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The wisdom of crowds in action: Forecasting epidemic diseases with a web-based prediction market system

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ABSTRACT

Background: The quest for an effective system capable of monitoring and predicting the trends of epidemic diseases is a critical issue for communities worldwide. With the prevalence of Internet access, more and more researchers today are using data from both search engines and social media to improve the prediction accuracy. In particular, a prediction market system (PMS) exploits the wisdom of crowds on the Internet to effectively accomplish relatively high accuracy.
Objective: This study presents the architecture of a PMS and demonstrates the matching mechanism of logarithmic market scoring rules. The system was implemented to predict infectious diseases in Taiwan with the wisdom of crowds in order to improve the accuracy of epidemic forecasting.
Methods: The PMS architecture contains three design components: database clusters, market engine, and Web applications. The system accumulated knowledge from 126 health professionals for 31 weeks to predict five disease indicators: the confirmed cases of dengue fever, the confirmed cases of severe and complicated influenza, the rate of enterovirus infections, the rate of influenza-like illnesses, and the confirmed cases of severe and complicated enterovirus infection.
Results: Based on the winning ratio, the PMS predicts the trends of three out of five disease indicators more accurately than does the existing system that uses the five-year average values of historical data for the same weeks. In addition, the PMS with the matching mechanism of logarithmic market scoring rules is easy to understand for health professionals and applicable to predict all the five disease indicators.
Conclusions: The PMS architecture of this study affords organizations and individuals to implement it for various purposes in our society. The system can continuously update the data and improve prediction accuracy in monitoring and forecasting the trends of epidemic diseases. Future researchers could replicate and apply the PMS demonstrated in this study to more infectious diseases and wider geographical areas, especially the under-developed countries across Asia and Africa.
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1. Introduction

Today's communication networks, computing power, and intelligent algorithms have enabled us to perform with multiple agents voting and rank aggregation, task and resource allocation, kidney exchanges, auctions and exchanges, charitable giving, and prediction markets over the Web [12]. Early in 1988, researchers in University of Iowa introduced a prediction market system (PMS), Iowa Electronic Markets, to predict the outcome of the 1988 U.S. presidential election. Since then PMSs have drawn much attention in betting political events [20,55,70,18,58]. Outside the political arena, a host of PMSs have been introduced such as HedgeStreet Exchange (www.nadex.com), Hollywood Stock Exchange (www.hsx.com), iPredict (www.ipredict.co.nz), Tradesports (www.tradesports.com), among others. Several commercial and open source software tools are available [6]. The former includes ConsensusPoint (www.consensuspoint.com) and InklingMarkets (www.inklingmarkets.com). The latter includes IdeaFutures and Zocalo provided by Sourceforge.net.

Regarding disease prediction, it is heartbreaking to know that epidemic diseases cause thousands of people to lose their lives each year. According to a recently World Health Organization report [68], cholera is one of the most common epidemic diseases. There are 1.4–4.3 million reported cases annually, causing 28–142 thousand deaths each year. This number is surprisingly high given the

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well-established and effectively-executed cholera prevention and treatment programs in many regions of the world. The quest for an effective system capable of monitoring and predicting the trends of epidemic diseases is a critical issue for communities worldwide.

Many quantitative models for epidemic prediction have been reported in the literature. One could classify them into three categories: mathematical models, computational models, and surveillance models [73,39,33,7,45,24]. While a mathematical model describes the behavior of a system using mathematical properties and language, a computational model uses computing resources to study the behavior of a system for which analytical solutions are not readily available. The former model includes operations research models [73,30,1,34,43,66,33], trend extrapolation models [37,54,38], compartment models [25,72,59,41], incubation-based models [13,22,65], among others. The latter model encompasses simulation models [17,19,3,40,46], agent-based models [60,9,47], neural network models [16,26,2,64], among others.

As [33,p. 411] puts it, "(a)ny mathematical model of the disease and its control is bound to be incorrect." Instead of using the aforementioned models which offer periodic predictions based on historical data, healthcare researchers of the [67] use surveillance systems, called early warning systems (EWSs), to predict trends of infectious diseases by including such environmental variables as climatic factors and vegetation patterns. However, an EWS faces difficulties in acquiring sufficient suitable epidemiological data and in updating the data continuously. Later in 2006, Boston Children's Hospital initiated another surveillance system, the HealthMap project [21], to bring together multiple heterogeneous data sources for a unified and comprehensive view of the current global state of infectious diseases and their local effects on human and animal health [7]. The project established a Website "Healthmap.org" and a mobile app "Outbreaks New Me" both are freely available to the public. More recently in 2008, Google introduced its "Flu Trends" (GFT) application to monitor the severity of flu epidemics weekly in most developed countries. The application uses aggregated Google search data to estimate current flu activities around the world in near real-time [23]. Instead of Google, Polgreen et al. [51] used a similar tool, the Yahoo! search engine, to produce flu trends that are strikingly similar to the actual influenza occurrence pattern. However, web searches for real-time influenza data can indicate only what has happened, but not what will happen; i.e., they are not predictions. In addition, GFT does not provide surveillance signals for most regions in Asia and Africa and can be used only to monitor the flu epidemic; it is not applicable to other diseases.

Soon after the debut of GFT [38], demonstrated with time-series analysis that GFT and emergency department data were good indicators for the early detection and monitoring of the 2009H1N1 pandemic waves in Manitoba 1–2 weeks in advance. Recently Pervaiz et al. [50], developed an EWS for flu epidemics, called FluBreaks (www.dritte.org/flubreaks), based on GFT data. An extensive review of 32 relevant studies recommends the continuance of using search queries and social media for disease surveillance, early detection, and epidemic effect mitigation [5]. Yom-Tov et al. [71] collected Internet data from Twitter and Bing search engine queries and demonstrated the feasibility of creating a public health surveillance system for mass gatherings based on Internet data. Contrary to using the data from search engines and social media [62], developed a Web-based survey for daily health symptomatic surveillance. During a seasonal influenza epidemic, the survey detected a rapid increase in the number of participants with fever through the early aberration reporting system. Finally, despite the popularity of search engine data, Google ceased to update and publish the GFT data on Thursday, August 20, 2015 (see http://www.google.org/flutrends/). Meanwhile, HealthMap began to combine search, social media, and traditional data sources to improve influenza surveillance [56].

In summary, in order to predict the trends of epidemic diseases dynamically and reliably, we need to overcome the aforesaid three difficulties: having real-time and updated data, incorporating experts' experience and knowledge, and offering continuous and long-term predictions. A plausible way to overcome these difficulties is to use a PMS. The PMS can accumulate the wisdom of crowds, continuously renew the relevant data, and make up-to-date predictions. It is useful for forecasting the spread of infectious diseases [52,53].

2. Research purpose

The purpose of this study is to demonstrate a real-life PMS and the matching mechanism of logarithmic market scoring rules (LMSR) for predicting the trends of epidemic diseases. The effectiveness of the system is briefly discussed. We first constructed a PMS specifically for epidemic disease prediction, following the requirements from Taiwan's Center for Disease Control (CDC). Encouraged by the CDC, thousands of health professionals in 543 hospitals and health institutions all over Taiwan were invited to use the system. Among them, 630 registered and were certified to use the system.

In order to prepare the participants for using the PMS, we delivered two lectures on the PMS hosted by the CDC and produced introduction brochures of the PMS in print and online to invited health professionals. Furthermore, we made ourselves available online or by phone to help health professionals understand, participate, and trade in the PMS. The system was open for 31 weeks, and the results confirm that the accuracy of epidemic disease prediction provided by the PMS is better than the historical-average approach being used by the CDC. Both academicians and practitioners could adapt the PMS of this study and create similar systems for epidemic disease prediction in their own regions, allowing the global community at large to benefit from the results of this study.

The remaining sections of this paper are organized as follows. Section 3 discusses the definition and applications of PMS, the architecture for PMSs, and the matching mechanism of logarithmic market scoring rules [28]. Section 4 describes the interface designs of the epidemic PMS implemented in this study as well as the procedure of experiment. Section 5 analyzes the data collected and interprets the findings from the results. Finally, Section 6 draws several conclusions and recommendations and discusses practical and social implications of EPMS.

3. Prediction market systems

A prediction market system (PMS), operating like a futures market [44], can be used as a mechanism to integrate information from different sources to predict the outcomes of future events [12]. PMSs have two major features: providing appropriate reward mechanisms and performing continuous prediction corrections. Traders in a PMS buy or sell the predictions of a future event based on public or private information. The actual results of the future event determine the rewards (or penalties) for the trader, whereas the price of the future event contract represents the entire market's prediction for the outcome of the future event.

In the last two decades, prediction markets have been empirically proven to be remarkably accurate in forecasting future events with a lower prediction error than conventional forecasting methods [8,35,61,69]. For instance [4], analyzed the performance of different predictions concerning five US presidential elections in the period of 1988–2004. They compared the predictions of the Iowa Electronic Markets with those of 964 polls conducted by two distinguished polling agencies, the Gallup Poll and the Harris Poll,

and by three television broadcasting networks, *ABC*, *CBS*, and *NBC*. The results showed that the predictions of PMS were closer to the actual outcomes than traditional polls 74% of the time. In addition to elections, PMSs recently have been applied to the business world in such companies as Hewlett-Packard [10,31], Google [11,14], Intel [29], and General Electric [32]. They have been built internally by a business for its members to trade on new product success [42], strategically important objectives, or key performance indicators (e.g., input costs, sales volumes, and project completion dates).

There are several unique characteristics that make PMS superior to polls and expert opinions in predicting future events. The participants in PMSs are voluntary and proactive; they can and will continuously and interactively express their opinions through trading event predictions on a futures market. The price of an event contract reflects, in real time, the common beliefs of the participants about the chance of occurrence for the prediction event.

Table 1 contrasts the differences in participation, method, incentives, and prediction accuracy between prediction markets, polls, and expert opinions.

Global warming has increased the occurrence and seriousness of infectious diseases, while convenient international travel further exacerbates the spread of such diseases. Geographically situated in the subtropical climate region, Taiwan is frequently subjected to infectious diseases, making it a good location to test the capabilities of prediction markets. In contrast to the Iowa Influenza Prediction Market (https://iemweb.biz.uiowa.edu/outbreak/), which is the most successful prediction market of epidemics to date, the epidemic PMS (EPMS) we constructed provided superior performance in terms of duration, the number of diseases, and the method of trading transaction. In our EPMS, we implemented the matching mechanism of LMSR to facilitate the integration of scattered and limited information from health professionals and resolve the chronic liquidity problem encountered when the number of participants is small.

3.1. The architecture for prediction market systems

The EPMS in this study was built as a Web-based service so that the participants could log into the system online. Fig. 1 depicts the architecture of the PMS implemented in this study which consists of three main integrated components: *Web applications*, *market engine*, and *database clusters*. The view functions of Web Applications component display the outputs of Market Engine component; both components use Database Clusters as the data sources.

The Web application component provides seven view functions for participants to interact with the PMS:

1. The Market Monitoring view shows the real-time information of each prediction event in the PMS, such as the latest circumstances of event prediction, historical trends of disease spread, related news, and discussion about the disease. The participants could also see the details of each prediction event including the price and expiry date.
2. The Orders view enables participants to make a transaction through buying or selling an event contract. Participants could choose a specific disease, indicator, area or location as a prediction target.
3. The Balance of Order view shows the details of participant transaction data; e.g., the volumes of an event which participants had bought. It helps the participants to understand their trading records in the inventory.
4. The Statement of Orders view shows how much a participant has gained or lost after the settlement of an event on the expiry date.
5. The Ranking List view provides a list of traders according to the ranking scores calculated by the market engine.
6. The Registration view helps new users register for the PMS.
7. The Issuing Future Event view includes the text field for the Website manager to type the title and description of a new prediction event. When issuing a new prediction event, the PMS automatically generates a record in the Market Monitoring view.
8. The Initializing Settlement view triggers the settlement mechanism of PMS on the expiry date and prepares the payoff report for each trader.

The second part of the architecture is the market engine. It includes three main functions for internal mathematical processing: market matching, computation, and ranking calculation. The market matching function employs a matching mechanism as to make a common estimate of a prediction event. The computation function computes the participant's return of the bet according to settlement process on the expiry date. After the settlement process, the system executes the ranking calculation function to identify the participant's ranking based on his or her credits.

The third component of PMS architecture is the database clusters which consist of six different datasets for data storage: event data, trader data, order data, transaction data, payoff report, and trader rankings. Data in these datasets could be stored, updated, and deleted via corresponding function codes.

3.2. The logarithmic market scoring rules

There are two matching mechanisms commonly implemented in PMS: continuous double auction (CDA) and LMSR. The former is often used by the futures market in which trades are executed whenever new limit orders in the form of bids (buy orders) and asks (sell orders) come in and the highest bid exceeds or equals the highest ask price, or else when a new market order comes in and the order book contains orders with which the market order can be matched [48]. If a trader thinks an event is likely to happen, he or she would buy the corresponding contracts, otherwise, would sell the contracts. In contrast to CDA, LMSR allows an individual in a PMS to estimate the result of a future event and get payoff according to his or her prediction accuracy. Anyone can at any time choose to be paid according to that rule and pay off the last person who used the rule. Thus if only one person uses a market scoring rule, it becomes a simple scoring rule. But if many people use that rule, it becomes an automated market maker facilitating trades between those people [27]. When the market is closed, each trader holding a prediction contract is paid off according to the price assigned by the rule [36].

Both CDA and LMSR offer acceptable accuracy of prediction when the number of traders is sufficiently large. However, the CDA will not work well in a thin market (i.e., the number of traders is small). The LMSR can better avoid the thin market problems, as well as irrational participation problems, by becoming automated market makers (i.e., betting markets) in the thick market case and adopting simple scoring rules in the thin market case. While betting markets can elicit good consensual estimates from groups, simple scoring rules can elicit good probabilistic estimates from individuals. The LMSR combines the advantages of both methods: inducing individuals to make estimates and combining them into a common estimate [27].

The simplicity of the PMS with LMSR is very important to the successful operation of EPMS, as health professionals have little knowledge of prediction markets and are often too busy to use the EPMS and participate in the trading activities. Each participant would have 10,000 virtual health dollars for each prediction event of epidemic disease indicators to trade in the EPMS. In addition, it would be very easy for health professionals to set the prediction range and place bets next to the historical average data. According to each participant's collected information or profes-

Table 1
Characteristics of prediction market, polls, and expert opinions.

Characteristic	*Prediction Market*	*Polls*	*Expert Opinions*
Participation	• Active	• Random	• Recommended
Period of opinion expression	• Continuous until the expiry date [a]	• One time	• One time or periodic
The manner of expressing opinion	• Interactive	• Independent (normal)	• Independent or interactive
The content of expression	• The chance of prediction event occurrence, e.g., who would win the vote?	• Express individual preference, e.g., "Which candidate would you like?" or "Which one would you support?"	• Express individual preference or the chance of prediction event occurrence
Weight of participant	• Based on the proportion of investment	• Equal weight	• Equal weight
Incentives to tell the truth	• Economic rewards or penalties • Use of real money or virtual money	• None	• Reputation • One time fixed return
Aggregation method of opinions	• The price reflects the common beliefs	• Static one time analysis	• One time analysis
Accuracy of prediction	• Very good	• Good	• Slightly better
Executing approach	• Building an electronic trading market	• Employing a large scale of interview or survey	• Cautiously choosing a list of experts

[a] Expiry date is the time and date when trading activities are terminated before the prediction event occurs.

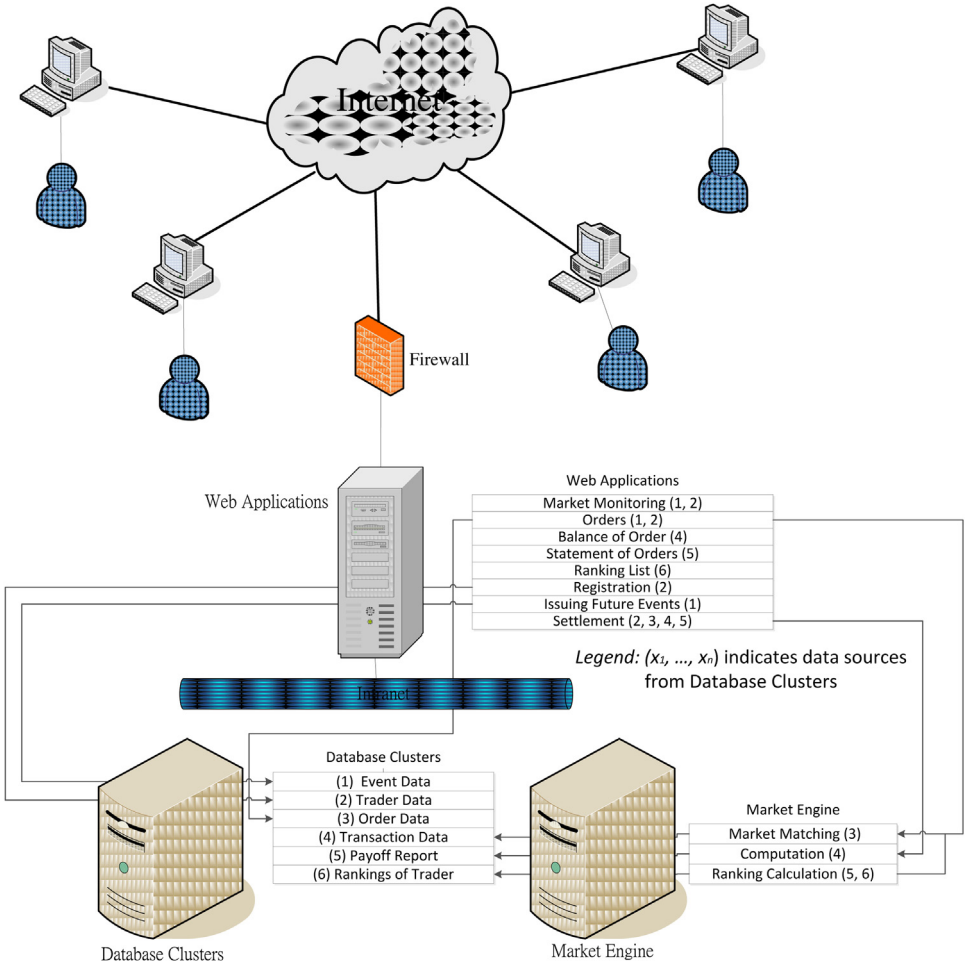

Fig. 1. The architecture for prediction market systems.

sional judgment, she/he could set a single-point estimation or a range estimation and place bets out of 10,000 virtual dollars, which would represent her/his confidence on the prediction. Then the EPMS would automatically calculate her/his expected return on each bet. If a prediction on one disease indicator in an area during one of the 8 prediction weeks was regarded as a prediction event,

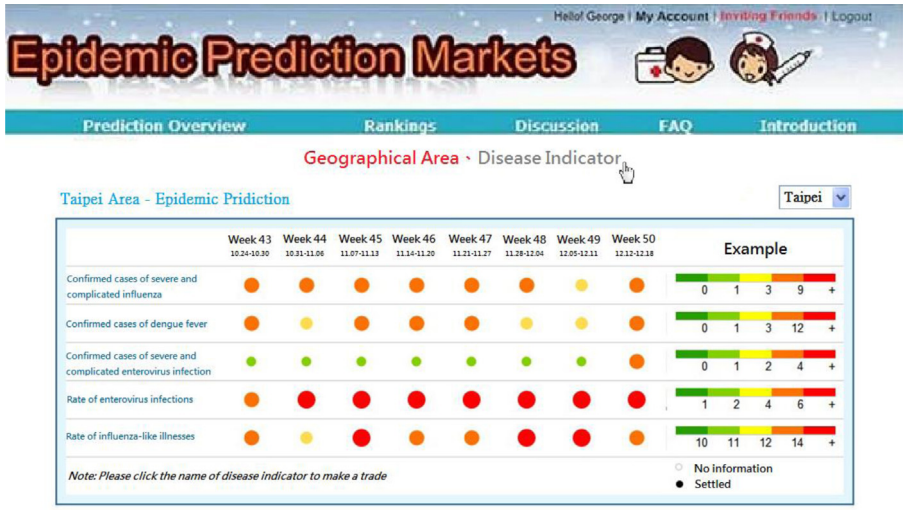

Fig. 2. Initial input screen of EPMS.

Source: [63].

there were 7945 prediction events in total, spanning 31 weeks. However, only 126 participants of very busy health professionals with little knowledge of prediction markets traded on the events. Therefore, our EPMS adopted LMSR as the matching mechanism in order to foster information aggregation and improve trading liquidity. Specifically, the mechanism of LMSR described by [28] is as follows. Consider an expected-utility maximizing market trader who has subjective beliefs p_i regarding a complete set of I with disjoint events i where $\sum_i p_{i\in I} = 1$. is market trader is paid a cash amount x according to a proper scoring rule $x_i = s_i\left(\vec{r}\right)$ [57]. Let x_i the cash payment if event i turns out to be the actual event, r_i is the probability that the trader reports for the event i and $\vec{r} = \left\{r_i\right\}_i$ is the full report. In order to maximize the expected monetary payoff, the trader will honestly report $r_i = p_i$, that is

$$\vec{p} = argmax\rightarrow r\sum_i p_i x_i = \sum_i p_i s_i\left(\vec{r}\right), given\sum_i r_i = 1.$$

For any scoring rule $s_i\left(\vec{r}\right)$ and any value of $\vec{\rho}$, a trader will be willing to accept a payment of the form:

$$x_i = \Delta s_i\left(\vec{r}, \vec{\rho}\right) = s_i\left(\vec{r}\right) - s_i\left(\vec{\rho}\right)$$

In this case, the trader can ensure oneself no effect $\left(\vec{x} = 0\right)$ by setting $\vec{r} = \vec{\rho}$ and expects a maximal profit if he or she sets $\vec{r} = \vec{p} \neq \vec{\rho}$ (all normalized). Then, if we continuously set $\vec{\rho}$ to the last report made and let traders make their own reports $\rightarrow r_t$ one at a time to a market scoring rule, where each report is paid $x_{it} = \Delta S_i(\rightarrow r_t, \rightarrow r_{t-1})$ with an initial reference report $\rightarrow r_0$. The total cost to pay for T reports, x_i, relies on the initial and final reports, and is thus the same as the cost for one final report with the same final values r_i.

$$x_i = \sum_{t=1}^{T} x_{it} = \sum_{t=1}^{T}\left(s_i(\rightarrow r_t) - s_i(\rightarrow r_{t-1})\right) = s_i(\rightarrow r_T) - s_i(\rightarrow r_0),$$

The total movement from $\rightarrow r_0$ to $\rightarrow r_T$ can split into smaller movements from $\rightarrow r_{t-1}$ to $\rightarrow r_t$ without additional cost, each smaller movement can be thought of an integral of infinitesimal movements $d\vec{r}$ along a line of changing reports $\vec{r}(t)$ as t varies continuously. This means that each trader can correct his or her prediction by making transactions in the PMS to achieve higher prediction accuracy.

To elucidate an example of LMSR, let q_1 and q_2 be the quantity of shares outstanding for each of two event outcomes, and the cost function be $C(q_1, q_2) = b \times ln\left(e^{(q1/b)} + e^{(q2/b)}\right)$ where b is a parameter that controls the maximum possible amount of money the market maker can lose, ln is the natural logarithm, and e is the exponent. A larger b means that traders can buy more shares at or near the current price without causing massive price swings. Suppose $b = 100$ and no one has purchased any shares yet, thus $q_1 = q_2 = 0$. If a trader wants to buy 10 shares of outcome 1, he or she needs to pay \$5.12 according to the cost function $C(q_1 + 10, q_2) - C(q_1, q_2)$ below, where negative value indicates the trader receives money instead of paying money [49].

$$C(0+10, 0) - C(0,0) = 100 \times ln(e^{(10/100)} + e^{(0/100)}) - 100 \times ln(e^{(0/100)} + e^{(0/100)}) = \$5.12$$

If another trader arrives and wants to buy 50 shares of outcome 2, he or she needs to pay the amount of $C(10,50) - C(10,0) = \$26.86$ because $q_1 = 10$. We can estimate the current prices of the two outcomes as:

$$P_1 = e^{(q_1/b)}/(e^{(q_1/b)} + e^{(q_2/b)}) = e^{(10/100)}/(e^{(10/100)} + e^{(50/100)}) = \$0.401$$

$$P_2 = e^{(q_2/b)}/(e^{(q_1/b)} + e^{(q_2/b)}) = e^{(50/100)}/(e^{(10/100)} + e^{(50/100)}) = \$0.599'$$

Thus, $P_1 = \$0.401$ and $P_2 = \$0.599$ when $q_1 = 10$ and $q_2 = 50$.

Now suppose the same trader above returns to the market and wants to sell the 10 shares of outcome 1, he or she will receive \$3.89 and take a loss of \$1.23. The payoff value is estimated as follows.

$$C(0, 50) - C(10,50) = 100 \times ln(e^{(0/100)} + e^{(50/100)}) - 100 \times ln(e^{(10/100)} + e^{(50/100)}) = -\$3.89$$

4. System experiment and results

Following the system architecture in Fig. 1, we implemented the EPMS with the LMSR matching mechanism as discussed in the last

Fig. 3. The trading view of EPMS.

section [49,28]. The interface designs of the EPMS and the procedure of experiment are described below.

4.1. Interface designs

Fig. 2 shows a view of the prediction event list in the EPMS. A participant could choose the geographical area (e.g., Taipei) to predict from the pull-down menu in the upper right corner of the view. When the participant clicked a specific prediction event name (e.g., confirmed cases of severe and complicated influenza), the system would navigate to the trading view page as shown in Fig. 3. The participant could make a transaction after viewing the orders.

In the trading view page, the participant needed to set the prediction range and place bets for each prediction event. The range is based upon the ceiling and floor of the historical data with two standard deviations of the average. In addition, we assume the probability of the range is a normal distribution and the initial price of each estimation point is the probability. Each of these traders was awarded an initial funding of 10,000 virtual dollars for each prediction event to trade; but he or she could not buy any event contract when those funds were exhausted. Then, as soon as the participant clicked the Predict button, the EPMS would automatically calculate his or her expected return on each bet and deduct the balance by the amount of the bets. Furthermore, with the new information inputs of participants by placing bets, the new price of each estimation point would be dynamically adjusted based on the calculation of the LMSR. Participants could make predictions of events for 7 weeks in advance; the predictions were settled every week. When a prediction-event order was settled, the system opened another week for predictions. Therefore, there were 8 weeks open for predictions each day.

At any point in time, an output screen allowed the participant to review the current status of the EPMS against the historical data of a particular disease indicator in a particular geographical area. For example in Fig. 4, the geographical chart on the left shows the epidemic prediction for the week of June 6 to June 13, 2010, and the chart on the right indicates the historical statistics in the past year from July 1, 2009, to June 30, 2010, while the 8 dots represent the 8 weeks of predicted diseases in the Taipei area.

4.2. Procedure of experiment

Immediately after the EPMS was implemented and released in January, 2010, we invited health professionals with the help of the CDC in 543 major hospitals and health institutions in Taiwan to use the system. On February 1, the system was opened to the invitees for registration purposes. When they registered, only their e-mail addresses and user names were requested; they did not need to enter any private information. Nevertheless, each registrant must provide his/her certificate proof of health professional before his/her account is activated. The trading function was open from March 1 until December 31. The performance of the EPMS was measured from the 10th week (March 7 ∼ 13) to the 40th week (October 3 ∼ 9) of 2010. During this 31-week period, 630 health professionals registered. To encourage trading, incentives such as weekly top winner lists, final prizes and certificates, and a lottery drawing were designed and implemented. Despite these incentives, only 126 registrants actually traded the prediction events.

The trader group was composed of 48 nurse specialists, 23 doctors, 13 medical inspectors, 4 pharmacists, 3 nurses, 2 Chinese medicine practitioners, and 33 other professionals. Regarding working institutions, 40 traders were from public hospitals, 40 from private hospitals, 21 from Taiwan's Department of Health and its related units, 7 from clinics, 4 from local public health bureaus, and the remaining 14 from other units. In terms of areas where the traders were working, 38 were from the Taipei area, 29 from the southern area, 21 from the northern area, 15 from

Fig. 4. The output screen of EPMS.

Table 2
The statistics of predictions for five disease indicators.

Disease Indicator	*Participants*	*Predictions*	*Trading Amount*
Confirmed cases of dengue fever	84	4,395	29,503,332
Confirmed cases of severe and complicated influenza	81	3,956	33,501,580
Rate of enterovirus infections	76	3,495	31,627,923
Rate of influenza-like illnesses	64	2,660	23,759,804
Confirmed cases of severe and complicated enterovirus infection	59	4,291	23,199,675
Total	126	18,797	141,592,314

Source: [63].

the Kaohsiung-Pingtung area in the south of Taiwan, 12 from the eastern area, and 11 from the central area. Table 2 shows the statistics of predictions for five disease indicators. There were a total of 126 participants making 18,797 predictions and the total trading amount was 141,592,314 virtual dollars. A participant could predict more than one disease indicator. The average number of predicted indicators per participant was 2.9.

5. Analyses and results

5.1. Prediction accuracy of the EPMS

Before using the EPMS, the CDC was using five-year historical average numbers of disease cases or rates (HAVG) to predict epidemics weekly. In this study, we compared the actual values from the prediction weeks of 2010 against the predicted values obtained from both the EPMS and the HAVG for the corresponding weeks. The difference between the actual value and each of these two values is the prediction error value, which determines the accuracy of the prediction.

A lower prediction error value means higher prediction accuracy, and vice versa. When the prediction error value of EPMS is less than that of HAVG, EPMS is credited with one win and the total number of wins for EPMS is increased by one. Therefore, the winning ratio for EPMS or HAVG is calculated as follows:

$$\text{Winning_ratio} = \text{Total_number_of_wins}/\text{Total_number_of_predictions}$$

5.2. Winning ratios of EPMS for the prediction of five diseases during the last eight weeks

Concerning the prediction performance, for the target week (i.e., 0 weeks in advance), EPMS was more accurate in 701 out of 1085 prediction events than HAVG, and the winning ratio of EPMS versus HAVG was 64.6% (=701/1085). EPMS's winning ratio was 55.5% for one week in advance, 54.4% for 2 weeks in advance, 53.0% for 3 weeks in advance, 52.8% for 4 weeks in advance, 52.3% for 5 weeks in advance and 50.5% for 6 weeks in advance. The winning ratio of EPMS, on average, was inferior to that of HAVG for the target 7 or more weeks in advance (see Fig. 5).

For each disease indicator, there were 1589 (=7945/5) prediction events. The winning ratios of EPMS for the confirmed cases of severe and complicated influenza, the rate of enterovirus infections, and the rate of influenza-like illnesses were clearly over 50% in all weeks. Respectively, the winning ratios of EPMS for these three indicators in the target week were 69.6%, 83.9% and 76.0%. In contrast, the winning ratios of EPMS for the confirmed cases of dengue fever and the confirmed cases of severe and complicated enterovirus infection were all below 50%. Particularly, the winning ratios of EPMS for the prediction of the confirmed cases of severe and complicated enterovirus infection were all under 31% prior to the target week.

It was surprising that the EPMS predictions were consistently inferior to HAVG's for confirmed cases of severe and complicated enterovirus infection and the confirmed cases of dengue fever, both consistently below the 50% winning ratio. One possible cause for this poor prediction is that both types of diseases require laboratory diagnosis through culture and serology which may take as long as one-month to confirm. Furthermore, the time recorded for both diseases is based on the actual onset points instead of doctor visits or case confirmation time. Yet, without the confirmation, the case cannot be recorded, making it lose the advantage of real-time information updating and impossible to track prediction accuracy.

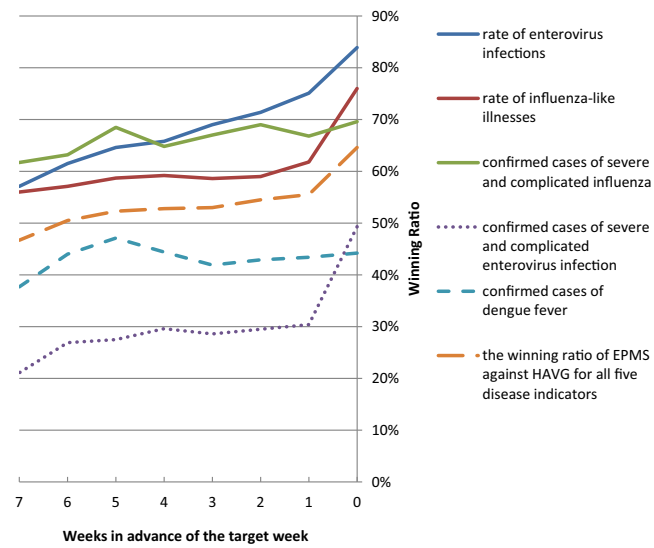

Fig. 5. The winning ratio of EPMS against HAVG for each disease indicator and for all five indicators.

6. Conclusions and recommendations

This study constructed an EPMS with the LMSR matching mechanism. The system was used by 126 health professionals to predict infectious diseases during a period of 31 weeks. The prediction obtained from the EPMS showed that the winning ratio of the EPMS for epidemic predictions constantly increased as target weeks approached the expiry date. Using a closed environment of professionals, the EPMS with a LMSR mechanism proved to be more accurate in predicting the values of three common epidemic disease indicators when compared with the five-year average values of historical data for the same weeks currently employed by the Taiwan CDC. Unlike the extant approaches that can only monitor (but not predict) the condition of diseases, the EPMS can continuously update the data to correctly predict the trends of these diseases.

In addition, the EPMS is highly suitable for applications to a wider range of infectious diseases and geographical areas, in contrast to GFT which is limited to search engine data and overlooks most of the under-developed regions in Asia and Africa. These regions are known for being prone to the spread of infectious diseases. GFT can be used only for monitoring flu trends, while the

Summary points

What was already known on the topic?

- The quest for an effective system capable of monitoring and predicting the trends of epidemic diseases is a critical issue for communities worldwide.
- The prediction market system (PMS) has been popular for event predictions since the 1988 U.S. presidential election.

What this study added to our knowledge?

- The PMS contains three design components: database clusters, market engine, and Web applications.
- Epidemic prediction of a PMS is better than that of historical five-year average values.
- The PMS is not suitable for diseases that take a long time to confirm through laboratory culture and serology.

EPMS could be applied to predicting, detecting, and monitoring the trends of infectious diseases. Generally speaking, if the EPMS is an effective instrument to deal with epidemic management and prevention in practice for the CDC in Taiwan, it should be effective for the rest of the world.

Based on the findings of this study, six recommendations seem helpful to future EPMS projects. First, EPMS should not be used for predicting a disease for which laboratory diagnosis to confirm the case takes a long time to perform. The reason is that the system cannot update the information in a real-time mode under such a condition. Second, EPMS should not be open to the public because it might cause panic in the society when the EPMS reveals a serious threat to public health. This policy was superimposed by the CDC before we conducted the experiment. Therefore, a closed system with health professionals as participants is an effective choice. Third, health professionals are extremely busy at work and tend to be skeptical about electronic systems; they are known to be late-adopters of health-information technologies [15]. Proper online training and a friendly system interface should be provided in order to allow self-paced learning so that potential participants can familiarize themselves with the EPMS. Fourth, additional access to the system, such as application software (APP) for mobile devices, might help attract more active participation from health professionals and keep them involved with the EPMS, given that only 126 of 630 health professionals registered actually participated in trading.

Finally, the architecture of the PMS identified in this study affords organizations and individuals to implement more PMSs for various purposes in our society. Through the better accuracy in predicting the trends of infectious diseases we obtain from using the PMS, we could save more lives in the world.

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