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Predicting medical fees for hospitalized inpatients and the determination of inflection point

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Abstract

Background: Taiwan's Bureau of National Health Insurance (BNHI) implemented an inpatient DRG payment system scheduled for January 2008. Many hospital managers urgently invent initiatives to decrease the impacts of DRGs. Predicting medical fees for hospitalized inpatients every day and the corresponding inflection points (IPs) are required for investigations. The aims of this study include (1) verifying the efficacy of the exponential growth model on accumulative publications of mobile health research between 1997 and 2016 in the literature; (2) building the model of predicting medical fees for hospitalized inpatients and determining the inflection points; and (3) demonstrating visualizations of the prediction model online in use for hospital physicians.

Methods: An exponential growth model was applied to determine the IP and predict the medical fees to help physicians contain the medical fees of a specific patient during hospitalization. The IP is equal to the item difficulty proven using the differential equation in calculus. An online visual display of the medically contained and predicted inpatient hospitalization was demonstrated in this study.

Results: We observed (1) a model accuracy ($R^2 = 0.99$) higher than that ($R^2 = 0.98$) in the literature based on identical data; (2) 231 samples of medical fees for inpatients in the study module with a length of days between 6 and 20 and an IPS falling in the range between 1 and 10 ($Q1=0.98$, $Q3=1.00$); and (3) online visualization demonstration of medical fees predicted for hospital inpatients and IP determination on ogive curves.

Conclusion: The exponential growth model can be applied to a clinical setting to help physicians consecutively predict medical fees for hospitalized inpatients and upgrade the level of hospital management in the future.

Keywords: inflection points, mixed diagnosis groups, medical fees, visualization, an exponential growth model

Backgrounds

COVID-19 infections worldwide have severely challenged global health systems [1-3]. As of November 26, 2021, it caused over 0.75 billion confirmed cases and 5.18 million deaths [1], impacting 187 countries [2], with its deaths surpassing those of SARS (774 in 2003) and MERS (858 in 2012) [3].

The proliferation of COVID-19 drew great attention from all over the world, particularly with more than 201,441 pieces of COVID-19-related research papers found on PubMed Central (PMC) [4]. Among them, the focus of public attention toward this disease was the turning point (or inflection point, IP)[5-9], which (1) geometrically means an IP between concavity and convexity of a continuous ogive curve and (2) medically means a confidence indicator of successful infection control for countries.

Notwithstanding many discussions of COVID-19 predictions [11-14], few articles elaborate the mathematical calculation of an IP. A group of researchers analyzing the growing research situation of mobile health from 1997 to 2016 utilized an exponential growth model

$(y(t)=a/(1+be^{-ct}))$ [15], where (1) a is the upper limit of the function $y(t)$ as t reaches its maximum and $\exp(-\infty)$ equal to 0; (2) the Rasch model is presented as both $a=b=c=1$ and t is replaced with differences $(\theta-\delta)$ between a student's ability (θ) and an item's difficulty (δ) [16].

The two-parameter item response theory (IRT) comes if and only if c is equal to or greater than 0 [17]. However, a crystal-clear derivation of mathematics that can be evident using the

differential equation in calculus has not been seen in the literature.

Taiwan's Bureau of National Health Insurance (BNHI) started an inpatient diagnosis-related group (DRG) payment system in January 2008 [18]. This brought phenomenal influences and challenges to local medical institutions [19,20], such as requiring (1) automatic predictions of medical fees for hospitalized inpatients [18], (2) intelligent solutions to offering patients fees reminders and medical records [21], and (3) clear manifestations of comorbidity and complications for medical personnel of patient classification [19,22].

A few studies used multiple regression analysis to foresee the DRGs' medical fees of patients with a single symptom either charged [23-26] or discharged from a hospital [27]. Although length of stay [28] and medical fee predictions [18] for a patient were available, the IP in medical fee predictions was not mentioned at all. We are thus interested in predicting medical fees for hospitalized inpatients and determining corresponding IPs so that more effective management of DRGs' medical fees can then be well administered.

This article aims to (1) present the mathematical derivation of the IP from an exponential growth model [15], (2) establish an operable method of medical fee predictions and IP determination based on a set of hospitalized inpatient data from a real medical scenario, and (3) demonstrate the online visualization of medical fees predicted and the IPs determined on ogive curves.

Methods

2.1 An Exponential Growth Model

Based on logistic regression, the function of an ogive curve is presented below:

$$p[\text{logit}(\pi)] = \frac{1}{[1+\text{Exp}(-\text{logit}(\pi))]} = \frac{\text{Exp}[\text{logit}(\pi)]}{[1+\text{Exp}(\text{logit}(\pi))]} \quad (1)$$

$$\text{logit}(\pi) = \ln \text{odds}(\pi) = a + \sum_{i=1}^k b_i \times X_i \quad (2)$$

where $p[\text{logit}(\pi)]$ is the probability of an event occurring and $\text{logit}(\pi)$ is a natural log of $\text{odds}(\pi)$ ($\ln \text{odds}(\pi)$) [29].

===Figure 1 inserted here===

The Rasch model comes out as $\theta_n - \delta_i$ is substituted for $a + \sum_{i=1}^k b_i \times X_i$ in $\ln \text{odds}(\pi)$ [16], as shown in Formula (3)]16,30] below:

$$\text{logit}(\pi) = \ln\left(\frac{\pi_{ni}}{1-\pi_{ni}}\right) = \theta_n - \delta_i \quad (3)$$

$$p(\theta) = \frac{1}{1 + e^{-a(\theta-\delta)}} = \frac{e^{a(\theta-\delta)}}{1 + e^{a(\theta-\delta)}} \quad (4)$$

Formula 4 is the expression of two-parameter (2PL) item response theory (IRT), in which the difficulty of an item (δ) and the discrimination (a) are to be estimated [17]. Formula 5 comes when δ equals 0, θ and a are replaced with t ($1 \leq t \leq T$) and c in Formula 4. More general forms are given in Formulas 6 and 7 (a , b , and c are positive constants).

$$f(t) = \frac{1}{1 + e^{-ct}} \quad (5)$$

$$f(t) = \frac{a}{1 + e^{-ct}} \quad (6)$$

$$f(t) = \frac{a}{1 + be^{-ct}} \quad (7)$$

2.2 Determination of the Inflection Point

Derived from Formula 7, its first-order derivative (Formula 8) and second-order derivative (Formula 9) are obtained.

2.2.1 First-order derivative

$$\begin{aligned} f'(t) &= \left(\frac{a}{1 + be^{-ct}} \right)' = a \left(\frac{1}{1 + be^{-ct}} \right)' = -a \frac{(1 + be^{-ct})'}{(1 + be^{-ct})^2} = -a \frac{0 + (be^{-ct})' (-ct)'}{(1 + be^{-ct})^2} \\ &= -a \frac{be^{-ct} (-c)}{(1 + be^{-ct})^2} \\ &= [a(1 + be^{-ct})^{-2}](bce^{-ct}) \quad (8) \end{aligned}$$

2.2.2 Second-order derivative

$$\begin{aligned} f''(t) &= [f'(t)]' = \{[a(1 + be^{-ct})^{-2}](bce^{-ct})\}' \\ &= [a(1 + be^{-ct})^{-2}]'(bce^{-ct}) + [a(1 + be^{-ct})^{-2}](bce^{-ct})' \\ &= [-2a(1 + be^{-ct})^{-3} (be^{-ct})'(-ct)'] (bce^{-ct}) + [a(1 + be^{-ct})^{-2}][(bce^{-ct})(-ct)'] \\ &= [2a(1 + be^{-ct})^{-3} (be^{-ct}) c] (bce^{-ct}) + [a(1 + be^{-ct})^{-2}][(bce^{-ct})(-c)] \\ &= [2a(1 + be^{-ct})^{-3} (b^2c^2e^{-2ct})] + \{[a(1 + be^{-ct})^{-2}] (-bc^2e^{-ct})\} \\ &= [abc^2 (1 + be^{-ct})^{-2} e^{-ct}] [2b(1 + be^{-ct})^{-1} e^{-ct} - 1] \\ &= [abc^2(1 + be^{-ct})^{-2} e^{-ct}] \left[\frac{2be^{-ct}}{1 + be^{-ct}} - 1 \right] = [abc^2(1 + be^{-ct})^{-2} e^{-ct}] \frac{be^{-ct} - 1}{1 + be^{-ct}} \\ &= [abc^2(1 + be^{-ct})^{-2} e^{-ct}] \frac{b - e^{ct}}{1 + be^{-ct}} \end{aligned}$$

$$= \frac{abc^2}{(1+be^{-ct})^2} \frac{b-e^{ct}}{e^{ct}} \frac{1}{(1+be^{-ct})} \quad (9)$$

2.2.3 Letting the second-order derivative be 0 to find the inflection point

Formula 9 exists only when:

- (1) a, b, and c are positive constants;
- (2) Two denominators $[(1 + be^{-ct})^2 e^{ct}]$ and $[(1 + be^{-ct})^2 e^{ct}]$ cannot be 0;
- (3) The second-order derivative $f''(t)$ must be 0.

$$e^{ct} = b \quad (10)$$

$$t = \frac{\ln(b)}{c} \quad (11)$$

where t belongs to the range $(1 \leq t \leq T)$; otherwise, the IP falls at T , which resonates with the aforementioned literature [15]. When formula 11 is applied, the IP calculated by the authors [15] is $19.4 (= \ln(1929.18)/0.39) \approx 20$ in year (i.e., $2016 - 1997 + 1$).

2.3 Research Subjects

2.3.1 Subject 1: an analysis of the exponential growth model and its IP determination

[15]

This paper applies (1) the Microsoft Excel add-in of Solver [8,9] to parameter estimations of the model (Formula 7) with a bulk of data (2,2,2,7,4,8,12,15,21,38,34,35,60,87,109,178,267,410,648,765) from prior research targeting years 1997 to 2016 [15], and (2) uses Formula 11 to compute the inflection point. An example

of IP determination using time-series data is displayed on the website once an integer number is an input in the box[31].

2.3.2 Subject 2: a model setup to predict medical fees of hospitalized inpatients and identify the IPs

Based on a data set from a given medical scenario in which 231 inpatients with different lengths of stay from 4 days to 20 days produce daily DRG fees of medical care, this study estimates parameters (Formula 7) and computes their inflection points for each category under the DRG. Before that, a global index R-square (Formula 12) to measure the quality of the model (how much the total variance of the data can be manifested by the proposed model) must be inspected.

$$R^2 = [1 - \frac{\sum_1^k (o_i - e_i)^2}{\sum_1^k (o_i - m_i)^2}] \quad (12)$$

$$\text{Squared Residuals} = \sum_1^k (o_i - e_i)^2, \quad (13)$$

$$\text{Sum of deviation from the mean} = \sum_1^k (o_i - m_i)^2, \quad (14)$$

where e_i is the i -th expected value of the model; m_i is the i -th mean of the data; and o_i is each observed dataset.

2.3.3 Subject 3: An online demonstration of visualization for medical fees of hospital inpatients

A web-based demonstration of the medical fees of hospital inpatients is shown with all elements in subject 2. The mechanisms inside include: a random case with medical fees spent is given to the system that tries to find the best match [the closest R^2] from previous data stored in the server; According to the most-possible pattern of that best match and the stay length (t-th day) of a patient who is currently hospitalized, both the curves of observed fees, predicted fees, and its IP is clearly pictured in a designated web with a zoom-in-and-out function.

2.4 Statistics and Tools

All tools are (1) Microsoft Excel for data storage and computation (Additional Files 1 and 2) and (2) JPgraph [32], an online graphic-designing module for all web-based data presentations.

The IP can be obtained through the Newton–Raphson Iteration Method (NRIM)[8,9,33- 35]; see the two examples in Figure 2. Seven cumulative observed data points (named item responses) are illustrated in Figure 3. The IPs on ogive curves for each score with the respective category the probability decrease as the items become more difficult, across the ordered item responses [36] shown in Figure 3. We can see that the IP (or the burst spot) is located on the point at item difficulty[37] based on the IRT feature[8, 9]. Similarly, examples of IP determination using time-series data are shown at the link[31] once an integer number is an input in the box[31].

===Figures 2 and 3 inserted here===

Results

3.1 Result 1: A report of the exponential growth model and its inflection point [15]

This study reports a function $y(t) = 4139636.37 / (1 + 2060690.85e^{-0.36t})$, $R^2 > 0.998$) with its inflection point falling at 20 ($= \ln(2060690.85) / 0.36 \approx 40.34 > 20$) (this is, 2016-1997+1), which is different from the antecedent study ($R^2 > 0.987$) [15]; see Figure 4.

==Figure 4 inserted here==

3.2 Result 2: A model setup to predict the medical fees of hospitalized inpatients and identify IPs

The basic structure of medical fees for 231 hospitalized inpatients (Table 1) tells us that 231 inpatients have different lengths of stay from 4 days to 20 days with their inflection points from Day 1 to Day 9.

===Table 1 inserted here===

3.3 Result 3: An online demonstration of visualization for medical fees of hospital inpatients

An example of a hospital inpatient with an inflection point on day 5 is summarized: 60,250 NTD (day 15), 73,980 NTD (in total on day 19), and $R^2 = 0.91$; see Figure 5.

===Figure 5 inserted here===

An example of a hospital inpatient with an inflection point on Day 3 is summarized: 13,000 NTD (Day 9), 20,000 NTD (in total on Day 12), and $R^2=0.88$; see Figure 6...

===Figure 6 inserted here===

An example of a hospital inpatient with an inflection point on Day 10 is summarized: 88,080 NTD (Day 16), 98,901 NTD (in total on Day 20), and $R^2=0.99$; see Figure 7.

===Figure 7 inserted here===

3.4 Application of line chart in presenting medical fees

JPgraph [32], with QR codes in Figures 1 to 5, is an online graphic-designing module for all web-based data presentations, including observed fees, expected fees, and inflection points.

Discussions

4.1 Principle findings

The key to the DRGs' prediction of medical fees for hospital inpatients is the accuracy of the medical diagnosis at first. This study reveals (1) our model ($R^2 = 0.99$) slightly better at variance explanation than other researchers' ($R^2 = 0.98$); (2) our establishment of an Excel

module with Solver that handles the medical fees for hospitalized 231 inpatients with different lengths of stay from 4 days to 20 days with their inflection points from Day 1 to Day 9; and (3) a successful online demonstration of data visualization.

Although Rutledge and Osler [38] found that its ICD-9 performed better at medical fee prediction than DRGs did, this paper (1) focused more on the intelligent management of medical fees under the DRG payment system, (2) was not limited to either medical fee management of a single symptom of patients discharged from a hospital [23-26] or the management of the length of stay [27] and (3) demonstrated medical fee management of patients staying in a hospital.

4.2 The management of medical fees for patients in hospitalization

Based on the prediction of medical fees in hospitalization for patients, the starting day of the DRGs is set at approximately half of the mean days in DRGs in comparison of differences between observed and expected medical fees in hospitalization. If the observed fees are beyond the expected fees, the alert appears on the computer screen when the physician checks patient data in the morning run around the wards[21]. Alternatively, physicians are able to review the reports shown in Figures 5 to 7 based on alerted medical fees beyond the expected fees that provide an efficient and proper management method for DRGs in healthcare settings [21,33].

In general, patients receive numerous treatments ahead of the IP days (or medical operations for the surgical patient), which leads to relatively high medical fees ahead of the IP days. If no such mechanism was provided for physicians as we did in this study, the containment of medical fees would last longer.

A study [18] shows that (1) the probability of all medical fees consumed beyond the DRG standard ahead of the middle LOD would eventually be extremely low and exceptionally be included in the outlier cases, (2) few cases are out of order due to the reasons of errors in setting standard LOD and fees in a real-world situation, and (3) not all cases with higher fees ahead of the middle LOS are beyond the DRG limit in practice. As such, the fees at the end time point would also be effectively detected using the model illustrated in the current study(e.g., Figures 5 to 7), (4) the in-hospital prediction of medical fees is better than those without the mechanism due to the too-late out of control in medical fees when patients are discharged from hospitalization, (5) all cumulative medical fees can be plotted on an ogive curve on which even a small increase in fees would be sensitively highlighted at the end[18].

4.3 The strength of the study

4.3.1 An exponential growth model

Different from previous studies where IRT models have a better model-data fit [8, 9], this study is to (1) apply the Microsoft Excel add-in of Solver [8, 9] and the online module

[31] to parameter estimations of the model and (2) find the inflection points through the second-order derivatives of ogive curves.

4.3.2 Determination of inflection points

Nevertheless, many have discussed COVID-19 predictions [11-14] and used the exponential growth model (Formula 7) [15], and it is almost impossible to find an article that illustrates the mathematical calculation of an inflection point as this paper tried (Formula 8 -11)[33-35].

These expressions of the exponential growth model (Formula 4) function similar to those of IRT models [8, 9, 18] but become much more concise than those of IRT models. It is also the second-order derivative (Formula 11) that makes the process of finding the turning point more scientific and reasonable.

4.3.3 An online demonstration of visualization

A web-based demonstration of the medical fees of hospital inpatients is shown with data presentations, including observed fees, expected fees, and inflection points. Readers are invited to scan QR codes in Figures 5 to 7 to manipulate the scenarios on their own.

An MP4 video of the analysis procedure makes this paper more understood and special to readers who are interested in IP determination; see Additional File 3.

4.4 Limitations and suggestions

The higher complexity of DRGs than the case payment is due to no such standard path being easily traced in hospitalization. Model building for comparing the difference in medical fees between observed and predicted fees is worthy of application in healthcare settings. Nonetheless, several limitations exist in the current study; for example, no such message was provided for physicians to understand the medical fees with significantly higher or lower features when compared to the predicted fees[18,39]. Next, based on the IP calculation in formula 11, the tentative IP days will be beyond the total LOD (i.e., the parameter t in formula 11). The particular setting of the IP days less than the maximum LOF is necessary to determine the IP, which is the second limitation. That is, Formula 11 only works when t belongs to the range $(1 \leq t \leq T)$; otherwise, the inflection point falls at T . The IRT-based model using the NRIM[8,9,33- 35] is recommended to readers to examine the online time-series data on the website[31].

The model aims to help physicians detect medical fees for hospitalized patients, not including the would-be fees that could be deducted by the issuance company. Readers are invited to apply the method shown in a previous study[40], which would be helpful for physicians to write discharge notes carefully and completely on the reasons for abundant medical fees consumed during hospitalization.

Finally, the lower R-square in modeling means the case is more complex in medical

fees that should be substantially focused on when this model was applied. How to address complex cases in medical fees is worth further study in the future.

Conclusion

This paper suggests that the exponential growth model can be applied to a clinical setting to help physicians consecutively predict DRG medical fees with inflection points for hospitalized inpatients and upgrade the level of hospital management in the future.

Declarations

Ethics approval and consent to participate

Not applicable.

All data were downloaded from the previous study [18].

Consent to publish

Not applicable.

Availability of data and materials

All data used in this study are available in SDC files.

The datasets generated and/or analysed during the current study are available in the repository of Additional File 1 or at <http://www.healthup.org.tw/dataset.xlsx>

Competing interests

The authors declare that they have no competing interests.

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Authors' Contributions

SY developed the study concept and design. JK, TWC, and WC analyzed and interpreted the data. SB monitored the process of this study and helped respond to the reviewer's advice and comments. TWC drafted the manuscript, and all authors provided critical revisions for important intellectual content. The study was supervised by SB. All authors read and approved the final manuscript.

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Additional Files

Additional File 1

Dataset deposited at <http://www.healthup.org.tw/dataset.xlsx>

Additional File 2

Excel VBA module used in this study. Online at <https://youtu.be/kEcVG1Fv1jk> (Accessed on 3 Oct. 2021).

Additional File 3

Abstract video using MP4 at <https://youtu.be/Cc4zTK7i7SI> (Accessed on 3 Oct. 2021).

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Figure 5

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