used 10-fold cross validation to validate the CART decision tree model. Besides, the area under the curve (AUC), sensibility and specificity are appropriate to evaluate the prediction model for predicting classification accuracy in medical data analysis[15].

3. RESULT

Our result shows the supervised learning approach, which includes CART and RF algorithms fitted using the CART algorithm and it has 17 partitions as Figure 1.

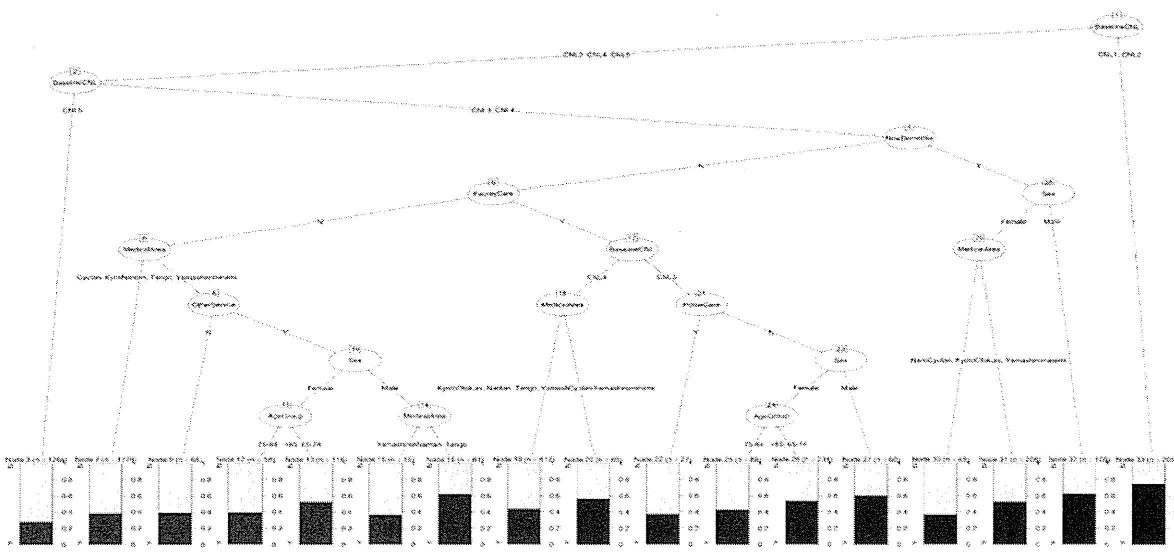


FIG. 1SUPERVISED LEARNING APPROACH, WHICH INCLUDING OF CART AND RF ALGORITHMS MODEL FITTED USING THE CART ALGORITHM.

The area under the curve (AUC) of CART and random forest is 0.6973 and 0.7279,respectively. And the sensitivity/specificity plot of both modelsare shown in Fig 2.Although the AUC of random forest is higher than CART, the discrepancy between AUC of CART and random forest is little.

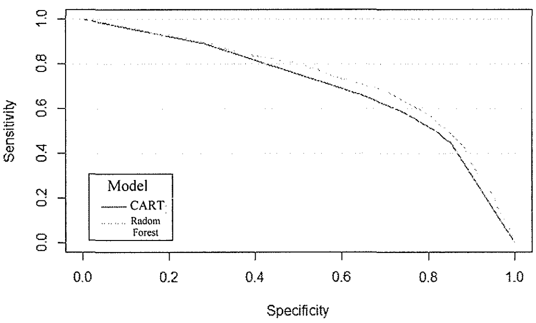


FIG. 2THE SENSITIVITY/SPECIFICITY PLOT OF CART AND RANDOM FOREST MODEL.

The classification accuracy is 66.59% and 69.54% of CART and random forest model, respectively.

To evaluate our model performance, we conducted sensitivity and specificity analyses. Sensitivity measures the proportion of actual positives (CNL stable or improved among all subjects), also known as the true positive (TP). Specificity measures the proportion of actual negatives (CNL deterioration among all subjects), also known as true negative (TN). Table 2 shows the formulae. The main purpose of this study is to find out the risk factors of individuals' CNL deterioration. Therefore, this study emphasizes sensibility evaluation.

TABLE2PERFORMANCE EVALUATION INDEX FORMULAE.

		(Classified as) CNL deterioration	(Classified as) CNL stable or improved
Actual	CNL deterioration	*TP*	*FN*
	CNL stable or improved	*FP*	*TN*
Sensitivity		$\frac{TP}{TP+FN}$	
Specificity		$\frac{TN}{TN+FP}$	

Table 3 summarizes the evaluation results on sensitivity, specificity, and averaged class error of CART and Random Forest model. As shown, both CART and random forest system appeared to have a high predictive value.

TABLE3 THE EVALUATION RESULTS ON SENSITIVITY, SPECIFICITY, AND AVERAGED CLASS ERROR OF CART AND RANDOM FOREST MODEL.

Evaluation	CART	Random Forest
Sensitivity	0.7396	0.7973
Specificity	0.5841	0.5742
AUC	0.6973	0.7279

Paths to each leaf of CART can be transformed into IF-THEN rules which are mutually exclusive and exhaustive on the IF parts. For the following rules, we also list the accuracy rate (accuracy) for predicting individual's CNL deterioration and the absolute number (occurrence) of individuals supporting the rule. The node including baseline CNL followed by new dementia, facility care service use, sex, medical area, other service, home care service, and age.

TABLE 4 RULES OF CNL DETERIORATION FROM CART

No	Rules	Prob	Occurrence	Proportion
1	Baseline CNL="1,2"	0.75	2,059	30%
2	BaselineCNL="3,4,5"ANDNewDementia="N" ANDFacilityCare="N"ANDOtherService="Y"ANDSex="Male" AND MedicalArea="Nantan/Tango"	0.62	61	1%
3	Baseline CNL="3,4" AND New Dementia ="Y" AND Sex ="Male"	0.62	108	2%
4	New Dementia="N" AND Facility Care="Y" AND Baseline CNL="3" AND Home Care="N" AND Sex="Male"	0.60	60	1%
5	New Dementia="N" AND Facility Care="Y" AND Baseline CNL="4" AND Medical Area="Cyutan"	0.57	60	1%
6	New Dementia="N" AND Facility Care="Y" AND Baseline CNL="3" AND Home Care="N" AND Sex="Female" AND Age Group=">85,65-74"	0.53	231	3%
7	BaselineCNL="3,4" AND New Dementia="N" AND Facility Care="N" AND Medical Area="Nantan,Tango,Yamashirominami" AND Other Service="Y" AND Sex="Female" AND Age Group=">85,65-74"	0.53	116	2%
8	Baseline CNL="3,4" AND New Dementia="Y" AND	0.52	208	3%

No	Rules	Prob	Occurrence	Proportion
	Sex="Female" AND Medical Area="Cyutan,KyotoOtokuni,Yamashirominami"			
9	New Dementia="N" AND Facility Care="Y" AND Baseline CNL="4" AND Medical Area="KyotoOtokuni,Nantan,Tango, Yamashirokita,Yamashirominami"	0.44	617	9%
10	New Dementia="N" AND Facility Care="Y" AND Baseline CNL="3" AND Home Care="N" AND Sex="Female" AND Age Group="75-84"	0.43	88	1%

Regarding to Random Forest, we list the mean decrease accuracy and mean decrease Gini of variables about CNL deterioration in Table 5. The most predictable factor is baseline CNL followed by home care service, facility care service, sex, new dementia, community based care service, other service, medical area, and age.

TABLE 5MEAN DECREASE ACCURACY AND MEAN DECREASE GINI OF VARIABLES ABOUT CNL DETERIORATION FROM RANDOM FOREST

Variables	NO	YES	Mean Decrease Accuracy	Mean Decrease Gini
Baseline CNL	118.43	121.09	157.11	264.2
Home Care	15.13	-6.8	20.17	12.47
Facility Care	19.54	-12.5	19.55	12.08
Sex	11.75	6.57	17.32	16.59
New Dementia	4.9	14.68	14.15	15.95
Community Based Care	16.38	-7.73	10.46	13.89
Other Service	1.51	5.35	5.83	16.91
Medical Area	6.03	-0.03	4.69	56.66
Age Group	-7.15	10.23	3.37	31.58

Both CART and Random Forest weightbaseline CNL represents that current dependent level is the utmost factors influencing CNL deterioration. Among type of service use, facility care service use occupied the highest ranking in CART but in Random Forest algorithms comes home care service. Previous study reported that dementia shows huge impact on CNL deterioration[13], however, since our subjects are limited to dementia patients, the impact may decrease.

4. CONCLUSION

The variables actually used in tree construction are baseline care needs level, home care service, facility care service,sex, new dementia diagnosis, community-based care service, other service, medical area, and age group.

This study responds to the challenge of predicting the risk factors of care needs level deterioration among elderly patients with dementia in Japan. Specifically, we applied the supervised learning techniques, including CART and random forest for improving predictive performance. According to our analysis of 6,876 long-term care service insured in Japan, both systems predict that the adequacy of deterioration around 0.7 is reliable.

Considering the complicated characteristics of dementia insured and long-term care system, this study shows that the decision support systems incorporating supervised learning approaches can serve as a supplementary tool due to the superior performance in predicting adequacy.

ETHICSSTATEMENT

This study was approved by the Ethics Committee of Kyoto University Graduate School of Medicine (Number E1023).

ACKNOWLEDGMENT

This study was supported by a Health and Labour Sciences Research Grant for Research on Research on Dementia from the Ministry of Health, Labour and Welfare, Japan [H27-Ninchisho-001].

REFERENCES

1. World Health Organization, *COUNTRY HEALTH INFORMATION PROFILES*, in *Western Pacific country health information profiles: 2011 revision*. 2011, Manila: WHO Regional Office for the Western Pacific. p. 139-141.
2. Tsutsui, T. and N. Muramatsu, *Japan's universal long-term care system reform of*

2005: containing costs and realizing a vision. J Am Geriatr Soc, 2007. **55**(9): p. 1458-63.

3. Health and Social Statistics Division of Statistics and Information Department *Comprehensive Survey of Living Conditions.* 2004 [cited 2013 17 September]; Available from: http://www.mhlw.go.jp/toukei/saikin/hw/k-tyosa/k-tyosa04/4-2.html.
4. Health and Social Statistics Division of Statistics and Information Department *Comprehensive Survey of Living Conditions.* 2007 [cited 2013 17 September]; Available from: http://www.mhlw.go.jp/toukei/saikin/hw/k-tyosa/k-tyosa07/4-2.html.
5. Health and Social Statistics Division of Statistics and Information Department *Comprehensive Survey of Living Conditions.* 2010 [cited 2013 17 September]; Available from: http://www.mhlw.go.jp/toukei/saikin/hw/k-tyosa/k-tyosa10/4-2.html.
6. Ministry of Health Labour and Welfare. *Health and Welfare Bureau for the Elderly.* 2013 [cited 2015 30 March]; Available from: http://www.mhlw.go.jp/english/policy/care-welfare/care-welfare-elderly/dl/health_and_welfare_bureau.pdf.
7. Arling, G., et al., *Impact of Dementia on Payments for Long-term and Acute Care in an Elderly Cohort.* Med Care, 2013. **51**(7): p. 575-81.
8. Lin, H.-R., T. Otsubo, and Y. Imanaka, *The relationship between dementia diagnosis and long-term care expenditures*, in *The 9th Annual Conference of Japan Health Economics Association (JHEA).* 2014, Japan Health Economics Association: Tokyo.
9. Abe, S. *Global Dementia Legacy Event Japan.* 2014 [cited 2015 30 March]; Available from: http://nettv.gov-online.go.jp/prg/prg10804.html.
10. Kim, J.-N. and K. Shiwaku, *The Effect of Utilization of In-home Services and the Changes in Levels of Care Needs of Frail Persons (2002-2004): Results of a Two-year Follow-up Study.* Journal of Rural Medicine, 2012. **7**(1): p. 6-14.
11. Kato, G., et al., *Relationship between home care service use and changes in the care needs level of Japanese elderly.* BMC Geriatr, 2009. **9**: p. 58.
12. Kijima, H., *A study on levels of care changes for individuals requiring long-term care at home — With reference to the level of care service use and changes in the level of care needs —.* Research reports of Suzuka University of Medical Science, 2007(14): p. 39-52.
13. Lin, H.R., T. Otsubo, and Y. Imanaka, *The Effects of Dementia and Long-Term Care Services on the Deterioration of Care-needs Levels of the Elderly in Japan.* Medicine (Baltimore), 2015. **94**(7): p. e525.
14. Lopez, V., et al., *An insight into classification with imbalanced data: Empirical results and current trends on using data intrinsic characteristics.* Information Sciences, 2013. **250**: p. 113-141.
15. Podgorelec, V., et al., *Knowledge discovery with classification rules in a cardiovascular dataset.* Computer Methods and Programs in Biomedicine, 2005. **80**: p. S39-S49.

資料4

厚生労働科学研究費補助金
認知症政策研究事業

平成28年度
継続課題

認知症の介護・医療地域体制の実態・課題の可視化と系統的把握方法の研究開発

平成26-27年度　中間報告
（平成28年2月）

研究代表者　今中　雄一

1

目的

研究目的超高齢・少子社会が著しく進展する中、認知症のケアの地域システムのあり方は社会･経済的に益々重大になってくる。

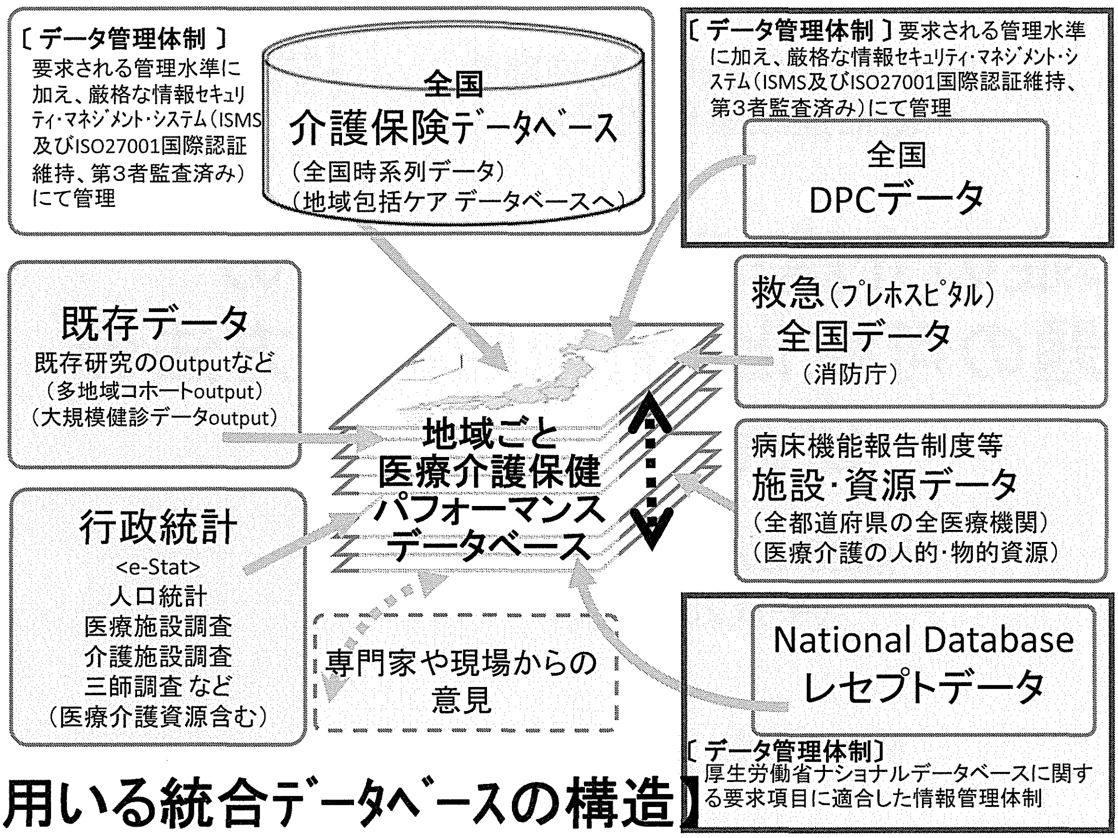
本研究は、認知症(地域ケア体制)施策の評価・立案に資するために、認知症の介護・医療･介護について、
1）全国及び広域の大規模データベースを活用して
・諸地域のケア実態を可視化し、
・地域の差とその関連要因を明らかにし、

2）地域ケア体制の系統的把握方法を研究開発する、

ことを、目的とする。

※　京都大学大学院医学研究科・医学部及び医学部附属病院医の倫理委員会承認（R0438；旧E1023）
※　この研究発表の内容に関する利益相反事項は、ありません

2



【用いる統合データベースの構造】

用いるデータ

○ 医療と介護レセプト 国・広域（多市町村）レベルの悉皆的・長期・大規模データベースを活用する。

○ 行政統計、医療機能情報提供制度、各種調査等含むデータを整理・統合し用いる

内容

認知症のケア（医療・介護）
について、政策施策に貢献すべく、下記を行う。

1. ケア・システムのアウトカムを可視化する

リスク調整を行い、ケア・システムのパフォーマンスを可視化する
アウトカム ＝ 要介護度悪化、介護・医療費等
アウトカムへのケアの質以外の影響要因を明確にする
ケアのパフォーマンス指標(リスク調整 要介護度悪化率) を開発

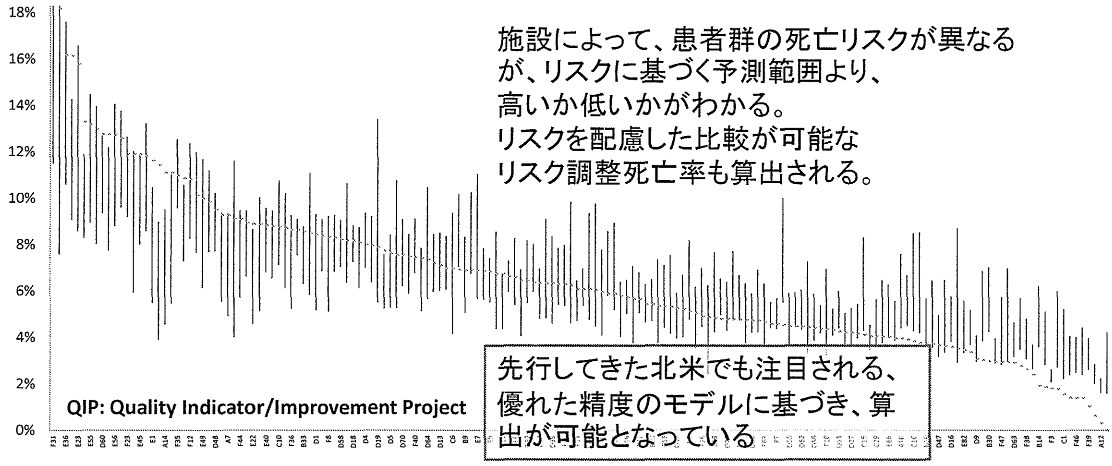
2. ケアの地域差を可視化し要因を明らかにする

診断・治療・ケアや費用に関する実態・パフォーマンスを地域別に可視化し、その地域差の要因を探索し解析する。

4

医療での事例

リスクで調整したアウトカム(医療の質)
(例)急性心筋梗塞の院内死亡率と予測範囲



下記の疾患でも施設別に同様の質指標(リスク調整死亡率)を算出できる。

脳梗塞: Lee, Imanaka, et al. *Cerebrovascular Disease*, 2013.

肺炎: Uematsu, Imanaka et al., *BMC Pulmonary Medicine* 2014.

急性心筋梗塞: Hayashida, Imanaka et al. *J Int Med Res* 2007. Park, Imanaka et al. *Int J Cardiol,* 2013

急性心不全: Sasaki, Imanaka et al. *Can J Cardiol,* 2013

5

医療での事例

リスク調整アウトカムの計測には予測モデルが必須

ELSEVIER

Canadian Journal of Cardiology 29 (2013) 1024–1026

Editorial

Predicting Heart Failure Mortality From Administrative Data: Can It Be Improved?

Jack V. Tu, MD, PhD, FRCPC[a,b]

[a] *Institute for Clinical Evaluative Sciences (ICES), Toronto, Ontario, Canada*

[b] *Sunnybrook Schulich Heart Centre/University of Toronto, Toronto, Ontario, Canada*

See article by Sasaki et al., pages 1055-1061 of this issue.

精度高いモデルに、北米も注目

Heart failure is the leading cause of hospitalizations for older people in Canada and many other industrialized countries. Despite progress in reducing the incidence of new heart failure cases, the prognosis for those who do develop heart failure rema[illegible] 16% [illegible] of 34% following an index hospitalization. Readmission following discharge from hospital is also very common, with approximately 16% of patients being readmitted within 30 days of discharge.[1] These mortality and readmission rates are higher than those for acute coronary syndromes and have attracted increasing attention because of the heavy burden heart failure places on the health care system.

In an effort to improve the quality of care provided to patients with heart failure, performance indicators have been developed in both Canada and the United States by a number of organizations.[2-4] These indicators have included important Medicare patients aged 65 years or older.[6] These data have demonstrated that heart failure mortality rates vary widely across US hospitals.

A critical issue involved in comparing hospital performance for heart failure [illegible] statistically adjust for differences in [illegible] various hospitals. [illegible] differences (eg, demographics, clinical characteristics, patient acuity) be accounted for in any comparison of outcomes across hospitals. Several statistical models have been developed to predict heart failure outcomes from both administrative and clinical data sources that potentially could be used for case-mix adjustment purposes. Administrative databases such as the Canadian Institute for Health Information (CIHI) hospital Discharge Abstract Database (DAD) consist of data collected for the administration of the health care system and have the advantage of being relatively inexpensive, routinely collected,

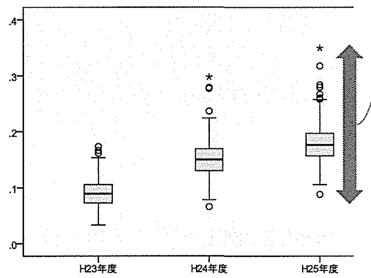
6

3. 技術普及を可視化し要因を明らかにする

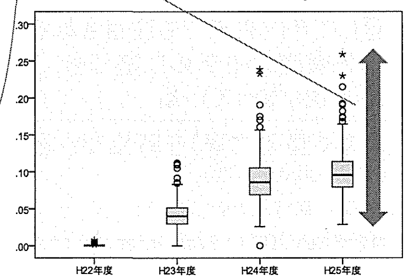
認知症の診断、薬･技術の推移･普及とその地域差について、可視化し、その普及要因を解析する。
（望ましいケアの普及施策への貢献を目指す）

この顕著な地域差は、資源充実を反映か？

メマンチン塩酸塩投与割合



ガランタミン臭化水素酸塩投与割合



新薬の普及：
メマンチン塩酸塩、ガランタミン臭化水素酸塩は、副作用がより強い等から、専門医がより関与している可能性があり、普及の地域差と、専門家等の医療資源の充実度とが、関係している可能性があり、検証を始めている。

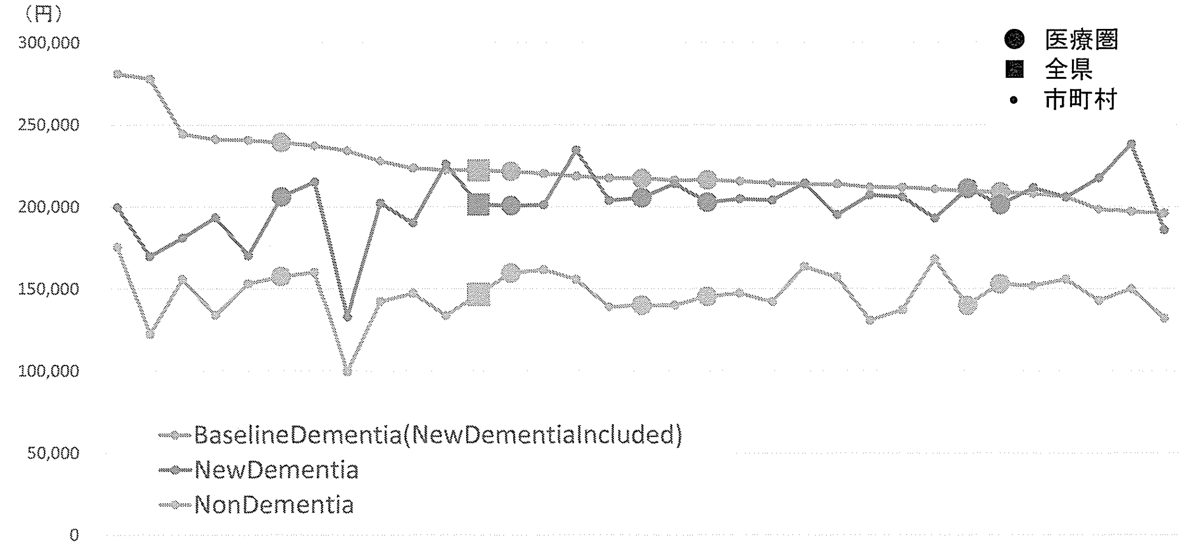
7

アウトカムの要因と認知症

- 要介護度悪化率
- 介護費用

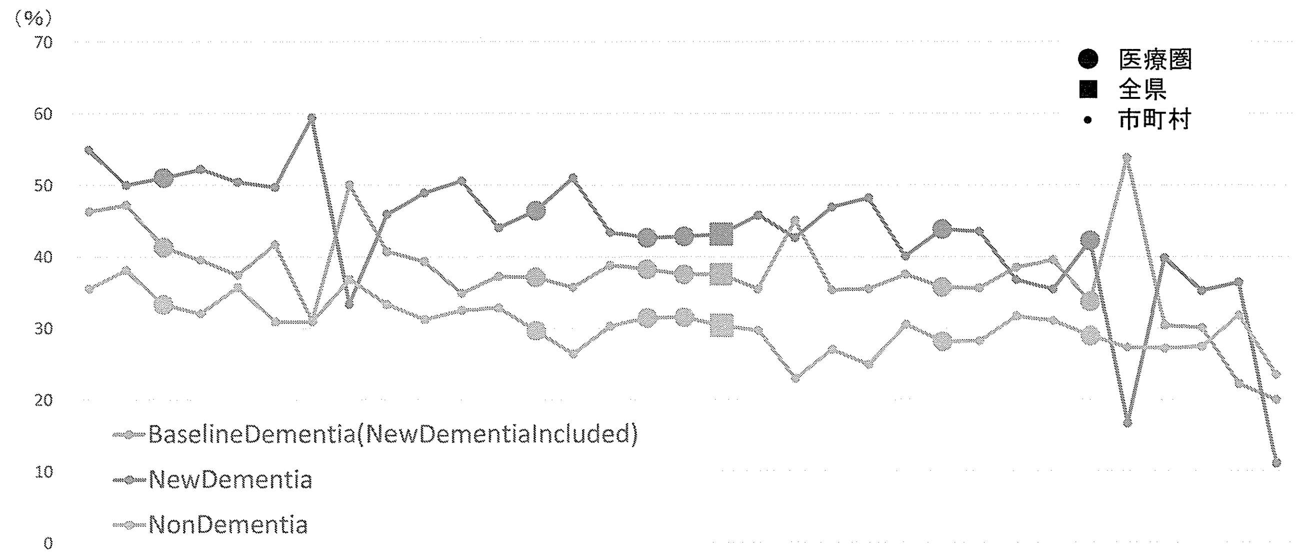
8

201006＆201005使用者一人当たり認知症状況別の月平均介護給付費



9

市町村別・各認知症状況別の要介護度悪化割合



*2010年6月2011年6月。
*市町村は悪化割合の順。

10

要介護度悪化関連因子

Lin, H.-R., T. Otsubo and Y. Imanaka (2015). "The Effects of Dementia and Long-Term Care Services on the Deterioration of Care-needs Levels of the Elderly in Japan." *Medicine* **94**(7): e525.

目的

介護保険の対象者が利用しているサービス内容、および各対象者の認知症罹患の状況と、要介護度悪化との関連を探索すること。

対象

京都府の介護保険と、後期高齢者医療制度と、国民健康保険データベースの集合で、65歳以上、要介護度認定が要介護度1から5の介護サービス利用者

方法

- 観察期間：2010年6月～2011年5月
- サンプル数：50,268
- 分析方法：Multiple Logistic Regression
- 説明変数：性、年齢、要介護度、認知症、利用サービス種類
- 被説明変数：

  2011年6月要介護度悪化（1）

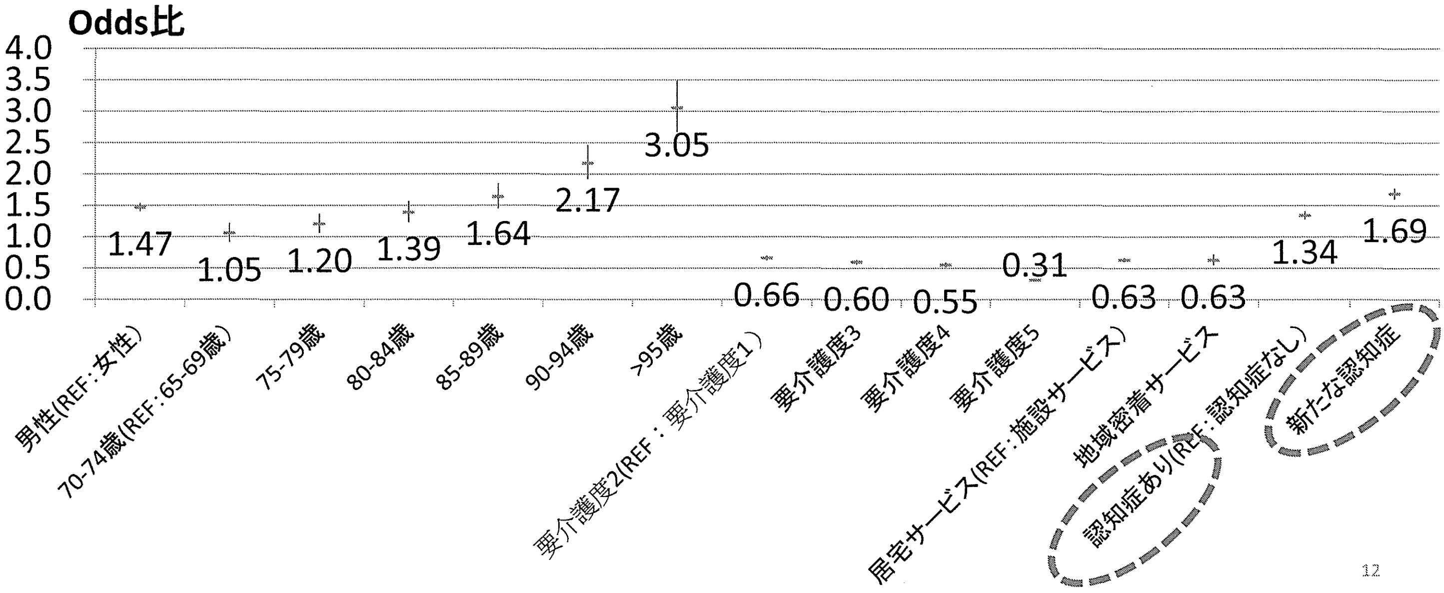
  2011年6月要介護度悪化してない（0）

11

結果

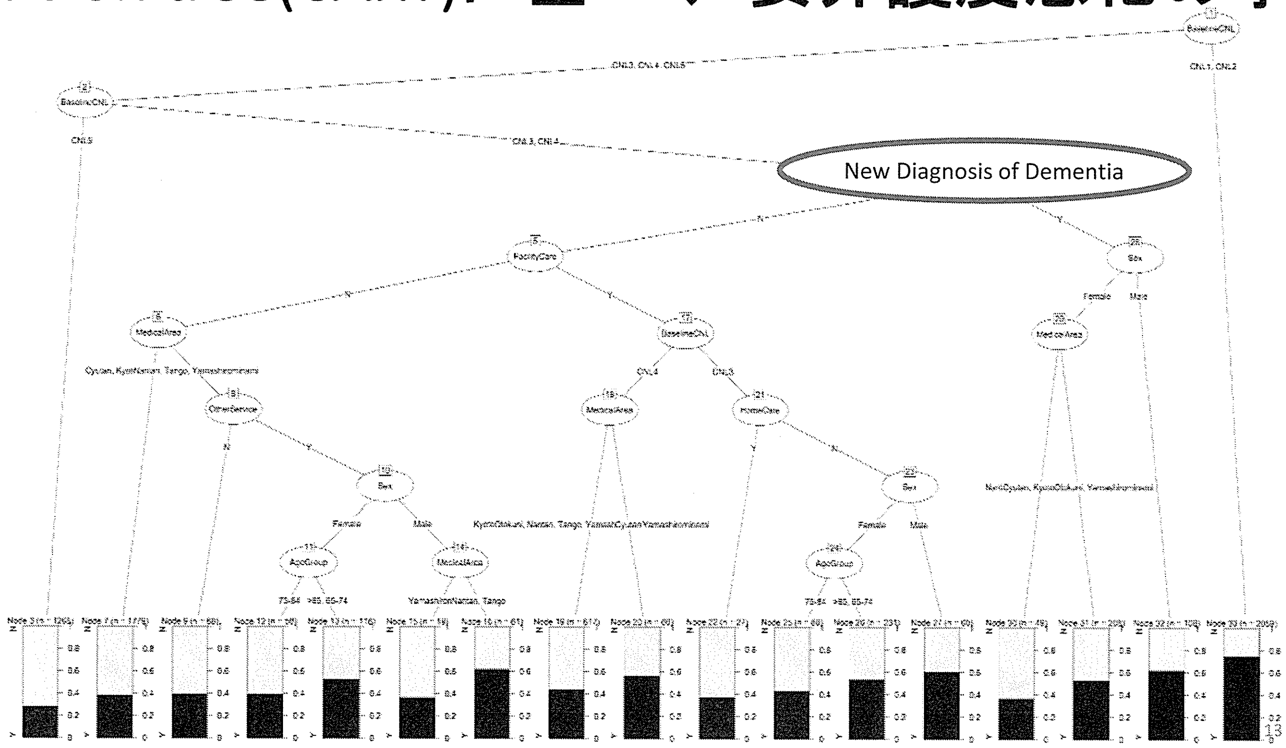
Lin, H.-R., T. Otsubo and Y. Imanaka. *Medicine* **2015**

- 被保険者における「施設サービスの利用」、「男性」、「高齢」、要介護度低いおよび「認知症あり」は、要介護度悪化のリスク要因である。
- C-statistic: 0.634



12

Decision tree(CART)に基づく 要介護度悪化の予測



介護費用関連因子(1)

Lin, H.-R., T. Otsubo and Y. Imanaka (2014). The relationship between dementia diagnosis and long-term care expenditures. The 9th Annual Conference of Japan Health Economics Association (JHEA): Tokyo, Japan Health Economics Association.

目的

認知症の状態を考慮して、各介護サービスの使用の状況を明らかにし、介護費用関連する因子を探索することを目的とする。

対象

京都府の介護保険と、後期高齢者医療制度と、国民健康保険データベースの集合で、65歳以上、要介護度認定が要介護度1から5の介護サービス利用者

方法

- 観察期間:2010年6月～2011年5月
- サンプル数:44,441
- 分析方法: Multiple Linear Regression
- 説明変数:性、年齢、要介護度、認知症、利用サービス種類
- 被説明変数:2011年6月の介護費用(円)

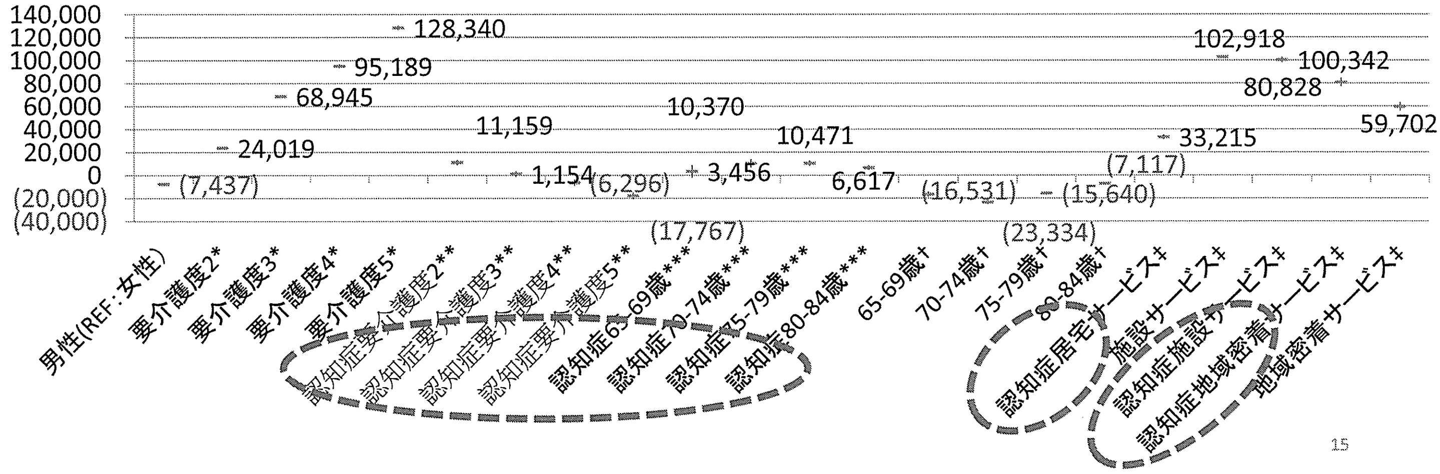
結果

Lin, H.-R., T. Otsubo and Y. Imanaka. *Japan Health Economics Association* **2015**

- 全体では、女性、施設サービスを利用する、高い要介護度、高齢、介護費用が高くなる。
- 認知症ありグループでは、居宅と地域密着型サービスを利用する、低い要介護度、若い、介護費用が高くなる。
- $R^2 = 0.484$

*レファレンス：要介護度1
**レファレンス：認知症要介護度1
***レファレンス：認知症85歳以上
†レファレンス：85歳以上
‡レファレンス：居宅サービス

介護費用(円)



15

介護費用関連因子（2）

Lin, H.-R., T. Otsubo, N. Sasaki and Y. Imanaka (2016). "The determinants of long-term care expenditure and their interactions."*Int J Healthc Manag*.(in press)

目的

認知症の有無による、性別に介護サービスの利用状況と、介護費用の増大との関連を明らかにする。

対象

京都府の介護保険と、後期高齢者医療制度と、国民健康保険データベースの集合で、65歳以上、要介護度認定が要介護度1から5の介護サービス利用者

方法

- 観察期間：2011年6月
- サンプル数：63,969
- 分析方法： Multiple Linear Regression
- 説明変数：性、年齢、要介護度、認知症、利用サービス種類
- 被説明変数：2011年6月の介護費用（円）

16