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Regional differences in electronic medical record adoption in Japan: A nationwide longitudinal ecological study

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ABSTRACT

Purpose: Regional differences in the adoption of electronic medical records (EMR) are a major problem, yet little is known about these differences internationally. We analyzed regional differences in EMR adoption in Japan and evaluated factors associated with these differences.

Methods: This nationwide ecological study used secondary data from all secondary medical service areas (SMSAs) in fiscal years 2008 (n = 348) and 2014 (n = 344). For each SMSA we collected the following information from a Japanese national database: the number of medical facilities that had adopted EMR, the population density, the average per capita income, the number of working doctors per 1000 people, and the proportion of interns to all working doctors. To adjust for medical facility characteristics in each SMSA, such as number of beds, public versus private hospital, and hospital type (psychiatric or other), we estimated the standardized adoption ratio (SAR) for EMR adoption, modeled on the standardized mortality ratio. We calculated Moran's I for the SAR and investigated whether the SAR had spatial autocorrelations. We evaluated the association between the SAR and regional factors with a conditional autoregressive model. We compared these results in 2008 and 2014, for both hospitals and clinics.

Results: While the EMR adoption rate in SMSAs increased, Moran's I of the SAR in hospitals was close to 1 in both 2008 and 2014, and Moran's I of the SAR in clinics increased from 2008 to 2014. For hospitals, there was a significant association between the proportion of interns to all working doctors and the SAR only in 2008. For clinics, average income in the SMSA was positively associated with the SAR, whereas the number of working doctors was negatively associated with the SAR in both 2008 and 2014. Population density was positively associated with the SAR only in 2014.

Conclusion: From 2008 to 2014, EMR adoption in Japan generally increased, but geographical differences did not improve. Regional factors associated with the SAR were different for hospitals than for clinics. Therefore, the government should take different approaches for clinics and hospitals to improve regional differences in EMR adoption, especially in providing financial and technical support.

1. Introduction

Several studies have described the positive effects of using electronic medical records (EMR), including improvements in healthcare quality, efficiency, and outcomes [1–3]. In addition, there has been recent rapid development of various data mining techniques for big data and machine learning methods such as deep learning; it is expected that these methods will improve the accuracy of analysis and prediction in healthcare.

Although the EMR adoption rate has been rising worldwide, the rate in Japan is lower than that in other countries [4–8]. According to the Survey of Medical Institutions conducted by the Ministry of Health, Labour and Welfare (MHLW), 32.2% of hospitals and 35.0% of clinics in Japan used EMR in fiscal year 2014 [9]. According to the same survey, 45.5% of hospitals and 60.8% of clinics in 2014 did not intend to adopt EMR in the future. To promote the more efficient spread of EMR, the government needs to understand the barriers to EMR adoption in detail. For example, a previous study reported the political background that small hospitals and clinics received less financial support than larger hospitals in Japan [10].

In the United States, regional variation in EMR adoption is a major problem [11], contributing to the risk of a "digital divide" [12].

Abbreviations: CAR, conditional autoregressive model; CI, credible interval; EMR, electronic medical records; MCMC, Markov chain Monte Carlo; MHLW, Ministry of Health, Labour and Welfare; SAR, standardized adoption ratio; SMR, standardized mortality ratio; SMSA, secondary medical service area; RR, relative risk

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However, few studies have evaluated regional differences in EMR adoption outside the United States. Factors associated with regional differences in EMR adoption have not been well studied, with a few exceptions, which include the associations between EMR adoption and healthcare professional shortage area status, metropolitan status, and concentration of minority populations [12–14]. No previous study has considered spatial characteristics when constructing a statistical model, although spatial proximity to prior EMR adopters is a key factor in EMR adoption [15].

A longitudinal study in Japan analyzed overall trends in EMR adoption rates [10]; another study used a questionnaire survey to determine the reasons facilities adopted EMR [16]. However, to our knowledge, no study has investigated regional differences in EMR adoption in Japan.

In view of previous studies in the United States, we hypothesized that there are regional differences in EMR adoption in Japan, and that regional factors are related to these differences. To verify this hypothesis, we analyzed regional differences in EMR adoption in Japan with a spatial statistical method.

2. Methods

2.1. Study design

This nationwide ecological study used secondary data and targeted the whole of Japan. Japan comprises 47 prefectures; the Japanese government established subprefectural medical regions called secondary medical service areas (SMSAs) [17]. An SMSA is defined as a medical unit that evaluates demand and supply of health resources. We analyzed the data for fiscal years 2008 and 2014 and considered time-series changes by comparing the results. We targeted all SMSAs in Japan according to the surveys (n = 348 in 2008; n = 344 in 2014).

2.2. Data sources

Geographical information, such as municipality boundary data, was obtained from the Municipality Map Maker for Web [18]. Because each SMSA consists of several municipalities, we determined SMSA data by combining municipality-level parameters with ArcGIS version 10.2.1 (ESRI Japan Inc., Tokyo, Japan).

We obtained data on EMR adoption from the Survey of Medical Institutions [9]. This detailed triennial survey of all medical institutions is conducted by the Japan MHLW. Data used in this study were from fiscal years 2008 and 2014. Because the survey is mandatory, in principle the response rate is 100% and all medical facilities are covered (hospitals: 8794 in 2008, 8493 in 2014; clinics: 99,083 in 2008, 100,461 in 2014) [9]. The survey was also conducted in 2011, but because of the Great East Japan Earthquake, data from some municipalities in Fukushima and Miyagi prefectures are missing from that survey. We defined EMR adoption as a response of 1 or 2 to the survey item, "Electronic medical record system adoption status: 1. Adopted in entire hospital/clinic, 2. Adopted in part of hospital/clinic, 3. Specific adoption scheduled, 4. No adoption scheduled." Detailed survey forms are available on the MHLW website [19]. The response "2. Adopted in part of clinic" indicates that medical records are digitized in only some departments of the clinic or that some doctors continue to keep handwritten records [20]. The definition of "clinic" in Japan is a medical institution with fewer than 20 beds. Although patients are free to choose medical institutions in Japan, they are strongly recommended by the health insurance system to be first seen in clinics and then seen in hospitals after referral from clinics. We obtained permission from the MHLW to analyze these survey data. After acquiring data on each medical facility, we aggregated the values of each SMSA for analysis. In addition, for each SMSA we calculated EMR adoption in hospitals and in clinics separately for further analysis.

As other regional factors, we used all available socioeconomic and macro health-environment factors identified in previous studies [12–14], which we collected from e-Stat, the national Japanese government database [21]. These factors were: population density (people per km^2), average per capita income (million JPY), the number of working doctors per 1000 people (separately for hospitals and clinics), and the proportion of interns to all working doctors. Because the population density distribution was extremely skewed, we categorized SMSAs according to quantile of population density, ranging from quantile 1 (lowest density) to quantile 4 (highest density).

2.3. Statistical methods

2.3.1. Standardized adoption ratio (SAR)

When analyzing regional EMR adoption, it is important to consider regional differences in medical facility characteristics. A previous study in Japan showed that EMR adoption was affected by characteristics such as practice size [10]. However, previous studies have not considered these regional differences when calculating EMR adoption rates [11–14]. Hence, to adjust for medical facility characteristics, we created a standardized ratio of EMR adoption, the standardized adoption ratio (SAR). The SAR is modeled on the standardized mortality ratio (SMR), which is a method of adjusting inter-regional population composition to calculate inter-regional mortality ratios. The SMR has commonly been used in epidemiology to calculate regional mortality ratios, adjusting for patient characteristics such as age and sex. For more details on the SMR, please refer to our previous study [22].

Using the SMR as a model, we calculated the SAR for EMR adoption, adjusting for the number of facility beds, public versus private hospital, and type of hospital (psychiatric or other). The SAR was calculated by dividing the observed number of hospitals with EMR adoption by the expected number. We calculated ratios for public hospitals and private hospitals and for three subgroups according to number of beds: 20–199, 200–399, and over 400 beds. We calculated ratios separately for psychiatric hospitals; thus we evaluated a total of seven hospital subgroups. We calculated national EMR adoption rates according to subgroup, then multiplied these national adoption rates by the number of hospitals in each subgroup in each SMSA to obtain the expected number of hospitals with EMR adoption. We classified clinics into two subgroups: those with versus without beds. We multiplied the national EMR adoption rates of clinics by the number of clinics in each subgroup in each SMSA to obtain the expected number of clinics with EMR adoption.

2.3.2. Conditional autoregressive model (CAR)

We estimated the SAR with a CAR Leroux model [23]. For more details on this method, please refer to our previous study [22]. We assumed a Poisson distribution for the observed number of hospitals with EMR adoption and set the expected number of hospitals with EMR adoption as the offset variable. We used Markov chain Monte Carlo (MCMC) simulations with 120,000 iterations and a burn-in period of 20,000. We used Geweke's diagnostic to check MCMC convergence [24]. We calculated Moran's I for the SAR and checked whether the SAR had any spatial autocorrelation [25]. Moran's I is an index of the extent of spatial autocorrelation of the data; values close to 1 suggest the existence of a positive autocorrelation and values close to -1 suggest a negative autocorrelation.

To investigate the associations between regional factors and SARs, we included these in the CAR Leroux model as explanatory variables. We estimated the relative risk (RR) and 95% Bayesian credible interval (CI) for each variable. According to a previous study [26], we considered an association to be not significant if the 95% CI of the RR included 1. We evaluated the multicollinearity of covariates using the variance inflation factor [27]; all variables had a variance inflation factor of < 2.5. These models were constructed separately for hospitals and clinics for fiscal years 2008 and 2014.

Descriptive statistics are shown as median and interquartile range;