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Impact of electronic medical records (EMRs) on hospital productivity in Japan

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ABSTRACT

Introduction: Consistent with the global trend, Japanese hospitals have increasingly adopted electronic medical record (EMR) systems in the last 20 years. Although improved productivity is emphasized as one of the benefits of information technology (IT), there is a paucity of data regarding how the use of EMR systems influences the productivity of Japanese hospitals.

Methods: This retrospective study focused on 658 municipal hospitals. The study period was from 2006 to 2015. We analyzed the labor productivity and multi-factor productivity (MFP) of the hospitals and their average rate of change during the study period. Logistic regression models were used to assess how EMR implementation influenced labor productivity and MFP growth. We considered the duration of EMR operation, and hospitals using EMRs were divided into three groups based on tertiles of time elapsed since the implementation of the EMR system: "early adopters", "followers", and "late adopters".

Results: We found that the implementation of an EMR system had a significantly negative impact on MFP growth for the 'late adopters' (OR 0.51; 95%CI 0.31–0.82; p = 0.006). No significant association was found between EMR implementation and labor productivity growth.

Conclusion: EMR implementation has an adverse effect on the productivity of municipal hospitals in Japan. This finding should be considered when developing future healthcare policies promoting the implementation of IT.

1. Introduction

The implementation of medical information systems in hospitals is progressing steadily throughout the world [1,2]. In Japan, the implementation of electronic medical record (EMR) systems began in earnest in 2000. Following legislation to facilitate the introduction of EMRs, the 2001 "Grand Plan" released by the Ministry of Health, Labor and Welfare (MHLW) set a goal to implement EMR systems in 60% of the hospitals housing over 400 beds [3]. Consequently, there was a rapid development of structural support, such as subsidies, medical reimbursement fee incentives, and vendor product development [4]. Since then, the number of medical institutions implementing an EMR system has increased steadily. In Japan, EMR systems implemented in hospital settings typically interface with systems related to clinical documentation, computerized provider-order entry, access to test and imaging results, and billing [13]. Alongside the use of such basic systems [3], hospitals varied in their use of clinical decision support systems [13]. Whereas the vast majority of the EMR market was comprised of products offered by a few vendors (e.g., 76% of the systems active in 2015 were offered by four vendors: Fujitsu, NEC, Software Service, and CSI) [12], the degree of standardization or interoperability among medical institutions has been very low because of the substantial customization at each hospital [4,56].

Such widespread expansion of EMR implementation might be due to the various benefits expected from the introduction of information technology (IT). Specifically, in addition to improved care, enhanced patient services, and increased safety for medical treatments, increased productivity has been consistently emphasized [1]. In particular, a reduced burden of work for healthcare professionals and the use of more efficient medical treatments due to a reduction in unproductive practices are supposed to lead to the suppression of medical costs by way of increased productivity [5,6]. Current moves to advance the further use of EMRs, which can presumably solve various problems in healthcare, are based on a consensus about the increased productivity and efficiency attributable to EMRs.

Previous studies on EMRs vary in methodology and topic, such as

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the work efficiency of doctors and nurses, the flow of patients and medical tests, and the financial trends in hospital revenues and costs [7–9]. As the impact of IT solutions on productivity is reported to be both positive and negative, it is difficult to derive a comprehensive outlook from these previous studies [10,49]. Although a variety of studies on the implementation of EMR systems, and a wide range of profiles of institutions in Japan using such systems, have been published [4,11–13,44,57], we do not know how EMR implementation contributes to the increased productivity of hospitals in Japan.

Thus, we conducted a multi-center study and analyzed the impact of the introduction of EMRs on participating hospitals' mid- to long-term measures of productivity. In particular, we focused on municipal public hospitals. Our research on the effects of the implementation of EMR systems is one of the few such studies in Japan. Examination of the impact of EMRs in public hospitals, which play an important role in the Japanese healthcare system, will produce useful findings relevant to the direction of future healthcare policies in this domain. The present study on Japanese cases will add much to the extant literature focused on other countries [8,9,18,21,23,24].

2. Method

2.1. Research design and sample

We conducted a retrospective, multi-center study treating municipal public hospitals as the units of analysis. The research was performed from the beginning of the 2006 Japanese fiscal year to the end of the 2015 Japanese fiscal year. (In Japan, fiscal years begin on April 1 and end on March 31.) Our research utilized two databases: the fiscal data of municipal hospitals, and data relating to status of EMR implementation. For the fiscal data, we relied on the 2006–2015 "Handbook of Regional Public Corporations" [14], which includes hospital profiles (year opened, number of hospital beds) for each hospital in each fiscal year as well as detailed statistical and financial data (e.g., numbers of staff and patients and financial records). For EMR implementation and its timing, we utilized the "White paper on electronic health records and picture archiving and communication systems", which was published by "New Healthcare" in conjunction with the Japan Association for the Healthcare Information Systems Industry (JAHIS) [15].

There were 943 municipal hospitals in Japan during the 2015 fiscal year. To focus on changes in long-term productivity markers between 2006 and 2015, we examined only those institutions with data that could be continuously, retrospectively traced to 2006 for the current study. Therefore, institutions that experienced mergers, division, reorganization andso forth during the study period, as well as institutions that began operating during that time, were excluded from the sample. Hospitals with missing data for the 10-year study period and psychiatric hospitals were also excluded.

2.2. Variables

2.2.1. Dependent variables

Productivity is typically calculated by dividing the amount produced by the amount of labor input [16]. However, there are various definitions of, and methods for, calculating productivity [16], and there is no single established method. However, "labor productivity" and "multi-factor productivity" (MFP) are regarded as generic markers indicating the organizational productivity of hospitals [17]. Thus, we utilized these two markers, which were calculated as follows:

$$Labor \quad productivity = \frac{\text{Value} \quad \text{added}}{Number \quad of \quad staff}$$

The "labor productivity" of a hospital is calculated by dividing its output by its labor input [16]. In this study, "added value", defined as revenue minus expenses, was used for output [18]. We calculated the labor productivity for each year by dividing this added value by the average number of staff members in each fiscal year. This method of calculation was used in previous studies regarding labor productivity [19] and is also consistent with the US Bureau of Labor Statistics' (BLS) definition of labor productivity [20]. Although some research uses total labor hours [17,19], others use number of employees as a proxy variable for the amount of labor invested [21]. In this study, due to limitations in our data, we utilized the latter.

$$MFP = \frac{\begin{array}{c}\text{(Deflated net revenues of the year)}\\ \text{/(Deflated net revenues of the previous year)}\end{array}}{\begin{array}{c}\text{(Deflated net expenses for the year)}\\ \text{/(Deflated net expenses of the previous year)}\end{array}}$$

"Multi-factor productivity" (MFP) is also a marker of the productivity of a business. The US BLS and other studies have defined this as a change in the level of outputs relative to a change in the level of two or more inputs [22]. This index of productivity considers not only labor but also capital investment and other inputs. Recent research examining hospital productivity has found MFP to be a useful indicator [23–28], and a number of methods of MFP prediction and calculation have been reported. We calculated MFP according to the method advocated by Cylus et al. [27,28], who defined it as follows: "the ratio of the change in the real quantity of outputs to the change in the real quantity of inputs provides an estimate of hospital MFP in a given year" [27,28]. Following this method, we calculated output and input from the revenue and expense items by deflating price changes, based on the relevant deflators, and then estimated MFP. Although Cyrus et al. used several price indices specific to the hospital sector [27,28], several of these indexes were not available in Japan. Thus, in such cases, we utilized more generic price indices, such as the corporate goods price index and the real wage index (we set 2015 for the base year). Finally, because the first available MFP data were for 2007, the labor productivity and MFP growth between 2007 and 2015 were analyzed in the study. These two productivity indicators were calculated based on data on revenues and expenses related to medical activities, payroll costs, materials costs, depreciation, external subcontracting costs, and employee numbers, which are included in the "Handbook of Regional Public Corporations" [14,15].

2.2.2. Independent variables

The JAHIS and the Japan Society for Instruction Systems in Healthcare (JSISH) [29] have suggested factors that are relevant to EMR, and a consensus has emerged with respect to the definition of EMR [4]. We assumed that the "White Paper" survey was aligned with such a conceptual definition. Indeed, the decision to implement EMR systems in hospitals was based on the information in the "White paper". Specifically, the month and year during the research period that each facility introduced EMRs were indicated. Using this information, we determined the presence or absence of EMRs and the time elapsed since their introduction. We defined the time of introduction as the time of initial EMR implementation at a facility; thus, we excluded other events, such as serial system updates and upgrades.

We also controlled for the following variables in the analysis. (1) Number of licensed beds: in accordance with the MHLW periodic reports on EMR implementation in the healthcare sector [30], we classified this variable into three categories (199 or fewer, between 200 and 399 beds, and 400 or more beds). (2) Government-designated emergency hospitals: this variable has two categories, yes and no [31]. (3) Facilities housing critical care emergency centers: this variable has two categories, yes and no [32]. (4) Training and educational facilities: this variable has two categories, yes and no [33]. (5) Hospitals in designated remote areas: this variable was defined by the Ministry of Internal Affairs and has two categories, yes and no [34]. Additionally, the annual averages for inpatient bed occupancy rates and number of outpatients were also added as independent variables. While these factors were treated as productivity outcomes in the previous study [21], we treated them as explanatory variables, given that they relate to labor productivity and MFP as intermediary variables.

2.3. Statistical analysis

Participating hospitals were divided into "EMR-implementation hospitals" and "others", and the characteristics of each group were analyzed using descriptive statistics (i.e., median, interquartile range (IQR), and frequency). Differences between groups were investigated with the Chi-square test for categorical data and the Wilcoxon rank sum test for continuous values. To examine the long-term effects of EMR, we evaluated annual changes in the rates of labor productivity and MFP. We calculated the average annual change rates for each year from 2007, the first year for which labor productivity and MFP can be calculated, to 2015. We then divided hospitals into two groups according to whether they performed higher or lower than the median rate of average annual change. Using this hospital-related variable, we examined differences in the two groups with regard to the study variables. To investigate associations between EMR implementation and productivity growth, we performed a logistic regression analysis including time elapsed since the implementation of EMRs in the model. Time elapsed was divided into three segments based on tertile points (48 months and 96 months). Thus, we created four hospital groups; non-EMR hospitals (referent), hospitals with 1–47 months of implementation ("late adopters"), hospitals with 48–96 months of implementation ("followers"), and hospitals with > 96 months of implementation ("early adopters"). Finally, we divided hospitals into two groups by the median number of licensed beds and performed individual logistic regression analyses to take into account the influence of the size of the hospitals on our analyses. To evaluate these logistic regression results, we examined goodness-of-fit indices. The significance level for all tests was $P < 0.05$ (two-sided). All statistical analysis was performed using JMP® 12 (SAS Institute Inc., Cary, NC, USA).

3. Results

Fig. 1 which presents the characteristics of study sample, shows that there were 658 hospitals that met the inclusion criteria. Fig. 2 shows the distribution of EMR systems among the participating institutions. Of the 658 participating institutions, 384 (58%) had introduced EMR by 2015. Table 1 outlines the characteristics of the 658 institutions in terms of EMR implementation status. Of the institutions that implemented EMR

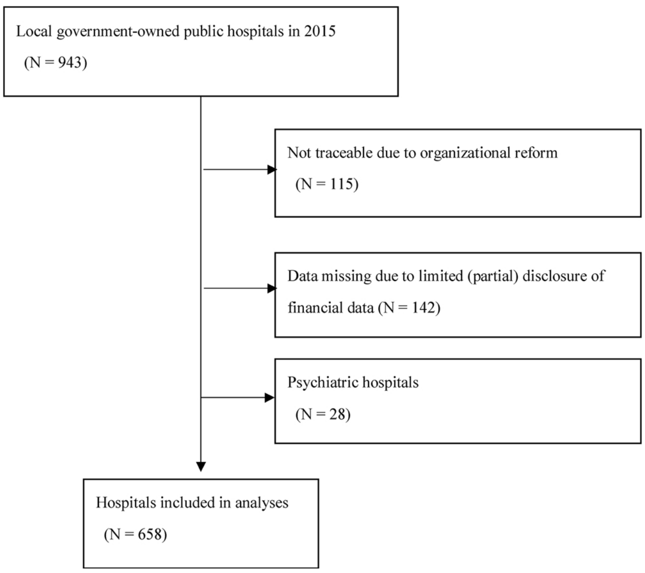

Fig. 1. Study Sample.

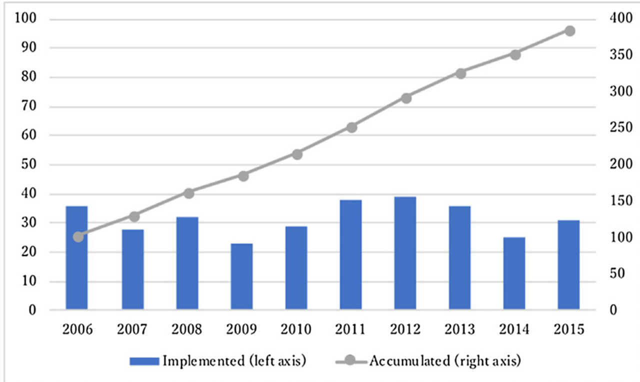

Fig. 2. Annual changes in the number of public hospitals with EMR systems.
The bars show the numbers of hospitals that initially implemented EMR systems in each fiscal year, and the line graph shows the total numbers of hospitals that implemented EMR systems by the end of the fiscal year. Of the 658 hospitals, 384 implemented EMR systems by the end of fiscal year 2015. These numbers do not include hospitals that replaced or improved their systems.

by 2015, 119 (31% of the total) had more than 400 beds, 70 (18.2%) had adjoining critical care emergency centers, 158 (41.2%) were educational institutions, and 76 (19.8%) were located in designated remote areas. With respect to these variables, there was a significant difference between the groups that did and did not implement EMR systems by 2015. Figs. 3 and 4 graphically present the annual rates of change in labor productivity and MFP according to bed size for the 658 institutions. As in Table 1, we divided hospitals into three groups based on number of licensed beds. The mean annual rates of change for all institutions during the study period were 0.24% and 0.07% for labor productivity and MFP, respectively. The analysis of data from the 8-year period for which trends can be examined (*i.e.,* 2008–2015) showed that, although the total growth rates of the two productivity markers for the three groups based on bed size were low, they showed some variability for each year. The present findings are mostly consistent with previous findings reporting that the rate of change was typically within the range of - 5% to +5%, which is lower than that in other industries [17–19,27,28].

Table 2 shows hospital characteristics by the rates at which labor productivity and MFP changed. For purposes of this comparison, we divided the labor productivity and MFP growth rates into two groups by the median value (high growth: ≧median, low growth: < median). High-growth hospitals tended to have more hospital beds, a critical care emergency center, a high growth rate in bed occupancy and numbers of outpatients, and longer times since implementation of EMR systems. They also tended to be teaching hospitals and located in urban areas (namely, areas other than designated remote areas). In terms of MFP, the characteristics of high-growth hospitals were similar to those of labor productivity.

Table 3 shows the results of a logistic regression analysis on the impact of EMR implementation on changes in labor productivity and MFP expressed as odds ratios. No clear relationship was found between EMR implementation period and labor productivity growth. In contrast, EMR implementation had a negative effect on MFP growth. Specifically, the results indicated an increased risk for a worsening MFP among "late adopters", whose period of implementation was short. To confirm the results of the logistic regression analysis, we calculated Spearman's rank correlation coefficients for all study variables (Table 4). Then, we performed logistic regression analyses excluding the member of each pair of independent variables with the highest correlation coefficient (absolute value of 0.5 or above) and obtained the same findings (no clear relationship in labor productivity growth and worsening MFP growth for hospitals introducing EMR relatively recently). Thus, we

Table 1
Hospital characteristics in 2015 according to EMR implementation status.

	Implemented EMR (N = 384)		Not implemented (N = 274)		p
	n	(%)	n	(%)	
Hospital characteristics					
Total number of licensed beds					
< 200	137	(35.7)	239	(87.2)	< .0001
200–399	128	(33.3)	23	(8.4)	
≧400	119	(31.0)	12	(4.4)	
Designated emergency hospital					
Yes	361	(94.0)	221	(87.6)	0.0037
No	23	(6.0)	34	(12.5)	
Critical care emergency center					
Yes	70	(18.2)	3	(1.1)	< .0001
No	314	(81.8)	271	(98.9)	
Teaching hospital					
Yes	158	(41.2)	11	(4.0)	< .0001
No	226	(58.9)	263	(96.0)	
Located in designated remote areas					
Yes	76	(19.8)	185	(67.5)	< .0001
No	308	(80.2)	89	(32.5)	
Operational activities					
	Median	(IQR)	Median	(IQR)	p
Bed occupancy rate	0.75	(0.67–0.82)	0.67	(0.53–0.77)	< .0001
Number of outpatients	500	(274–851)	150	(93,256)	< .0001
LP and MFP[a]					
	Median	(IQR)	Median	(IQR)	p
Total revenue for medical activities[b]	5,341	(2,299–10,362)	868	(513–1,740)	< .0001
Total cost of medical activities[b]	5,963	(2,564–11,041)	1106	(702–2,151)	< .0001
Salary[b]	3,140	(1,337–5,415)	640	(381–1,170)	< .0001
Material[b]	1,099	(413–841)	140	(85–335)	< .0001
Depreciation[b]	448	(208–841)	75	(42–158)	< .0001
Outsourced services[b]	485	(216–946)	97	(53–185)	< .0001
Number of employees (n)	370	(170–662)	86	(47–153)	< .0001
Organizational productivity (outcome)					
	Median	(IQR)	Median	(IQR)	p
Labor productivity[c]	9,753	(8,418–11,067)	7,751	(6,055–9,508)	< .0001
MFP[d]	1.01	(0.99–1.03)	1.01	(0.96–1.04)	0.392

[a] In million yen unless otherwise specified.
[b] The data for fiscal years 2006–2014 were deflated and expressed in terms of the 2015 value of the yen.
[c] In thousand yen per person. Hospital labor productivity is measured as value-added per staff.
[d] Hospital MFP is measured by output and input, derived from financial revenues and costs.

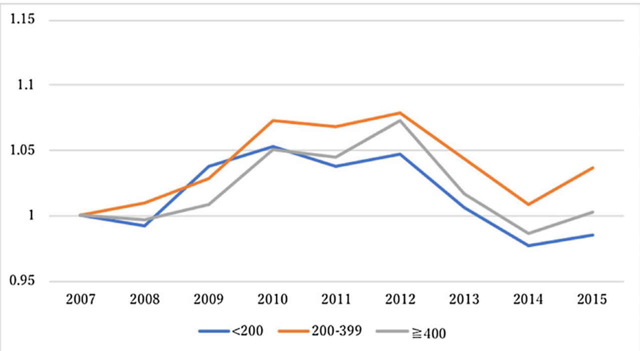

Fig. 3. Annual trends in labor productivity from 2007 to 2015 according to bed size.
The lines show aggregated annual percentage changes in labor productivity for the three groups of hospitals stratified by bed size, treating the 2007 data as 1.0. The average annual growth rate of labor productivity for all hospitals between 2007 and 2015 was 0.24%.

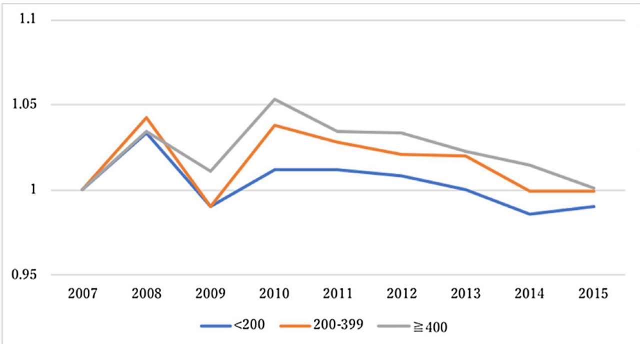

Fig. 4. Annual trends in MFP from 2007 to 2015 according to bed size.
The lines show aggregated annual percentage changes in MFP for the three groups of hospitals stratified by bed size, treating the 2007 data as 1.0. The average annual growth rates of MFP for all hospitals between 2007 and 2015 was 0.07%.

Table 2
Hospital characteristics by growth rate of LP and MFP.

	Labor Productivity Growth				p	MFP Growth				p
	≧Median (N = 331)		< Median (N = 327)			≧Median (N = 318)		< Median (N = 340)		
	n (%)		n (%)			n (%)		n (%)		
Total number of licensed beds										
< 200	150	(45.3)	224	(68.9)	< .0001	191	(60.1)	185	(54.4)	0.001
200–399	98	(29.6)	53	(16.3)		82	(25.8)	70	(20.3)	
≧400	83	(25.1)	48	(14.8)		45	(14.2)	69	(25.3)	
Designated emergency hospital										
Yes	300	(90.6)	299	(92.3)	0.450	285	(89.6)	315	(92.9)	0.133
Critical care emergency center										
Yes	51	(15.4)	22	(6.8)	0.0004	24	(7.0)	49	(14.4)	0.002
Teaching hospital										
Yes	114	(34.4)	55	(16.9)	< .0001	70	(22.0)	99	(29.1)	0.037
Located in designated remote area										
Yes	96	(29.0)	164	(50.5)	< .0001	143	(45.0)	118	(34.7)	0.007
Growth rate in bed occupancy rate										
≧Median	225	(68.6)	103	(31.4)	< .0001	181	(57.6)	148	(44.1)	0.001
Growth in number of out-patients										
≧Median	213	(65.9)	110	(34.1)	< .0001	167	(52.7)	157	(46.2)	0.096
EMR implementation duration[a]										
1–47 months (“Late adopter”)	64	(19.3)	60	(18.4)	< .0001	50	(15.7)	74	(21.8)	0.022
48 –96 months (“Follower”)	83	(25.1)	46	(13.9)		56	(17.6)	73	(21.5)	
97 months or more (“Early adopter”)	82	(24.8)	49	(15.0)		61	(20.1)	70	(20.6)	

[a] Number of months since implementation of EMR from 2007 to 2015.

Table 3
Association between EMR implementation duration and growth by LP and MFP.

	Labor Productivity Growth			MFP Growth		
	OR	(95% CI)	p	OR	(95% CI)	p
Total number of licensed beds						
≦199	Referent					
200–399	2.03	(1.10–3.73)	0.023	2.16	(1.23–3.81)	0.008
≧400	1.48	(0.69–3.19)	0.311	1.03	(0.50–2.11)	0.933
Designated emergency hospital						
No	Referent					
Yes	0.61	(0.33–1.14)	0.121	0.68	(0.38–1.22)	0.196
Critical care emergency center						
No	Referent					
Yes	1.17	(0.57–2.39)	0.675	0.67	(0.35–1.30)	0.239
Teaching hospital						
No	Referent					
Yes	1.31	(0.75–2.29)	0.346	0.89	(0.53–1.49)	0.662
Located in designated remote area						
No	Referent					
Yes	0.95	(0.58–1.57)	0.850	1.90	(1.19–3.03)	0.008
Growth rate in bed occupancy rate						
< Median	Referent					
≧Median	3.68	(2.58–5.24)	< .0001	1.84	(1.31–2.58)	0.0004
Growth in number of outpatients						
< Median	Referent					
≧Median	2.23	(1.55–3.20)	< .0001	1.44	(1.02–2.05)	0.0406
EMR implementation duration						
No implementation	Referent					
1–47 months (“Late Adopter”)	0.98	(0.59–1.62)	0.936	0.51	(0.31–0.82)	0.006
48–96 months (“Follower”)	1.50	(0.88–2.54)	0.133	0.61	(0.37–1.01)	0.053
97 months and more (“Early Adopter”)	1.27	(0.72–2.25)	0.404	0.81	(0.48–1.37)	0.432

OR: odds ratio, CI: confidence interval.

Table 4
Correlation coefficients of variables in the logistic regression model.

	1	2	3	4	5	6	7
1. Number of Beds (< 200:0, 200-299:1, ≧400:2)							
2. Designated emergency hospital (No: 0, Yes: 1)	−0.14***						
3. Critical Care Emergency Center (No: 0, Yes: 1)	0.5***	−0.11**					
4. Teaching hospital (No: 0, Yes: 1)	0.68***	−0.18***	0.41***				
5. Located in Remote Area (No: 0, Yes: 1)	−0.65***	0.08*	−0.29***	−0.46			
6. Growth of bed occupancy rate (< Median: 0, ≧Median: 1)	0.08	0.01	0.09*	0.10*	−0.10*		
7. Growth of outpatients (< Median: 0, ≧Median: 1)	0.25***	0.01	0.17***	0.21***	−0.28***	−0.27***	
8. EMR implementation duration (No implementation:0, Early adopter:1, Follower: 2, Late adopter: 3)	0.55***	−0.11**	0.33***	0.50***	−0.49**	−0.12**	−0.25***

Spearman's rank correlation coefficient.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 5
Results of logistic regression for groups stratified by number of licensed beds.

	Group 1			Group 2		
	Number of beds≧Median			Number of beds < Median		
	OR	(95% CI)	*p*	OR	(95% CI)	*p*
Labor Productivity						
No Implementation	Referent					
1–47 months ("Late Adopter")	1.61	(0.70-3.75)	0.261	0.94	(0.48-1.83)	0.857
48–96 months ("Follower")	2.83	(1.23-6.51)	0.014	1.02	(0.48-2.23)	0.942
97 months and more ("Early Adopter")	2.29	(1.00-5.25)	0.050	0.93	(0.33-2.62)	0.883
MFP						
No Implementation	Referent			Referent		
1–47 months ("Late Adopter")	0.52	(0.36-1.60)	0.093	0.51	(0.27-0.98)	0.043
48–96 months ("Follower")	0.56	(0.27-1.19)	0.277	0.66	(0.31-1.40)	0.281
97 months and more ("Early Adopter")	0.75	(0.32-1.49)	0.360	1.07	(0.41-2.83)	0.882

OR: odds ratio, CI: confidence interval.
For the analysis, hospitals were divided into two groups by the median of the total number of licensed beds (median = 137.5). We controlled for teaching hospitals, emergency hospitals, critical care emergency centers, and location.

believe multicollinearity does not pose a serious problem in the study.

Table 5 shows the results of the logistic regression analyses for the two groups of hospitals divided according to number of beds. Among hospitals with more beds (≧median), labor productivity was increased among the "followers" and "late adopters", whereas there was no clear relationship in terms of MFP. Among those with fewer beds (< median), the results indicated the worsening of MFP for "late adopters".

4. Discussion

The current research confirmed that implementation of EMR systems had a short-term negative effect on MFP. In particular, the parallel analysis of groups according to number of beds also indicated the negative effect of EMR systems on MFP among hospitals with fewer beds. These findings are the first to illustrate statistically the impact of EMR implementation on productivity in Japanese hospital settings. Also, our study was the first to consider the period since implementation and to clarify the negative impact of EMRs on productivity. In Japan, municipal hospitals constitute an important hospital sector, with strong connections to policy-based healthcare, such as emergency care and care for remote areas; in 2015, they comprised 11.1% of all hospitals in Japan. There were a number of benefits related to the current study's focus on municipal hospitals. The first is that the ownership structure is controlled for; indeed, much of the research regarding EMR performed to date has highlighted the effects of differences in ownership structure (public or private) on performance [21,23]. Second, the compliance of municipal hospitals with uniform financial accounting standards should limit the variability of financial disclosures. Third, as all these hospitals received the identical compensation under the national uniform insurance system, the expressed value of medical activity revenues can be considered to be a reflection of the volume of healthcare services carried out at each facility; this rendered a comparison of these fiscal data easy to perform.

Much of the research to date has found that the introduction of IT or an increase in IT investment does not necessarily lead to increased productivity and output, and this phenomenon has been referred to as the "IT paradox" [35]. The IT effect exerts a varied influence for a certain period of time, ranging from several months post-implementation to 6–7 years later, on organizations in both the healthcare and other industries [36–39]. For instance, prior research reported doctors required about 2 years to become familiar with data entry [40–42]. Our study identified that such a lag effect, one of the major elements of the IT paradox [38], was also relevant to the performance of hospitals and showed that this effect had been negative in cases of hospitals that had introduced EMRs relatively recently. There may be several explanations for this phenomenon. First, the study period included the early stage of EMR implementation in Japan. Indeed, there were many cases in which EMR systems were not necessarily successful. For example, one MHLW report highlighted the fact that EMR implementation required a large investment in, and dedication of, human resources to create an IT system [43]. Similarly, previous studies underscored the burden of costs [43,44,57,58] and the influential role of management issues, such as staffing and leadership, in the success or failure of EMR systems [45–47,51–55]. We believe that these factors presented challenges to EMR implementation at institutions participating in our research.

From a conceptual perspective, MFP is considered "to reflect the joint effects of many factors including research and development (R& D), new technologies, economies of scale, managerial skill, and changes in organization of production" [22]. However, even considering the example of Japan, one can see that it is likely that the sequelae of the implementation of EMR systems will mitigate the impact of such joint effects at the organizational level. Furthermore, these results seem to be related to our use of the municipal hospital sector, which is an unprofitable segment of the healthcare market. It is difficult to increase the profitability of these hospitals by simply focusing on efficiency.

The results of our research form the basis for several suggestions regarding future EMR implementation. First, when considering healthcare policies, it is crucial that it be understood that EMR implementation will have a temporary adverse impact on hospital management and operations. Specifically, based on our results, hospitals with fewer beds should be given special consideration in this regard. Second, hospitals, as well as vendors, should also be aware of the aforementioned adverse effects. Even hospitals that have implemented EMR systems attempt to update their systems at 6–7-year intervals. Such updates or upgrades also require careful preparation with regard to managerial resources.

The current study had several limitations. First, as our research analyzed data from municipal hospitals, care must be taken when applying these results to hospitals with a different ownership structure. Second, the productivity markers used in this study are focused on financial variables. There are ongoing discussions about whether healthcare productivity should be evaluated in terms of clinical outcomes, such as re-admission, infection, or death rates, or only by volume or throughput [50]. It has further been argued that, rather than examining only financial and operational markers, research on healthcare productivity should also focus on quality of care or health outcomes [48]. Indeed, our results might have differed if we had used different indicators. We need to acknowledge that our measure did not consider these factors due to the lack of relevant data. Third, to control for the identity of the patient population served by these hospitals, we included "teaching hospital" and "located in designated remote areas" in the analyses as variables of interest. We believe that we were able to largely control the effect of patient mix on hospital productivity. However, we could not include more direct variables due to lack of data. Also, despite our treatment of EMR implementation as an intervening variable, we did not consider the type of system introduced at each facility or its degree of success. If such data were available, the current study may have yielded additional insights. Fourth, as the explanatory variables in our analysis were regarded as endogenous, additional analysis (e.g., an instrumental variable analysis) may yield a more appropriate estimate of the relationship between the outcome and the explanatory variables. An instrumental variable (IV) included in such an analysis should not directly affect productivity (Y); indeed, its effect should operate indirectly, through its effect on EMR implementation (X). As we were not able to obtain data on appropriate IVs that strictly meet this condition, an instrumental analysis was not performed in this study. This is the subject of our future research.

5. Conclusion

We confirmed that the introduction of EMRs had a short-term adverse effect on hospital productivity. Our findings will be useful in efforts to develop healthcare policies related to the implementation of IT systems, but we need to acknowledge that this study was confined to an examination of financial and operational markers and disregarded factors related to the quality of healthcare.

Authors' contributions

Kaneko made a substantial contribution to the study design, literature searches, data gathering, analysis, and interpretation of data, as well as drafting of the article. Onozuka contributed to the data analysis and interpretation of data. Shibuta contributed to interpretation of data. Hagihara made contributions to critically revising the manuscript. All authors read and approved the final manuscript.

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Conflicts of interest

Kozo Kaneko, first author of the manuscript, and on behalf of other authors declares that there is no conflict of interest with regard to the present manuscript.

Summary points

What was already known

- The implementation of electronic medical record (EMR) systems in hospitals is progressing steadily throughout the world
- Consistent with the global trend, Japanese hospitals have increasingly adopted EMR systems in the last 20 years.
- Although improved productivity is emphasized as benefit of EMR introduction, there is a paucity of data regarding how the use of EMR systems influences the productivity of Japanese hospitals.

What this study has added

- This study is the first to illustrate statistically the impact of EMR implementation on productivity in Japanese hospital settings.
- Our analysis confirmed that implementation of EMR systems had a short-term negative effect on multi-factor productivity (MFP), one of the important productivity markers.
- This insight should be considered when developing future healthcare policies promoting the implementation of IT systems in Japan.

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