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# Constructing a Novel Early Warning Algorithm for Global Budget Payments

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Received: 27 August 2020; Accepted: 3 November 2020; Published: 10 November 2020



**Abstract:** The National Health Insurance Administration of Taiwan has implemented global budget payments, the Diagnosis-Related Group (DRG) inpatient diagnosis-related group payment system, and the same-disease payment system, in order to decrease the financial burden of medical expenditure. However, the benefit system reduces the income of doctors and hospitals. This study proposed an early warning payment algorithm that applies data analytics technology to diabetes hospitalization- and treatment-related fees. A model was constructed based on the characteristics of the Exponentially Weighted Moving Average (EWMA) algorithm to develop control charts, which were first employed using the 2001–2017 health insurance statistical database released by the Department of Health Insurance (DHI). This model was used to simulate data from inpatients with diabetes, to create an early warning algorithm for diagnosis-related groups' (DRGs') medical payments as well as to measure its accuracy. This study will provide a reference for the formulation of payment policies by the DHI.

**Keywords:** machine learning; statistical model; decision science analysis; global payment; Exponentially Weighted Moving Average (EWMA); early warning system decision model

## 1. Introduction

Taiwan has been providing health insurance for more than 20 years. After several years of implementation and continuous improvements, the system is highly praised around the world [1–3]. Chiang et al. [4] compiled five main features of health insurance after two reforms: universal coverage, payroll tax financing, comprehensive benefits, public single-payment plan, and a national global budget. These five main features came about due to financial and payment problems that led to a reform of the healthcare system and changes in social values and attitudes toward healthcare. For example, in the five-year period of 2010–2014, Taiwan diagnosis-related groups (TW-DRGs) were introduced to allocate similar amounts of money for patients diagnosed with the same disease. Medical information systems can be used to monitor whether there are improper referrals, and patients can avoid unnecessary tests and waiting periods for hospital beds. For hospitals, this system can improve manpower crunches. However, Lin et al. [5] found that the same amount of money for patients diagnosed with the same disease produced the following consequences: (1) mild diseases being reported as serious diseases; (2) an increase in the number of rejected critically ill patients, in addition to difficulty in obtaining beds in critical care units in medical centers; and (3) a cost transfer to physicians, causing a higher turnover of critical care physicians in large hospitals and the problem of rejected patients becoming more seriously ill. This resulted in hospitals focusing only on treating mild cases. Many researchers have jointly studied the periods before and after the implementation of the TW-DRGs and found that there was no significant difference in medical resource consumption. If there were any abnormalities, most were differences caused by a reduced length of hospitalization [6–9]. Zhang [10] found that Taiwan has the least expensive health insurance rate among developed countries and is a country that

simultaneously maintains a high level of medical quality. However, after the implementation of the TW-DRG global budget payment system, it was found that this system did not match the Taiwanese people's medical consultation habits of seeking medical treatment, no matter how sick or pain they were, which hospital to go to was completely determined by the individual. The referral system is not implemented, resulting in restrictions in the number of hospital outpatient registrations, and the public is willing to spend more on registration fees to register at the emergency department to alleviate suffering. This causes the emergency department to be filled with patients and leads to a shortage of hospital beds. Liang [11] found that the long-term implementation of the DRG system can increase hospital efficiency, and hospitals can use the DRG-based payment system to encourage "product-range specialization," which will maximize hospital profits. Cheng and Wu [8] found that under the TW-DRG payment system, when different surgeries are conducted for the same disease, there is a fold difference in health insurance payouts. This can directly affect the medical behavior of physicians, and the medical resources consumed are also different.

In Taiwan, the health insurance rate is fixed, and the rate cannot be adjusted when there is an increase in expenditure, resulting in a health insurance operating loss. In order to reduce losses, the Department of Health Insurance (DHI) implements a total payment system and transfers the financial problem of variable expenditure to medical institutions. The medical institution can only maintain the same profit when the income is limited. In order to decrease the overall expenditures of the DHI and obtain a balance with income from hospitals and clinics, this study used data analytics technology on diabetes hospitalization fees as an example, to construct an early warning algorithm for DRG payments of diabetes inpatient treatments, from the perspective of the DHI. First, Exponentially Weighted Moving Average (EWMA) control charts were employed using the 2001–2017 health insurance statistical database that was released by the DHI to simulate surgery inpatient data in order to create an early warning algorithm for DRG medical payments. This model's accuracy was subsequently validated. These results will provide a basis for the formulation of payment policies by the DHI and medical treatments by hospitals.

The remainder of this paper is structured as follows. Following the present section (Introduction), Section 2 (Literature Review) provides an overview of previous research on machine learning and data mining, DRG global budget payment policy, and the early warning algorithm for global budget payment. In Section 3 (Methodology), this paper focuses on the construction of the early warning algorithm decision model. Section 4 (Results) provides an insight into the development of a diabetes inpatient DRG early warning algorithm. Finally, in Section 5 (Conclusions), a summary of the findings will be presented, highlighting how the global budget payment policy will enable a balance to be reached between the finances of the DHI and hospital incomes.

## 2. Literature Review

### 2.1. Machine Learning and Data Mining

Lee et al. [12] employed five data mining techniques (multiple regression, stepwise regression, multivariate adaptive regression splines, support vector regression, and two-stage model) to predict medical resources used for diabetic nephropathy, and found that support vector regression and two-stage model have better prediction accuracy. Kuo et al. [13] used C4.5 to carry out the data mining and classification of the 2010–2013 data and employed random forest methods to predict the medical costs of TW-DRG49702 (posterior and other spinal fusion without complications or comorbidities). The results showed that the prediction accuracy was 84.30%, and it was hoped that the random forest method could inform hospital strategy in terms of increasing the financial management efficiency of this operation. Daniel et al. [14] combined machine learning and mixed-integer programming to predict the assignment and use of early DRGs in hospital resources. Rodge [15] proposed the misdiagnosis minimization approach method, which was used for data analysis and used the Patient Informatics Processing Software Hybrid Hadoop Hive for data summarization, query, and analysis to identify traumatic brain

injury survival rates by data mining. Shafqat et al. [16] proposed a “SmartHealth” monitoring system, which integrated healthcare systems, and described the various applicable healthcare data analytics algorithms, techniques, and tools that may be deployed in wireless, cloud, and Internet of Things settings to unified standard learning healthcare systems in the future. Zaman et al. [17] used a large dataset of Facebook reviews to construct a taxonomy of potential service attributes for each service attribute to aid healthcare policy-makers and providers in rapidly monitoring concerns and adjusting policies or resources to improve the service.

The above-mentioned literature suggests that machine learning and data mining are useful for forecasting the assignment and use of resources in hospitals as far as diabetes is concerned. This research proposes a new algorithm through literature discussion, hoping to achieve a balance between the overall expenditure policy payment conditions for diabetes of the DHI and the income of the hospital or clinic using a more accurate financial forecasting algorithm.

### 2.2. DRG Global Budget Payment Policy

Mihailovic et al. [18] described the experience of introducing DRG-based payments in several countries and reported on the advantages of the system, increased efficiency and transparency, and reduced average length of stay in hospitals. On the contrary, the DRG can also present some disadvantages, such as creating financial incentives for earlier hospital discharges. Occasionally, such polices are not in full accordance with clinical benefit priorities. The TW-DRG payment system divides inpatients into different groups based on a series of factors, including condition diagnosis, surgical procedure or treatment, age, gender, comorbidities or complications, discharge status, and so on [19].

The global budget payment criteria for TW-DRGs divide disease treatments into categories A, B, and C, as shown in Figure 1. In Figure 1, category A includes patients who recovered after receiving treatment and used pay-as-you-go, which is a payment that is dependent on treatment costs. Most cases fall into category B. Categories B and C can be explained as follows. The DHI has defined the upper and lower limit for payment for DRGs into different groups, and the median amount is taken as a fixed score. After disease treatment is completed, a fixed amount is paid according to the DRG of that disease. If the cost of treatment is low, the hospital earns money. Otherwise, the hospital incurs a loss. If the hospital earns money, the case falls into category B, but if the hospital loses money, the case falls into category C. When treatment exceeds the upper limit of DRG payments for various groups and the costs fall into region C, a fixed payment plus 80 percent of the excess cost is paid to the hospital. The lower-limit threshold for fees is calculated based on the 2.5 percentile of DRG medical points, while the upper-limit threshold for fees is calculated based on the 88.5 percentile of the DRG medical points.

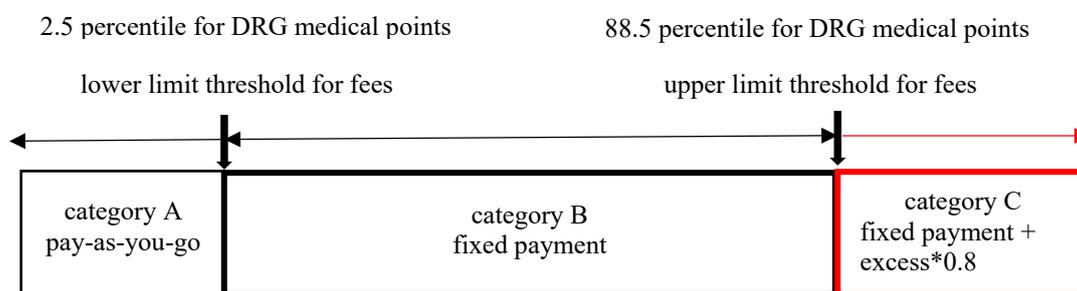
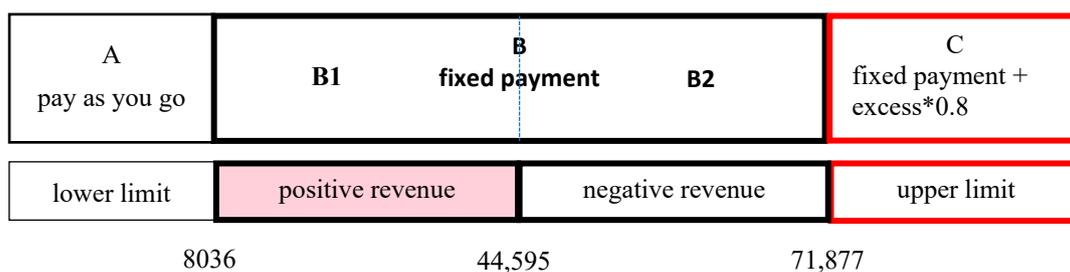


Figure 1. Taiwan diagnosis-related group (TW-DRG) payment system.

The 2019 treatment DRG for diabetes inpatients promulgated by the DHI was used as an example to illustrate the payment method in Figure 1. The DHI fixed payment is 44,595 points, the lower limit is 8036 points, and the upper limit is 71,877 points (see Figure 2). The DHI payment is explained as follows:



**Figure 2.** Execution of the TW-DRG medical payment system in hospitals.

Case 1: If treatment falls into region A (lower limit), pay-as-you-go is used.

If 5000 points are used for inpatient treatment and the case falls into category A, the DHI will employ the pay-as-you-go principle and pay the hospital 5000 points.

Case 2: If treatment falls into category B, a fixed payment is carried out.

After treatment, if medical costs fall into category B, the DHI will give a fixed payment of 44,595 points, regardless of how much was spent by the hospital. At this point, the hospital further segments category B into categories B1 and B2. If the physician spends 40,000 in treatment costs, this falls into category B1, which is the positive revenue category, as it provides a profit of 4595 points to the hospital ( $44,595 - 40,000 = 4595$ ). Conversely, if the physician spends 60,000 points on treatment costs, this will fall into category B2, which is a negative revenue category and causes the hospital to incur a loss of 5084 points ( $60,000 - 44,595 = -15,405$ ).

Case 3: If treatment costs fall into category C (upper limit), 80% of the excess cost is paid to the hospital.

If inpatient treatment costs 80,000 points, the DHI administration payment method is a fixed payment of 44,595 points +  $(80,000 - 44,595) \times 0.8 = 72,919$  points. At this point, the DHI will only pay 72,919 points to the hospital, resulting in a loss of 7081 points to the hospital. This means that the more medical interventions carried out, the greater the loss incurred by the hospital, which directly affects the income of the hospital and physicians.

### 2.3. Exponentially Weighted Moving Average (EWMA)

Roberts [20] proposed EWMA control charts to detect mean offsets in a process. When an offset occurs in the process, the control chart can be used to identify its cause. This is achieved by assigning different weights to historical and current data: weighting of historical data results in a decreasing index that will improve the process and reduce process variability [21,22]. Cook et al. [23] proposed risk-adjusted EWMA that plots the EWMA of the observed and predicted values obtained from a logistic regression model for all hospitals in Queensland. Pan and Jarrett [24] proposed multivariate exponentially weighted moving average (MEWMA) and sensitivity ratios as a measure of the effects of the mean shift and dispersion shift in processes in a bio-surveillance study. Scagliarini [25] EWMA control charts were applied retrospectively to monitor the mean and variability of a hospital organizational performance indicator, which reflected process performance, allowing continuous monitoring and prompt detection of changes in process performance. Aslam et al. [26] proposed that EWMA charts on healthcare issues may reduce the risk of heart disease by monitoring diabetic levels in an effective way. The EWMA of the predicted values is a moving center line, reflecting the current patient case mix at a particular hospital.

### 3. Methodology

In this study, the characteristics of EWMA control charts were utilized to develop an early warning algorithm for surgical inpatient treatment-related costs and to avoid substantial losses to the DHI, hospitals, and clinics under the global payment system. The EWMA statistic that is calculated is

$$EWMA_t = \lambda Y_t + (1 - \lambda)EWMA_{t-1} \text{ for } t = 1, 2, \dots, n. \tag{1}$$

where  $\lambda$  is the weight (which is the payment model value that is most suitable for diabetes inpatient medical costs according to a sensitivity analysis on data analytics on daily diabetes inpatient medical costs).  $EWMA_0$  is the historical mean of the DRG costs.  $Y_t$  is the observation at time  $t$ .  $n$  is the number of observations to be monitored, including  $EWMA_0$ . Moreover,  $0 < \lambda \leq 1$  is a constant that determines the depth of memory of the EWMA [27–29].

$$\begin{cases} UCL = \mu_x + L\sigma \sqrt{\frac{\lambda}{2-\lambda} [1 - (1-\lambda)^{2t}]} \\ CL = \mu_x \\ LCL = \mu_x - L\sigma \sqrt{\frac{\lambda}{2-\lambda} [1 - (1-\lambda)^{2t}]} \end{cases} \quad t = 1, 2, \dots, n \tag{2}$$

where  $\sigma$  is the variance, UCL is the upper-limit threshold for fees, LCL is the lower-limit threshold for fees, and  $CL = \mu_x$  is half of the fixed payment for DRG costs. When  $t$  increases, the term  $(1 - \lambda)^{2t}$  in Equation (2) gradually converges to 1. Therefore, the with the EWMA control, in a few periods, the upper and lower limits tend to a stable value. The upper and lower limits tend to be stable. When  $\lambda \rightarrow 0$ , the effects of historical data on the statistic in the EWMA control chart are lower; when  $\lambda \rightarrow 1$ , the EWMA control chart is a Shewhart control chart [30], as shown in Equations (3) and (4).

$$UCL = Z_0 + \frac{3S}{\sqrt{n}} \sqrt{\left(\frac{\lambda}{1-\lambda}\right) (1 - (1-\lambda)^{2t})} \tag{3}$$

$$LCL = Z_0 - \frac{3S}{\sqrt{n}} \sqrt{\left(\frac{\lambda}{1-\lambda}\right) (1 - (1-\lambda)^{2t})} \tag{4}$$

where UCL is the upper-limit threshold for fees, LCL is the lower-limit threshold for fees,  $Z_0$  is the initial value, a target value for diabetes inpatient DRG costs defined by decision makers or the mean value of diabetes inpatient payments;  $i$  is the sample size; and  $n$  is the size of the group.

To determine the efficiency of the EWMA forecasting model, this work employs the residual error (RE) test method to compare the forecasted and actual values. The following equation was used:

$$RE(k) = \frac{|x(k) - \hat{x}(k)|}{x(k)} \times 100\% \tag{5}$$

where  $x(k)$  is the original hospitalization fee and  $\hat{x}(k)$  is the EWMA forecasting hospitalization fee. The accuracy was  $1 - RE(k)$ .

### 4. Results

In order to increase hospital income as well as decrease both hospital losses and expenditure by the DHI, our study used inpatient medical fee data for diabetes mellitus inpatient DRGs, as an example, to construct a diabetes inpatient DRG early warning algorithm from the perspective of DHI global payments, so that a balance between hospital income and expenditure by the DHI can be reached. The early warning algorithm decision model involves the following steps:

Step 1: Data Collection

Data published by the DHI regarding health insurance of diabetes inpatients between 2001 and 2017 were used in this study. The DHI [31] announced that the international classification of diseases (ICD) 9 and ICD 10 DRG payment systems would be implemented as health insurance policies for Taiwan from 2001 to 2017.

Step 2: Data Integration

The ICD 9 DRG system was implemented before 2015, followed by the ICD 10 DRG system in 2016. DRG payments for ICD 10 diabetes can be divided into four types: DRG-29401 (diabetes, age ≥ 36 years, with complications), DRG-29402 (diabetes, age ≥ 36, without complications), DRG-29501 (diabetes, age ≤ 35, with complications), and DRG-29502 (diabetes, age ≤ 35, without complications). Before the construction of the early warning algorithm, diabetes ICD 9 DRG-related fees before 2015 were combined with the number of people treated under ICD 10 DRG and its inpatient payments after 2016. The compiled data are shown in Table 1.

**Table 1.** Hospitalization fees and number of people treated for diabetes in 2001–2017 under the global payment for Department of Health Insurance (DHI) (USD).

Year	DRG	Number of People Treated	Diabetes Hospitalization Fees	Average Hospitalization Fees per Person	Annual Change in Number of People Treated (%)
2001	ICD 9	169,981	50,794,623	299	6%
2002	ICD 9	184,362	58,638,789	318	8%
2003	ICD 9	185,743	58,922,637	317	1%
2004	ICD 9	207,873	67,946,566	327	11%
2005	ICD 9	213,198	65,071,657	305	2%
2006	ICD 9	217,095	56,350,534	260	2%
2007	ICD 9	229,785	55,012,426	239	6%
2008	ICD 9	241,114	54,930,503	228	5%
2009	ICD 9	255,518	54,226,727	212	6%
2010	ICD 9	268,749	53,501,090	199	5%
2011	ICD 9	277,628	52,527,147	189	3%
2012	ICD 9	283,388	48,676,208	172	2%
2013	ICD 9	283,367	47,430,722	167	0%
2014	ICD 9	288,049	49,155,901	171	2%
2015	ICD 9	295,267	48,869,911	166	2%
2016	ICD 10	291,832	49,233,100	169	−1%
2017	ICD 10	298,558	56,161,894	188	2%
Average		241,766	54,625,281	237	4%

Diabetes inpatient medical costs and the number of people treated in Table 1 were used for trend analysis, as shown in Figure 3. From Figure 3, we can see that the number of people treated for diabetes is increasing at an average of 4% per year. First, the implementation of the ICD 9 payment system was divided into two parts for analysis. The first part (2001–2004) shows a growth in inpatient fees, with an average payment of 59,075,654 USD by the DHI, an average growth of 6% in fees, and an average inpatient medical fee per person of 315 USD. The second part (2004–2015) shows a decrease in inpatient fees, with an average payment of 53,250,257 USD by the DHI, inpatient fees decrease of 3%, and an average inpatient medical fee per person of 210 USD. Next, the new ICD 10 DRG payment system was implemented (2016 onward), and the payment points for medical costs were recalculated, and inpatient medical costs started showing an increasing trend.

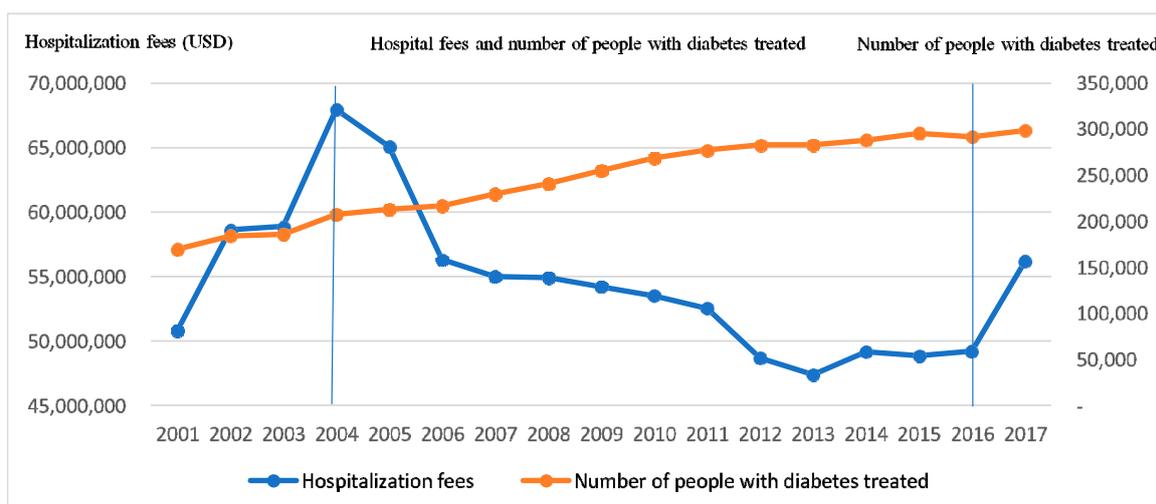


Figure 3. Hospitalization medical fees and number of people with diabetes treated.

### Step 3: Constructing an Early Warning Algorithm

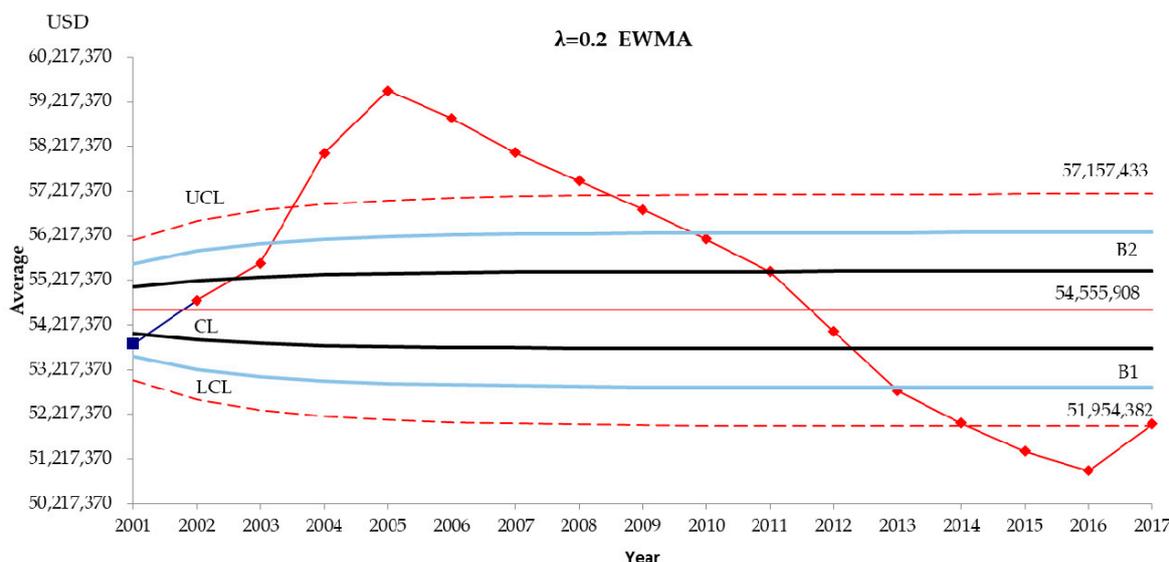
Based on the 2001–2017 diabetes health insurance inpatient data, Equation (2) was used to construct an EWMA control chart for an early warning algorithm.

### Step 4: Sensitivity Analysis

Sensitivity analysis was used to identify the  $\lambda$  weight most suitable for diabetes inpatient payments and the accuracy of the early warning algorithm. This was done to provide decision support for real-time monitoring of diabetes inpatient treatment by the DHI and hospital. Taking  $\lambda = 0.15$  as an example, we used Equation (1) to calculate the predicted value of EWMA for the diabetes hospitalization expenses in Table 1 from 2001 to 2017, and then  $\lambda = 0.2, 0.25$ , and  $\lambda = 0.3$  for sensitivity analysis. The calculated predicted values of EWMA are summarized in Table 2. Table 2 shows the compiled results. From Table 2, we can obtain the accuracy of the algorithm from Equation (5). The mean accuracy is the highest (97.38%) when  $\lambda = 0.2$ . In Figure 4, when  $\lambda = 0.2$ , using Equation (2) to calculate the mean value (CL) of diabetes inpatient global budget payments, and using Equations (3) and (4) to calculate the result is 5,455,907 USD, the upper limit of payments (UCL) is 57,157,433 USD, and the lower limit of payment (LCL) is 51,964,382 USD in the EWMA early warning algorithm.

Table 2.  $\lambda$  sensitivity analysis of diabetes hospitalization fees in 2001–2017 (USD).

Year	Original Hospitalization Fee	$\lambda = 0.15$		$\lambda = 0.2$		$\lambda = 0.25$		$\lambda = 0.3$	
		EWMA	Accuracy	EWMA	Accuracy	EWMA	Accuracy	EWMA	Accuracy
2001	50,794,623	53,991,715	94.58%	53,803,651	94.25%	53,615,587	93.92%	53,427,523	93.59%
2002	58,638,789	54,688,776	95.80%	54,770,679	95.95%	54,871,387	96.12%	54,990,902	96.33%
2003	58,922,637	55,323,855	96.92%	55,601,070	97.40%	55,884,200	97.90%	56,170,423	98.40%
2004	67,946,566	57,217,262	99.77%	58,070,169	98.27%	58,899,791	96.82%	59,703,266	95.41%
2005	65,071,657	58,395,421	97.70%	59,470,467	95.82%	60,442,757	94.12%	61,313,783	92.59%
2006	56,350,534	58,088,688	98.24%	58,846,480	96.91%	59,419,702	95.91%	59,824,808	95.20%
2007	55,012,426	57,627,249	99.05%	58,079,669	98.26%	58,317,883	97.84%	58,381,094	97.73%
2008	54,930,503	57,222,737	99.76%	57,449,836	99.36%	57,471,038	99.32%	57,345,916	99.54%
2009	54,226,727	56,773,335	99.46%	56,805,214	99.51%	56,659,960	99.26%	56,410,160	98.82%
2010	53,501,090	56,282,499	98.60%	56,144,389	98.35%	55,870,243	97.87%	55,537,439	97.29%
2011	52,527,147	55,719,196	97.61%	55,420,941	97.09%	55,034,469	96.41%	54,634,351	95.71%
2012	48,676,208	54,662,748	95.76%	54,071,995	94.72%	53,444,904	93.63%	52,846,909	92.58%
2013	47,430,722	53,577,944	93.86%	52,743,740	92.40%	51,941,358	90.99%	51,222,053	89.73%
2014	49,155,901	52,914,638	92.70%	52,026,172	91.14%	51,244,994	89.77%	50,602,207	88.65%
2015	48,869,911	52,307,929	91.63%	51,394,920	90.03%	50,651,223	88.73%	50,082,518	87.73%
2016	49,233,100	51,846,704	90.83%	50,962,556	89.28%	50,296,692	88.11%	49,827,693	87.29%
2017	56,161,894	52,493,983	91.96%	52,002,424	91.10%	51,762,993	90.68%	51,727,953	90.62%
Average	57,083,882		91.04%		97.38%		96.86%		96.42%



**Figure 4.** EWMA early warning algorithm simulation for diabetes inpatient treatment global payments when  $\lambda = 0.2$ .

EWMA, exponentially weighted moving average.

Step 5: Model Verification

In this study, we set two warning values:  $\pm 1$  (the black line in Figure 4) and  $\pm 2$  (the blue line in Figure 4) standard deviations for diabetes global budget payments. A warning was released in 2003: if the value increases, the global budget payment will decrease, and the financial burden on the government will increase. At the same time, the amount of health insurance payments received by the hospital would decrease. Results showed that in 2004–2008, the global budget payments for diabetes inpatient medical costs were above the upper limit. After efforts were made by the DHI in which the upper-limit, lower-limit, and standard payment amounts were revised, a warning was found in 2008, and global budget payments were within the standard payment range. In 2009–2014, the global budget payment by the DHI was between the upper and lower limits, showing that diabetes payments by the DHI were controlled within the expected reasonable range. When looking at category B1 in Figure 2, it is clear that hospitals could have obtained more positive revenue in 2013 and 2014. At the same time, the algorithm also issued an early warning: if the global budget payments had continued to decrease, the government’s financial burden would decrease, and hospital income would also decrease under the global budget payment algorithm. Therefore, the DHI proposed reforms to the DRG system in 2016 and promulgated the ICD 10 DRG payment policies. In addition, global payments gradually returned to their lower limits. At the same time, the system issued a warning in 2015: if the upper-limit, lower-limit, and standard payments were not drastically revised, hospital income would gradually decrease under the global payment system, resulting in a vicious cycle, and medical quality could also decrease. After the implementation of the ICD 10 DRG payment policies in 2016, the global payments returned to the standard payment range in 2017.

5. Conclusions

In this study, we used data analytics technology to propose an early warning algorithm model that was constructed based on EWMA. This model has been developed to be used for global budget payments and for diabetes inpatient medical costs in particular. The contributions of this study are as follows:

1. After simulation analysis, we found that the early warning algorithm accuracy for diabetes inpatient costs was 97.38% when  $\lambda = 0.2$ .

2. Hospitals can utilize online data and real-time early warning algorithms, so that physicians are notified under the global budget payment environment. This will enable physicians to provide suitable medical packages, medical services, and medical quality to diabetes inpatients within the payment range for health insurance. This, in turn, will help to control medical costs within category B1 in Figure 2, increase hospital income, and reduce medical costs. The policy recommendations of this study are as follows:
  - From medical big data, identifying DRGs with severely deficient payments for diabetes inpatient treatment, reexamining resource allocation, adding new DRG items, and increasing payment range are in line with the purpose of setting up the health insurance system.
  - From the DRG packages for diabetes inpatient treatment, when the same amount of money is spent on patients diagnosed with the same disease, as proposed by global budget payment and the DHI, it is easy for hospitals to incur losses. The key to achieving a balance between the finances of the DHI, hospital income, and patient hospitalization is to ensure that patients are psychologically prepared to pay additional medical costs. Therefore, there is a need to formulate suitable commercial medical insurance to supplement fully self-paid items as well as health insurance payment items and enable sufficient lengths of hospitalization for treatment completion.
3. With regard to the formulation of DHI policies, establishing standard diabetes payments and upper- and lower-limit boundaries every year for diabetes inpatient medical costs under the overall global budget payment policy will enable a balance to be reached between the finances of the DHI and hospital incomes.

The EWMA early warning algorithm constructed in this study can accurately alert and predict diabetes inpatient medical costs. In the future, big data of different diseases can be obtained from the DHI for model construction, to identify suitable  $\lambda$  parameters, so that the model can be generalized to provide warnings and predictions for other diseases.

**Funding:** This research received no external funding.

**Acknowledgments:** The author would like to thank the DHI for providing the case studies.

**Conflicts of Interest:** The author declares no conflict of interest.

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