User adoption of wisdom of crowd: usage and performance of prediction market system

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Abstract: Prediction markets have been adopted to forecast events (trends) and manage risks related to the events in different projects. This paper scrutinises the first prediction market system (PMS) established in Taiwan, which shows favourable accuracy of the PMS in predicting infectious diseases comparing with expected value of historical data for the same period. It further analyses the incentive structure as well as system quality of PMS to attract initial as well as continuous participation. The paper concludes that public welfare and hedonic motivations are the most significant factors driving members' initial participation in the PMS. And prize motivation influenced the trading performance in this prediction system. Finally, based upon theory of planned behaviour (TPB), this paper finds that satisfaction and perceived behaviour control of participants in the PMS have positive influences on continuance intention and actual participation, while peer influence has little positive impact.

Keywords: wisdom of crowd; PMS; prediction market system; MSRs; market scoring rules; CDA; continuous double auction; epidemic prediction; TPB; theory of planned behaviour; continuance intention.

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1 Introduction

Prediction market (PM) is a forecasting mechanism capable of processing the dynamic aggregation of dispersed information from various participants (Forsythe et al., 1992). It is modelled after the century-old structure of financial markets. Similar to stock and futures markets, a PM also contains securities, or contracts, which can be bought or sold by the traders. The price of a security represents the likelihood of a future event that may occur (e.g., Barack Obama will win the election in 2012.) A competitive market achieves market efficiency through the price mechanism which is one of the most efficient instruments for aggregating asymmetrically dispersed information possessed by market participants (Hayek, 1945; Smith, 1982). New information is continuously absorbed by the traders and reflected on the market prices (Snowberg et al., 2007).

A PM operates like a futures market, and can be used as a mechanism to integrate information from different sources to predict the outcomes of future events. By definition, a PM is a market where the participants are allowed to trade 'future event contracts' based on their judgement of contract price trends as well as event result predictions. Contract prices may be used as references to evaluate the chances of occurring of specific events, as well as how much they will occur. For each contract, the PM will set the 'prediction event', 'settlement basis' and 'expiry date'. The gain or loss of each trader on the expiry date will be determined by whether the event has occurred or not and how much it occurs, according to the settlement basis.

In the recent two decades, prediction markets have been proven empirically to be remarkably accurate in forecasting future events (Wolfers and Zitzewitz, 2006; Manski, 2006), such as elections (Bruggelambert, 2004; King, 2006; Walker, 2006; Chen et al., 2008; Berg et al., 2008), sports competitions (Luckner et al., 2007; Spann and Skiera, 2009) and movie box offices (Gruca, 2000; Gruca et al., 2003; Foutz and Jank, 2007). Generally speaking, prediction markets have two major characteristics which are advantageous in prediction accuracy over traditional methods of prediction. First is the incentive structure of reward and punishment, which induces participants to provide real and effective information. Market manipulation, though occurs occasionally, is hard to prevail in most situations (Camerer, 1998; Rhode and Strumpf, 2009). Second is the continuous update of information for the predicted events. Traditionally, expert deliberations or surveys could be conducted from time to time, yet it is impossible to provide continuously updated information and reach consensus constantly. In contrast, on prediction markets, participants conduct trade online to provide real-time information. As a result, prediction markets have been adopted recently as a research method to forecast events (or trends) and manage risks related to the events in different projects, institutions, societies or countries. Understanding what factors significantly affect the performance effectiveness of a PM becomes increasingly important.

As a prediction market system (PMS) is an information system, the adoption of the system follows the process prescribed by technology adoption models (e.g., Davis, 1989; Bhattacherjee, 2001). The process contains two stages: initial use and continuance. In the context of PMS, initial use refers to the act of a user in registering to become a member of the system; while continuance refers to the act of a user in using the PMS after having the initial use. The success of a PMS lies in whether most of its users are in continuance stage and how good its trading performance is. It is therefore important to understand what factors affect the initial use, continuance intention, degree of participation and trading performance of a user. To our disappointment, after an extensive review of the related literature, we found a dearth of research related to this research issue. To fill this research gap, this study constructs a PMS for predicting the occurrences of infectious diseases in Taiwan and collects empirical data to address the following research questions:

1 What motivates people to register in the PMS?
2 What entices participants to begin trading in the PMS?
3 What drives participants to keep trading in the PMS?
4 What factors influence the degree of participation in the PMS?
5 What factors contribute to the differences between good traders and poor traders?
6 What factors contribute most to trading performance of participants?

The remaining sections are organised as follows. The next section provides extensive literature review on PM and related theory and applications in information system field. The third section elaborates the research model and explains the survey methodology in which a PMS was constructed to compare the prediction of infectious disease from the PMS with the expected value of historical data. The fourth section presents empirical results and the final section gives conclusions and implications.

2 Literature review

2.1 Prediction markets and their applications

Prediction markets have been applied to many areas. In the business world, companies such as Hewlett-Packard (Chen and Plott, 2002; King, 2006), Google (Coles et al., 2007; Cowgill et al., 2009), Intel (Hopman, 2007) and General Electric (LaComb et al., 2007) have already established internal information markets for employees to trade on strategically important objectives or key performance indicators, such as input prices, sales and project completion dates. Other firms whose internal prediction markets have been mentioned in the public domain include Abbott Labs, Arcelor Mittal, Best Buy, Chrysler, Corning, Microsoft, Electronic Arts, Eli Lilly, Fritos Lay, Inter-Continental Hotels, Masterfoods, Motorola, Nokia, Pfizer, Qualcomm and Siemens.

Spann and Skiera (2003) show rather encouraging results of prediction markets for business forecasting purposes. In addition, they point out that prediction markets work well under different incentive structures and even with a limited number of participants. Gruca et al. (2003) find that PM prices summarise the information contained in survey forecasts and improve those forecasts by reducing the variability of the forecast. Ho and Chen (2007) argue that prediction markets can work in a wide range of industries, such as movie industry, information technology industries and healthcare industry. Chen and Plott (2002), Gruca et al. (2003), Spann and Skiera (2003), and Ho and Chen (2007) all elaborate their particular system designs of prediction markets, but none of them assess and compare benefits and costs of different system design, including incentive structure, the initial portfolio structure and financial incentives.

Another important application of PM is infectious disease prediction which has been an important issue in health policy risks management. In 1918–1920, the flu pandemic (the 'Spanish flu') of influenza-A virus subtype H1N1 was deadly and spread across the world, even to the Arctic and remote Pacific islands. Historical and epidemiological data were inadequate to identify the geographic origin of the virus. Most victims were healthy young adult. Between 50 and 100 million, or 3% to 6% of world population, died and some 500 million, or 27%, were infected (Barry, 2005). In 2009–2010, the flu pandemic or swine flu appeared first in April 2009. It is thought to be a mutation of four known strains of influenza-A virus subtype H1N1: one endemic in humans, one endemic in birds and two endemic in pigs (MacKenzie, 2009). According to the statistics of the World Health Organization published in July 2010, the virus has killed more than 18,000 people. Therefore, how to detect, monitor and predict the trend of the infectious diseases has been an urgent mission and the Centers for Disease Control and Prevention (CDC) can allocate timely and sufficiently its health resources (e.g., vaccine, antibiotic, medicine, antidote, trained personnel, etc.) to prepare for and prevent the spread of the diseases based upon the prediction information. Nevertheless, the current surveillance system in Taiwan relies on healthcare professionals to report cases of the infectious diseases to the CDC and cannot predict the future trend of the diseases. This remains a staggering challenge for the CDC of Taiwan.

Recently, Polgreen et al. (2006, 2007) established the first PM for forecasting infectious diseases, such as severe respiratory syndrome and avian influenza. Originally, the market was called Iowa Influenza Market; it was re-named to Iowa Health Prediction Market (http://fluprediction.uiowa.edu). Data from a pilot study in the state of Iowa suggested that these markets can accurately predict statewide seasonal influenza activities

2–4 weeks in advance. Despite the outstanding performance of the prediction markets, Polgreen et al. (2007) briefly elaborated the system design of the prediction markets without further examination of system features or different scenarios of system designs.

In terms of decision-making, Berg and Rietz (2003), Sprenger et al. (2007) argue that prediction markets with expectations about the likelihood of events conditional on other events occurring could be used for decision support and provide a more effective mechanism for aggregating information than group deliberations. Hahn and Tetlock (2005) concur that prediction markets can be an efficient way to implement well-informed policy decision. The Department of Defense of the United States has conducted experiments (policy analysis market) of using PM mechanism to integrate the forecasts of various intelligence agencies on geo-political risks (Hanson, 2007b). Rajakovich and Vladimirov (2009) confirm the effectiveness of prediction markets to forecast future events as overall demand for hospital services (i.e., risk of demand) is forecasted with an error of only 0.3%.

2.2 *Accuracy of forecast from PMSs*

Analysing the factors which influence the accuracy of PMSs, some scholars (e.g., Berg et al., 1997; Gruca et al., 2005) assert, based on trading data of Iowa electronic markets (IEMs), that number of contracts (degree of competition), trading volume and bid-ask price spread are the most important factors. Others (e.g., Forsythe et al., 1999; Oliven and Rietz, 2004) find that number of marginal traders is the major factor for prediction accuracy. Kambil and Heck (2002) and Ledyard (2006) advocate that major factors include large number of traders, sufficient information as well as incentives for traders to reveal effective information. Obviously, prediction markets have a very good record of prediction accuracy and have been applied to many areas, either public or private domain. Nevertheless, none of the above literature provides detailed analysis on the utility of incentive structure and characteristics of trading system.

Some prediction markets use real money, while the others use play money. Often-cited play-money markets include the Hollywood Stock Exchange (http://www.hsx.com), the Foresight Exchange (http://www.ideosphere.com) and the Exchange of Future Events (http://xfuture.org). Well-known real-money markets include the IEMs (http://www.biz.uiowa.edu/iem) (Forsythe et al., 1999; Berg et al., 2001) and InTrade (http://www.intrade.com). Servan-Schreiber et al. (2004) argue that providing proper trading incentives, virtual currency information markets can be as accurate as their real-money counterparts. Luckner et al. (2006) find that, comparing two sports forecasting exchanges, the play-money market STOCCER performs better than the real-money market BLUEVEX. Nevertheless, they notice that more experiments need to be done for assessment of several differences between these two exchanges. Rosenbloom and Notz (2006) argue in the opposition that real-money markets are significantly more accurate for non-sports events.

2.3 *Trading mechanisms in prediction markets*

In prediction markets, there are two common trading mechanisms: continuous double auction (CDA) and market scoring rule (MSR). With the CDA mechanism, buyers and sellers can set their own prices and quantities for their orders and the clearing house will settle trades automatically. If a trader thinks an event is likely to happen, he or she would buy the corresponding contracts, otherwise, would sell the contracts. Traders submit ask (buy) or bid (sell) orders to a centralised market exchange. These orders are stored in an order book. For the limit orders, i.e., traders set the price of orders they can accept, once the bid price is no less than the ask price, the market exchange will settle a trade at the agreed price level. In contrast to limit orders, market orders (i.e., traders accept for any possible prices) have highest priority to deal with other orders. Thus the trade price always satisfies the prices requested by buyers and sellers.

Conversely in a PM with MSR, an individual estimates the result of a future event and gets payoff according to his or her prediction accuracy. Any trader can change the score continuously, thus paying margins and acquiring contracts. Once the market is closed, each trader holding a prediction contract is paid off according to the price assigned to the MSR. Both CDA and MSR 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 MSR overcomes the thin market problems that plague standard information markets. It also avoids opinion pooling problems in the thick market case, by becoming automated market makers in the thick market case and simple scoring rules in the thin market case (Hanson, 2003, 2007a). The MSR model has been applied in a Facebook application, Yoopick (Goel et al., 2008) and Inklingmarkets Website (2012).

Such a prediction mechanism seems to have great potential to integrate corporate information flows and thus reduces institutional operation risks. For instance, Chen and Plott (2002) find that a PM inside Hewlett-Packard for the purpose of making sales forecasts performs better than traditional methods. Hopman (2007) suggests that market-developed forecasts are meeting or beating traditional forecasts in terms of increased accuracy and decreased volatility, while responding well to demand shifts. Guo et al. (2006) emphasise that a macro PM effectively elicit and aggregate useful information about systematic demand risks (corporation risks management) in the supply chain system.

If a system of prediction, markets could not attract sufficient participants to engage trading in the market, it is in vain to appraise the predictive power of prediction markets. To explore the factors affecting the performance effectiveness of a PM and the continuance intention of its participants, the following sections will introduce the related theories, respectively, information systems success model and theory of planned behaviour.

2.4 Appling information systems success model to prediction markets

The success of a PMS lies in the continuous use of its registered members. As the PMS in essence is a web-based information system, the extant information system (IS) success models in the literature may offer a framework for conceptualising and operationalising its success. One of the models which has high robustness and been widely tested is the IS success model proposed by DeLone and McLean (1992, 2003). The model initially postulated information quality and system quality as the antecedents of user's satisfaction and use. User satisfaction and use have an iterative relation which implies high satisfaction will result in continuous use. Later in 2003, the authors presented an updated model (DeLone and McLean, 2003) and included service quality as an additional antecedent. It was because the changing nature of IS function in which service quality has become ever important when evaluating information system success. Another modification was replacing individual impact and organisation impact with an aggregate measure of impacts, called net benefit. Therefore, the updated model can assess the benefit at any level of analysis. DeLone and McLean (2003) further suggested that their updated IS model can be adapted to measure the success of the new internet websites. On the basis of the updated IS success model, this study intends to use continuance intention as the dependent variable in the research model and explore its antecedents in the prediction market context.

2.5 Continuance intention and usage

Many researchers have studied why users initially use information systems (Davis, 1989) and why they are willing to continue using the systems (Roca et al., 2006; Lee, 2010). The frameworks of these studies may be applied to PMSs. Bhattacherjee (2001) adapted Expectation Confirmation Theory (Oliver, 1980) to explain user's continuance intention of IS usage. He believes that user's initial adoption of information systems is the first step towards realising IS success and it is continuance intention that helps information systems attain long-term viability and ultimate success. For example in the PM context, the factors that attract customers to make trades on the system after they register into the system are vital to the sustainability of the PMS. In addition, Bhattacherjee and Premkumar (2004) showed that users may change their beliefs and attitudes towards information systems according to their perceptions and satisfaction with the initial IS usage. They further exhibited that beliefs and attitudes have significant impacts on the continuance intention of IS usage. In this study, we follow the three-stage (belief–attitude–intention) process of Bhattacherjee and Premkumar (2004) and use continuance intention as a dependent variable of beliefs and attitudes. However, to comply with the prescription of theory of planned behaviour (TPB) (Ajzen, 1991), we extend this process with a nomological linkage between continuance intention and usage.

2.6 Theory of planned behaviour

Theory of planned behaviour (TPB) is a psychology theory that was designed to provide parsimonious explanation of social behaviour (Ajzen, 1985). According to TPB, a behaviour can be explained by intention to perform the behaviour, and intention is explained as immediate predictor of behaviour by three predictors: attitude, subjective norms and perceived behaviour control. The attitude is a feeling of favourableness or unfavourableness towards the behaviour (Ajzen, 1991). For example, if a person believes that using a prediction market (PM) system can help in obtaining more accurate prediction about the market, then an individual is more likely to regard such use is worthwhile and desirable. That is, the person is more likely to have a positive attitude towards the use of PMS. Likewise, subjective norm is defined as the perceived opinions from other people who might think that the person should or should not perform a behaviour (Ajzen, 1991). It means the individual's perception may be influenced by significant referents. The TPB depicts behaviour as a function of behavioural intentions and perceived behaviour control. The latter refers to the individual's perceived presence of requisite resources and opportunities to perform a behaviour (Ajzen, 1985). For example, if an individual believes that it is difficult to use an information system, he or she may feel less control over the use of the system. Since its inception, many researchers have used TPB to understand the behaviour of the information system usage (Conner and Armitage, 1998; Notani, 1998; Sutton, 1998).

2.7 Hedonic and utilitarian motivations

The hedonic and utilitarian motivations have been regarded as factors influencing the IS usages such as graphics programs (Davis et al., 1992) and online shopping websites (Childers et al., 2001). They can be applied to the use of a PMS. The dual characteristics of two motivations demonstrate the essential determinants of behaviour intention to use a system. The utilitarian motivation refers to those forces that activate mission-critical, decision effective, instrumental, beneficial or goal oriented behaviours (Stoel et al., 2004; Batra and Ahtola, 1990). It represents participants would like to use an information system as an effective means to complete a specific task. In the case of purchasing a book, people may shop from the online store instead of a physical one because of convenience and time saving. In contrast, hedonic motivation refers to those forces that activate behaviours in search for happiness, fantasy and enjoyment (Hirschman and Holbrook, 1982). It means that a user would like to seek for self-fulfilling values such as fun and playfulness while he or she interacts with an information system. Research revealed that utilitarian and hedonic elements are the precursors that influence different behaviours of online shopping (Overby and Lee, 2006; To et al., 2007) and social networking (Xu et al., 2012).

3 Hypothesis development

3.1 The research model

On the basis of DeLone and McLean's IS success model and Ajzen's TPB, we propose a research model as shown in Figure 1. This model represents the complete relationship network of EPM continuance intention and usage, following the four stages of behavioural process prescribed by TPB: belief, attitude, intention and behaviour. There are 10 constructs in this model and nine linkages between the constructs. Each linkage corresponds to a postulated hypothesis. The justifications of these nine hypotheses are presented as follows.

3.2 The relationship of quality and satisfaction

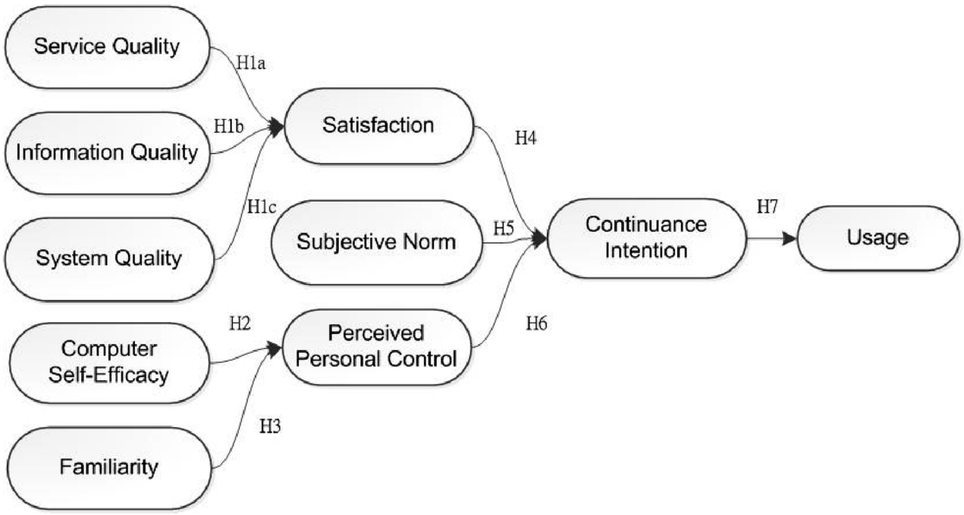
Early researches in the marketing field suggest that customers assess service quality by comparing what they feel a seller should offer with the seller's actual provision (Gronroos, 1982; Lewis and Booms, 1983). This constitutes an expectation–performance gap. If a customer perceived the quality provided from the vendor meets customer's expectation, they would form positive attitude towards the service received from the service provider. Prior studies in the IS field (Seddon, 1997; DeLone and McLean, 1992) verified that user satisfaction is impacted by beliefs about the IS quality, including the information quality and system quality. This finding is consistent with the TPB, where attitude towards using a system is impacted by beliefs about the system. Researchers in the marketing and IS fields also reveal that service quality, information quality and system quality after actual system use are the antecedents of overall customers/users satisfaction (Spreng et al., 1996; Cronin et al., 2000; Hellier et al., 2003; Lewis and Soureli, 2006). Thus, we hypothesise:

H1a: Service quality has a positive influence on satisfaction.

H1b: Information quality has a positive influence on satisfaction.

H1c: System quality has a positive influence on satisfaction.

Figure 1 Research model



3.3 The relationship of computer self-efficacy and perceived behavioural control

Self-efficacy is the belief 'in one's capabilities to organise and execute the courses of action required to produce given attainments' (Bandura, 1997, p.3). This concept refers to an individual's self-evaluation regarding the effort and persistence put forth when facing with obstacles, and finally, the mastery of the behaviour. Such evaluation of an individual would influence decisions about what behaviours to undertake. In the IS literature, Marakas et al. (1998) provided a comprehensive summary of the relevant studies of computer self-efficacy (CSE) and drew a distinction between general CSE and task-specific CSE. General CSE stands for "an individual judgement of efficacy across multiple computer application domains" whereas the task-specific CSE refers to "an individual's perception of efficacy in performing specific computer-related tasks within the domain of general computing" (p.128). In this study, we apply the CSE concept and consider it as "individual assessment of a person's ability to use the computer and internet". In our context, if a person has a belief that he or she can operate the computer or internet, it implies that the person is more likely to consider he or she has the capabilities to use the PMS. Evidence shows that there is a positive relationship between the self-efficacy and perceived behaviour control (Pavlou and Fygenson, 2006; Taylor and Todd, 1995), thus we hypothesise:

> *H2: CSE has a positive influence on perceived behaviour control.*

3.4 The relationship of familiarity and perceived behavioural control

Familiarity stands for an understanding, often based on prior interaction, experience or learning of what, why, where and when others do what they do (Luhmann, 1988). It deals with the understanding of the current interaction with the objects or people and would reduce the uncertainty about the objects. For example, if someone is familiar with a particular website, it means that the person has the knowledge of what this website is or how to access this website. In this context, familiarity is based on comprehension of the PMS due to prior related experience. If a person is familiar with the PMS, he or she should have the related knowledge about the system. It would reduce the uncertainty about the PMS and enforce someone's self-judgement about whether he or she has the ability to use the PMS. Therefore, we hypothesise:

> *H3: Familiarity with the PMS has a positive influence on perceived behaviour control.*

3.5 The relationship of satisfaction and intention

DeLone and McLean (1992) indicated that "successful interaction by management with the information system can be measured in terms of use satisfaction" and that "user satisfaction (as a success measure) is especially appropriate when a specific information system was involved" (p.68). Satisfaction towards the information and system quality represents "object-based attitudes that serve as external variables shaping behavioural beliefs" (Wixom and Todd, 2005). In other words, level of satisfaction subsequently may have the influence on beliefs about the consequences of using the object (system). Researches revealed that overall user satisfaction with the system is strongly associated with the behavioural intention to reuse the same system and can be regarded as a reliable predictor of continuance intention (LaBarbera and Mazursky, 1983; Cronin et al., 2000). Furthermore, other researchers found e-satisfaction exhibits a positive impact on e-loyalty (Anderson and Srinivasan, 2003; Yang and Peterson, 2004). On the basis of these findings, we hypothesise:

> *H4: Satisfaction has a positive influence on continuance intention.*

3.6 The relationship of subjective norm and intention

According to the TPB, subjective norm means "the person's perception that most people who are important to him think he should or should not perform the behaviour in question" (Fishbein and Ajzen, 1975, p.302). This is because people may act based on the perception of what referent others think he or she should or should not do. Prior researches showed that there is a positive relationship between the subjective norm and behaviour intention towards the system use (Karahanna et al., 1999; Taylor and Todd, 1995; Kwon and Onwuegbuzie, 2005). In this research, the users of the PMS are healthcare professionals. Their attitude towards the PMS use may be influenced by the colleagues or friends who are in the same profession. Therefore, we hypothesise:

H5: Subjective norm has a positive influence on continuance intention.

3.7 The relationship of perceived behaviour control and continuance intention

Perceived behaviour control (PBC) refers to a person's perception of ability to carry out a behaviour with the given resources (Ajzen, 1991). It means that PBC denotes a subjective level of control over the performance of a behaviour. Therefore, PBC is the user's perception of control over using the PMS. The higher the perception that one thinks he or she can have the ability to use the PMS, the higher the intention the one has towards the PMS usage. A number of empirical studies show the positive relationship between the perceived behavioural control and use intention (Taylor and Todd, 1995; Pavlou and Fygenson, 2006). Consequently we hypothesise:

H6: Perceived behaviour control has a positive influence on continuance intention.

3.8 The relationship of continuance intention and usage

According to TPB, behaviour intention refers to that people are willing to perform a specific behaviour (Ajzen, 1991), representing as an important predictor of an actual behaviour. That is, a person will do what he or she intends to do. Several empirical evidences show that intention has a positive influence on actual usage (Pavlou and Fygenson, 2006; Taylor and Todd, 1995). On the basis of the argument, we expect a positive relationship from continuance to usage. Thus, we hypothesise:

H7: Continuous intention has a positive influence on usage.

4 Methodology

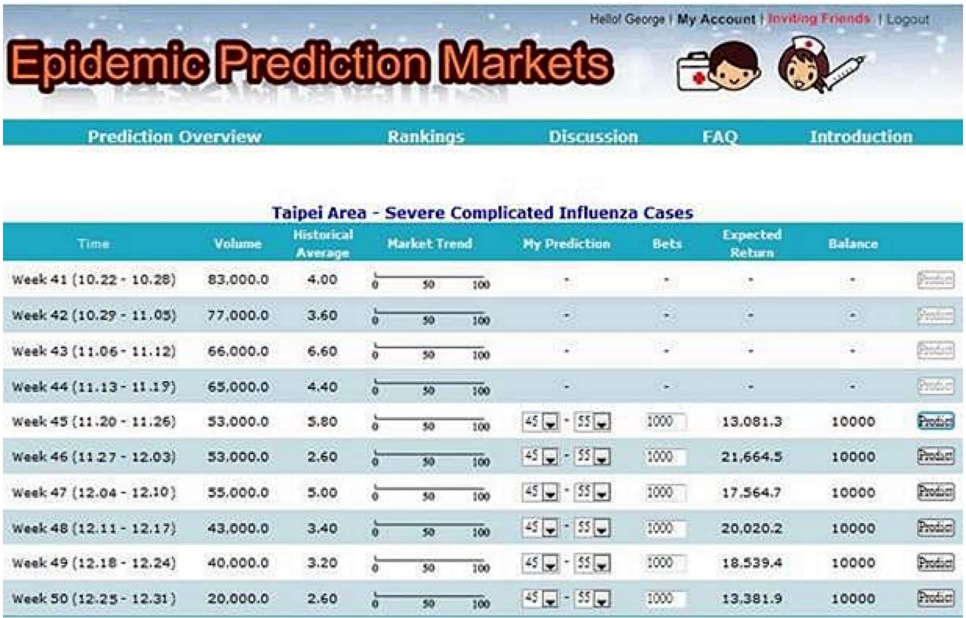
4.1 Epidemic prediction market

This paper designed and built an epidemic prediction market (EPM) system sponsored by the Centers for Disease Control in Taiwan. The PMS was established at National Chengchi University (http://epm.nccu.edu.tw) during the trading period, from the 10th week of 2010 (7–13 March) to the 40th week (3–9 October). In total, 630 healthcare professionals registered for this system as participants. They were encouraged to predict three epidemic diseases with five indicators, including severe complicated influenza case, confirmed cases of Dengue fever, confirmed cases of Enteroviruses infection, ratio of Enteroviruses infection cases and ratio of influenza-like illness cases.

To improve trading liquidity and efficiency to aggregate information, the PMS adopted the trading mechanism of MSR. Comparing with another popular mechanism called CDA which is often used by the stock or futures markets and regarded as a matured trading mechanism, the MSR mechanism makes the trading interface much easier for the traders and avoids the problems of opinion pooling in the think market case

(Hanson, 2003, 2007a). This is very important if participants are scarce and too busy to actively participate in the trading. The PMS offers each participant 10,000 points of bets to play for each prediction event. The participant needs to set the prediction range and place the bets for each prediction event. Then, the EPM will automatically calculate his or her expected return of the bets (See Figure 2.)

Figure 2 Epidemic prediction markets in Taiwan (see online version for colours)



Participants in the system were encouraged to predict the three epidemic diseases with five indicators during the eight weeks of trading period. If every week's prediction of each disease in each region is a prediction event, there are 7945 prediction events in total which were traded by the EPM members. The system gives betting points to participants who made accurate predictions, and vice versa. Prediction performance can be assessed by four indicators: cumulative credits, average credits per prediction, number of winning cases and ratio of winning cases over total cases. In this study, we regard a participant obtaining high total payoff at the end of the 7-month trading period as a 'good trader', whereas a participant with low total payoff is a 'poor trader'. To increase the degree of participation in the trading period, we provided three awards of USD 33 each month on a lottery basis to those who traded during the month. The more a participant trades, the higher the chance he or she could win the lottery.

4.2 Questionnaire

All questionnaire items are adapted from the extant studies. Table 1 exhibits all the questionnaire items and their corresponding constructs, along with the sources of each construct. For face validity, two professors, one post-doctor and one PhD student checked the wording and meaning of each item in a corresponding construct. There are several ways of eliciting behavioural intention according to Zeithaml et al. (1996). They argued that favourable behavioural intention of a customer is present when a company is able to get its customer to

1 say positive things about the company
2 recommend the company to other consumers
3 remain loyal to (i.e., repurchase from) the company
4 spend more time with the company
5 pay price premiums to the company.

In this study, we adapted items 3 and 4 (i.e., loyalty and spending more time) and we defined continuance intention as a participant's intention to reuse and spend more time with the PMS in the future. The items were adapted from relevant studies in the IS field (Davis, 1989; Taylor and Todd, 1995; Ahn et al., 2007). Finally, usage was defined as the frequency of times a participant logs into the PMS during the 7-month period; while degree of participation was measured by the frequency of making trades. Other than the data of usage and degree of participation which are retrieved from the system logs, all other items are listed in the questionnaire and each was measured by a six-point Likert-type scale, ranging from 1 (strong disagree) to 6 (strong agree). For the purpose of the study, we designed two versions of questionnaire for traders and non-traders, including long edition and short edition of questionnaire, respectively. The long questionnaire includes all items listed in Table 1, whereas the short version includes only the items from constructs of peer influence, utilitarian motivation, hedonic motivation and CSE to understand the user' factors of registering for the PMS.

4.3 Survey procedure

After implementing the PMS, we sent an email to invite healthcare professionals. In our invitation letter, there was a description about purpose of predicting the trend of Taiwan's infectious diseases. Professionals were encouraged to participate in the EPM platform for predicting the range of the five infectious disease indicators. At the end of the 10-month trading period, the top three of outstanding trader according to the trading performance would receive winning certificates from the CDC. They also would receive, respectively, the awards of USD 1000, USD 666 and USD 333 provided by the organiser.

After the trading period, researchers checked the trading records of each member from the PMS to confirm whether the user actually traded in the PMS. As the result, 630 registered members participated in our system. However, 126 participants actually engaged in trading in the PMS, and 504 participants registered but did not make any trades during the period. Consequently, the long questionnaires were sent to the 126 traders and the short ones were distributed to the 504 non-traders. All of them were encouraged to fill out the questionnaire through the Web URL link provided in the questionnaire, which linked to an online survey instrument. To give incentive to the participants for filling out the questionnaire, each was awarded a coupon of convenient store worth USD 8.25. A statement guaranteeing anonymity in the research results was attached in the questionnaire as well.

Table 1 Questionnaire items for this study

Factor	*Item*	*Resource*
Service Quality	You think the service personnel of Epidemic Prediction Market can quickly response to my inquiry	Parasuraman et al. (1988)
	You think the attitude of service personnel in the Epidemic Prediction Market is good	
	The service personnel of Epidemic Prediction Market system have professional knowledge to solve my problems quickly	
System Quality	The response from Epidemic Prediction Market system is fast	Liu and Arnett (2000)
	It is easy to navigate in the Epidemic Prediction Market system	
	The operations of Epidemic Prediction Market system are reliable	
	The protection of personal privacy in the Epidemic Prediction Market system is safe	
Information Quality	The instructions of Epidemic Prediction Market system are complete and easy to understand	Wixom and Todd (2005)
	The format of text and illustrations in the Epidemic Prediction Market is applicable	
	The content shown in the Epidemic Prediction Market is easy to understand	
Satisfaction	Using the Epidemic Prediction Market is wise	Oliver (1980)
	Using the Epidemic Prediction Market is pleasant	
	Overall, I am satisfied with the experience of using the Epidemic Prediction Market	
Computer Self-Efficacy	You can search the desired information from the Internet without any help	Compeau and Higgins (1995)
	You can solve the computer or Internet problems by yourself	
Familiarity	You had made trades in the financial market, including stocks, futures, and mutual funds	Gefen (2000)
	You had heard the approaches of prediction market before using the Epidemic Prediction Market	
	You used other prediction markets, for example the xFuture, before using the Epidemic Prediction Market	

Table 1 Questionnaire items for this study (continued)

Factor	*Item*	*Resource*
Peer Influence	You join Epidemic Prediction Market due to the recommendation of your friends.	Ajzen (1991)
	You use the Epidemic Prediction Market because your co-workers are using the system	
	You join the Epidemic Prediction Market because you heard of many healthcare professionals are using the system	
Perceived Behavioural Control	You think you have the free time to join prediction activities in the Epidemic Prediction Market	Ajzen (1991)
	You think you have the environment and resources to join the prediction activities in the Epidemic Prediction Market	
	Regardless of joining the Epidemic Prediction Market or not, you think the prediction you make in the Epidemic Prediction Market would be precise	
Continuance Intention	You will continuously use the Epidemic Prediction Market in the future	Zeithaml et al. (1996)
	You will actively use the Epidemic Prediction Market in the future	
	You are willing to use the Epidemic Prediction Market in the future	
	Whenever you are free, you will join the prediction activities in the Epidemic Prediction Market	
Hedonic Motivation	Your participation is based on the fun and curiosity	Ahn et al. (2007)
	Your participation with the prediction market is based on the innovation and novelty of the Epidemic Prediction Markets	
	You participate in Epidemic Prediction Markets because it is challenging	
Utilitarian Motivation	Your participation is based on the enhancement of protection of epidemic situation and advancement of social benefit	Overby and Lee (2006)
	Your participation is because you may receive commendation as rewards for the winners provided by the CDC	
	Your participation is because of the prize for the winners provided by the organiser	
	Your participation is because the superior told you that the participation of Epidemic Prediction Markets could be parts of the criteria in your performance	

5 Analysis and results

Comparing predictions of infectious diseases from the EPM and the expected value of historical data for the same period, we found that the winning ratio for the EPM was rising gradually along with approaching target week of prediction. Overall, the prediction performance of the EPM was excellent: the winning ratio for the EPM was 46.7% for 7 weeks before the target week of prediction, 50.5% for 6 weeks before, 52.3% for 5 weeks before, 52.8% for 4 weeks before, 53.0% for 3 weeks before, 54.4% for 2 weeks before, 55.5% for 1 week before and 64.6% for the target week (see Table 2). Particularly, the winning ratio for the EPM has been more than 50% for 6 weeks before the target week or shorter.

Table 2 Performance of the epidemic prediction markets vs. the expected value of historical data

Period	*No. of predicted events*	*Winning ratio of the EPM* (%)
Current week	1085	64.6
1 week in advance	1085	55.5
2 weeks in advance	1050	54.4
3 weeks in advance	1015	53.0
4 weeks in advance	980	52.8
5 weeks in advance	945	52.3
6 weeks in advance	910	50.5
7 weeks in advance	875	46.7
Sum/average	7954	54.0

5.1 *What entices people to participant in the EPM?*

Out of 126 distributed long edition questionnaire, 51 responses were obtained. After removing 4 having excessive missing values, 47 usable samples remain. In contrast, out of the 504 distributed short questionnaires, 81 responses were collected and 74 samples were usable. To comprehend what entices participants to register for the PMS, we conducted a one-sample *t*-test analysis against the midpoint (3.5) as the test value for the 15 attribute items listed in the short questionnaire, using the 121 usable samples. According to the results shown in Table 3, most of the items are significant except three, namely, recommendation of friends, commendation as rewards for the winners provided by the CDC and prize provided by the organiser. Among the 12 significant items, 4 mean values are significantly lower than the midpoint, contrary to our expectation. This finding suggests that most users registered for the system were not because they wanted to kill time or improved their job ratings, nor were they affected by their peers who were using the system. There are eight items exhibiting significantly high mean values, including convention of giving assistance to the CDC, public welfare, hedonic motivation (fun, novelty and challenging) and CSE (skills, self-solving and self-searching).

Table 3 The results of t-test for high construct items in registrants

Item	*Mean difference*	*T*	*df.*	*Sig.*
You join Epidemic Prediction Market due to the recommendation of your friends	–0.188	–1.354	121	0.178
You use the Epidemic Prediction Market because your co-workers are using the system	–0.540	–3.716	121	0.000
You join the Epidemic Prediction Market because you heard of many healthcare professionals are using the system	–0.565	–4.081	121	0.000
Your participation is based on the convention of giving assistance to the CDC	0.770	5.717	121	0.000
Your participation is based on the enhancement of protection of epidemic situation and advancement of social benefit	1.393	12.562	121	0.000
Your participation is because you may receive commendation as rewards for the winners provided by the CDC	–0.008	–0.057	121	0.955
Your participation is because of the prize for the winners provided by the organiser	–0.065	–0.460	121	0.646
Your participation is because the superior told you that the participation of Epidemic Prediction Markets could be parts of the criteria in your performance	–1.500	–14.060	121	0.000
Your participation is based on the fun and curiosity	0.598	4.536	121	0.000
Your participation with the prediction market is based on the innovation and novelty of the Epidemic Prediction Markets	1.147	12.051	121	0.000
You participate in Epidemic Prediction Markets because it is challenging	0.983	9.742	121	0.000
You participate in Epidemic Prediction Markets because it can kill the time	–0.852	–7.900	121	0.000
Your think you can use the Epidemic Prediction Markets smoothly within your computer skills	1.012	11.613	121	0.000
You can solve the computer or Internet problems by yourself when using it	1.380	15.309	121	0.000
You can search information what you need from the Internet without any help	1.500	17.324	121	0.000

5.2 What entices participants to begin trading in the EPM?

We further wanted to understand what drives participants to make trades in the PMS. Among the sample we collected, 74 participants registered for the PMS, nevertheless, they did not make any trades. And only 47 participants actually traded during the 10 months. To identify the significant mean differences between the trading and non-trading groups in elements that trigger initial motivations of trading in the PMS, we conducted a series of independent-samples *t*-tests for the items of peer influence, utilitarian motivation, hedonic motivation and CSE between the two groups. The results of this process are shown in Table 4. Three construct items are significant, including assistance-giving, fun and self-solving. All other items are not significant. It is intriguing to know that five construct items significant in the initial motivation of registering for the system are now dissipated. These include public welfare, novelty, challenging, skills and self-searching; their influences are not strong enough to entice a registrant to make a trade in the system.

5.3 What drives participants to continuously trade in the EPM?

In this section, we used partial least square (PLS) to analyse our collected data to understand what drives participants to continuously trade in the EPM. The PLS places minimal restrictions on measurement scale, sample size and residual distributions (Chin et al., 2003). It is suitable for analysis with small sample size. Owing to the limited population of traders, we applied PLS to assess the measurement model and the structural model as follows.

5.4 Measurement validation

Measurement validation was assessed by the convergent validity and discriminant validity. Fornell and Larcker (1981) indicated that the average variance extracted (AVE) of each construct should be more than 0.5 to achieve an acceptable level of convergent validity. As the results shown in Table 5, the AVE of each construct in our research model is above 0.5. It indicates that our research model has achieved convergent validity. Furthermore, we verified the discriminant validity of each construct in this study. Chin (1998) suggested that the discriminant validity is confirmed when the square root of AVE of each construct is larger than its correlation coefficients with other constructs. According to the results shown in Table 5, we can conclude that all measures have adequate discriminant validity.

Furthermore, the common method variance (CMV) is always an issue in a survey study. It exists whenever a single factor merges from the factor analysis or one general factor accounts for most of the covariance among the measures. Podsakoff et al. (2003) suggested that Harman's one-factor tests (Harman, 1976) with un-rotated factor solution could be used to estimate and verify such problem. On the basis of the results, 14 factors were extracted from the Harman’s test, accounting for 84.23% of total variance. The first five factors explain 57.93% of variance. This indicated that there is no single factor accounting for the majority of the variance and CMV shall not threaten validity of the measurement.

Table 4 Results of *t*-test for trading and non-trading groups

Item	*Mean difference*	*T*	*df.*	*Sig.*
You join Epidemic Prediction Market due to the recommendation of your friends	–0.154	–0.544	121	0.587
You use the Epidemic Prediction Market because your co-workers are using the system	–0.258	–0.883	121	0.379
You join the Epidemic Prediction Market because you heard of many healthcare professionals are using the system	0.0272	–0.098	121	0.922
Your participation is based on the convention of giving assistance to the CDC	–0.619*	–2.364	121	0.020
Your participation is based on the enhancement of protection of epidemic situation and advancement of social benefit	–0.000	–0.001	121	0.999
Your participation is because you may receive commendation as rewards for the winners provided by the CDC	–0.482	–1.658	121	0.100
Your participation is because of the prize for the winners provided by the organiser	–0.595	–2.096	121	0.038
Your participation is because the superior told you that the participation of Epidemic Prediction Markets could be parts of the criteria in your performance	–0.146	–0.681	121	0.497
Your participation is based on the fun and curiosity	–0.745*	–2.819	121	0.006
Your participation with the prediction market is based on the innovation and novelty of the Epidemic Prediction Markets	0.056	0.298	121	0.766
You participate in Epidemic Prediction Markets because it is challenging	–0.202	–1.008	121	0.315
You participate in Epidemic Prediction Markets because it can kill the time	–0.351	–1.619	121	0.108
Your think you can use the Epidemic Prediction Markets smoothly within your computer skills	–0.179	–1.039	121	0.301
You can solve the computer or Internet problems by yourself when using it	–0.481*	–2.778	121	0.006
You can search information what you need from the Internet without any help	–0.352	–1.764	121	0.080

*<0.05.

Table 5 Correlation matrix and average variance extracted of constructs

	AVE	*SerQ*	*InfQ*	*SysQ*	*S*	*PI*	*PBC*	*SE*	*F*	*CI*	*U*
SerQ	0.81	*0.90*									
InfQ	0.76	0.52	*0.87*								
SysQ	0.56	0.71	0.69	*0.75*							
S	0.71	0.54	0.61	0.60	*0.84*						
PI	0.73	0.20	0.16	0.22	0.37	*0.85*					
PBC	0.55	0.18	0.23	0.41	0.39	0.39	*0.74*				
SE	0.62	0.48	0.57	0.52	0.37	0.15	0.31	*0.79*			
F	0.73	0.19	0.19	0.17	0.08	0.19	0.49	0.15	*0.85*		
CI	0.73	0.24	0.35	0.31	0.63	0.34	0.52	0.21	0.26	*0.85*	
U	0.76	0.09	0.21	0.18	0.14	–0.10	0.15	0.36	0.11	0.40	*0.87*

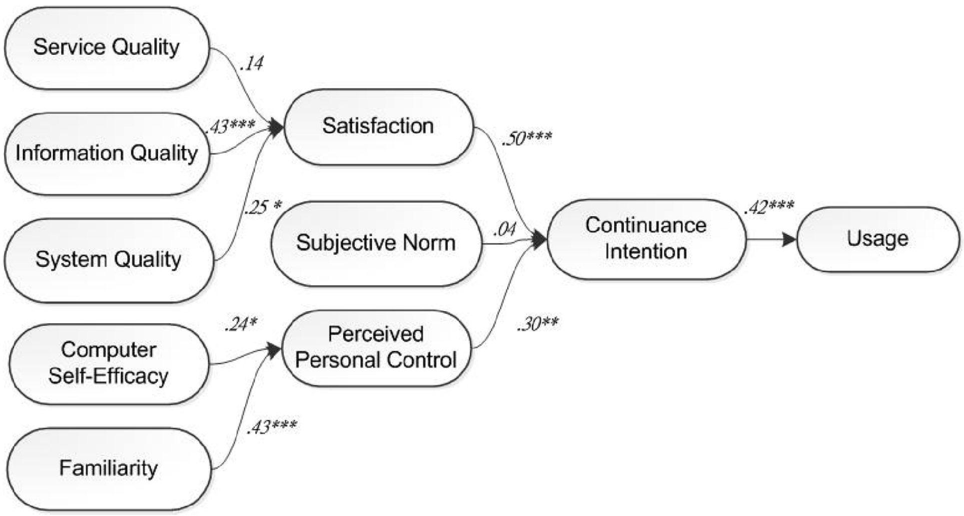
AVE: average variance extracted; SerQ: service quality; InfQ: information quality; SysQ: system quality; S: satisfaction; PI: peer influence; PBC: perceived behaviour control; SE: self-efficacy; F: familiarity; CI: continuance intention; U: usage.

The diagonal elements (in italic) represent the square root of the average variance extracted.

5.5 *The structural model*

The PLS path coefficients are shown in Figure 3. Most of the paths are significant and positive; however, the paths from peer influence to continuance intention and from service quality to satisfaction are not significant. The results of hypothesis testing are shown in Table 6 in which most hypotheses are supported except H1a and H3.

Figure 3 PLS results of the research model



*Significant at $p < 0.05$.
**Significant at $p < 0.01$.
***Significant at $p < 0.001$.

Table 6 Results of hypothesis testing

Hypothesis	*Hypothesised relation*	*Result*
H1a	Service quality → Satisfaction	Not supported
H1b	Information quality → Satisfaction	Supported
H1c	System quality → Satisfaction	Supported
H2	Computer self-efficacy → Perceive behaviour control	Supported
H3	Familiarity → Perceive behaviour control	Supported
H4	Satisfaction → Continuance Intention	Supported
H5	Subjective norm → Continuance Intention	Not supported
H6	Perceived behaviour control → Continuance Intention	Supported
H7	Continuance Intention → Usage	Supported

5.6 *What factors influence the degree of participation in the EPM?*

To understand what factors influence the degree of participation (trading frequency) in the PMS, we employed the stepwise regression analysis using trading frequency as the dependent variable and the 15 items listed in Table 3 as the independent variables. Only the variable of prize entered the regression model. The final regression model is shown in Table 7 with the coefficient of prize being significant and positive at $p = 0.023$ level. This implies that many participants exerted continuous effort to make trades simply because they wanted to obtain more chances to win the prize. Therefore, the PM provider should set up a prize mechanism to attract a participant to make more trades on the system.

Table 7 Results of regression for degree of participation ($N = 47$)

Step	*Item*	*B*	*Std. error*	*β*	*R-square change*	*Sig.*
1	Prize	173.479*	81.893	0.301	0.091	0.040
	Intercept	–361.358	332.970			

*<0.05.

5.7 *What factors contribute to the differences between good traders and poor traders?*

To figure out what factors lead participants to become good traders, we conducted a series of independent-sample *t*-tests to identify significant mean differences in 15 attribute items listed in Table 3 between good traders and poor traders. We divided the participants into four quartiles according to the levels of total payoff, from very low performance in the first quartile to very high performance in the fourth quartile. We then selected participants in the first quartile as the poor traders and those in the fourth quartile as good traders for the *t*-tests. The result reveals that only two attribute items (i.e., public welfare and self-searching) were significantly different as shown in Table 8. It implies that participants good at searching information re more likely to achieve high trading performance. Those who have dedicated oneself to public welfare are prone to make trades for the sake of social benefits and achieve high trading performance. To increase prediction accuracy of PMS, the system provider should attract more of these two types of participants into the system.

Table 8 Results of *t*-test for trading performance

Item	*Mean of good traders*	*Mean of poor traders*	*Mean difference*	*Std. error difference*	*Sig.*	*95% confidence interval of the difference*	
						Lower	*Upper*
Public welfare	5.33	4.08	1.25*	0.575	0.041	0.058	2.442
Self-searching	5.67	5.17	0.50*	0.219	0.032	–0.954	–0.046

*<0.05.

5.8 What factors contribute most to trading performance of participants?

The reputation of a PMS lies in the prediction accuracy of its traders. A PMS having high reputation can easily draw media attention and attract more traders to join the system. Knowing what factors contribute most to trading performance allows PM providers to tailor the systems to these factors and assist the traders to improve prediction accuracy. To identify the factors contributing to trading performance, this study employed the stepwise regression analysis using trading frequency as the dependent variable and the 15 attribute items as the independent variables. Only the variable of prize entered the regression model. The final regression model is shown in Table 9 with the coefficient of prize being significant and positive at $p = 0.041$ level. This implies that the participants cared very much about the prize offered by the PM provider, they would trade frequently to get one prize and carefully to get another according to our prize mechanism. This reinforces the importance of prize mechanism in a system design strategy for PM providers to increase trading performance and prediction accuracy of their participants.

Table 9 Results of regression for trading performance ($N = 47$)

Step	*Items*	*B*	*Std. error*	*β*	*R-square change*	*Sig.*
1	Prize	1191170.913*	565641.940	0.300	0.090	0.041
	Intercept	–3051211.909	2299869.445			

*<0.05.

6 Conclusions and implications

This paper constructed an EPM system with MSR trading mechanism to examine the success factors influencing the PMS participation. The system was used to predict infectious diseases by 126 medical professionals during March to October in 2010. The result predicted by the PMS shows that winning ratio for the EPM was increasing gradually along with approaching target weeks of prediction. Furthermore, this paper conducted an empirical survey to understand what factors motivate people to register for the PMS as an initial participation. According to the analysis results, eight items, including convention of giving assistance to the CDC, public welfare, hedonic motivation (fun, novelty and challenging) and CSE (skills, self-solving and self-searching), were important items leading the people to register for the PMS. Indeed, among the above items, three of them relate to the participants who make a trade in the PMS, namely, assistance-giving, fun and self-solving.

This paper also extended Ajzen's (1991) TPB to explain the process of PMS adoption by healthcare professionals. The results show that the satisfaction and perceived behaviour control had a positive impact on continuance intention of using the system, whereas the relationship between peer influence and continuance intention was not significant. This result is similar with the prior study. Davis (1989) and Mathieson (1991) found that there was no significant relationship between the subject norm and behaviour intention in the TPB model. Such a result might be due to the fact that there were no real consequences associated with the behaviour under study and little external pressure to perform the behaviour (Davis, 1993; Davis et al., 1992; Barki and Hartwick, 1994). In our research context, the 630 registered members came from medical institutions/hospitals across different regions. As such, the behaviour may not be instigated by the peer pressure from the colleagues.

Regarding the qualities of PMS, information quality and system quality were the essential factors that a user might pay more attention to. These two factors had a positive effect on the satisfaction. That is, system quality is a fundamental to a PMS. The reliability, navigation and security are the basic requirement of running a system. Users would be satisfied while the system use was smooth and navigable. In contrast, users might be unwilling to use the system if the system often breaks down. Furthermore, information quality is the other quality influencing the satisfaction. The format and instruction of the content displayed in the system also need to be taken into consideration. However, in the context of the PM, service quality provided by the website is not an important factor influencing on user satisfaction. On the basis of the empirical result, user satisfaction had a positive influence on the continuance intention. This result is consistent with the prior studies using the expectation confirmation model to theorise IS continuance (Bhattacherjee, 2001; Bhattacherjee and Premkumar, 2004). As DeLone and McLean (2003) suggest, positive experience with 'use' would increase the 'user satisfaction', and then 'user satisfaction' would increase 'the intention to use', then 'use.' These close-loop relationships between those factors occurred specially in the post-use condition. The result of this study supports this evidence.

According to the result of the study, the prize has a positive relationship with trading frequency. Participants would view the prize as the incentive to made trade frequently to increase the chance of winning the prize at the end of the trading period. Intriguingly, the motivation of winning the prize also leads to higher trading performance. In addition, participants would dedicate more effort to obtaining better prediction consequences when the results of prediction activities relate to public welfare. Indeed, to make a precise forecast on PMS, they are cautious about making each trade by searching the related information.

Furthermore, comparing the motivations between different stages of using PMS, hedonic motivations may be the essential factor that influences participants on early usage stage to register for the PMS. However, as time passes, there is an increasing growth of utilitarian motivation (i.e., prize and public welfare in this study) driving people to continuously use the system in the later stages. This finding is similar to prior studies by Xu et al. (2012) and Magni et al. (2010). Participants would initially use the technologies mainly for the hedonic purpose. As the understanding of technology grows, people would explore the advanced functions to engage in the activities provided by the systems for utilitarian purpose.

6.1 Theoretical implications

We draw from the theoretical perspective of TPB and information system success to recognise that adoption of prediction system. On the basis of the theory perspective, we identified related constructs influencing the system use, such as system quality and information quality and familiarity. Further research should examine the generalisation of these findings and aim at identifying additional constructs in a different research context. Indeed, researchers should further identify the elements of each kind of quality applied to the prediction system. Finally, comparing with the prior studies that log-in duration and trading frequency (Davis, 1993; Szajna, 1996), this paper regarded user's system logging frequency as system usage. It provided empirical evidence supporting the positive relationship between the continuous intention and actual system usage.

6.2 Practical implications

Because of the sensitivity of the infectious diseases, the CDC preferred a closed professional market to avoid any civil disturbance. This closed EPM with MSR mechanism has been proven more accurate in predicting influenza, Dengue fever and Enteroviruses comparing with expected value of historical data for the same period. The EPM is an effective instrument to detect, monitor and predict epidemic disease activities in Taiwan and is helpful to reduce management risks for health resources of the CDC to prevent the related diseases. With the outstanding prediction performance of the EPM, this paper further investigates critical factors to promote participation and improve performance of traders in the EPM. Based upon the findings of this study, a similar system of closed EPM with MSR mechanism could be applied to detecting, monitoring and predicting more infectious diseases in Taiwan as well as other countries, vis-à-vis Google flu trend prediction using search engine query data (Ginsberg et al., 2009). Finally, business corporations could use such a system to reduce their risks of resource management if they do not want to reveal their management information to the public and can only attract a few participants into the PMS.

Moreover, this study extended TPB with constructs of system quality, information quality, familiarity and CSE. It identified a set of items that stimulate initial use of PMS, including volunteer work for public welfare, fun, novelty, challenging and CSE (skills, self-solving and self-searching). For example, the motivation from public welfare would be an attractive incentive when the prediction event is about the public issue. It would motivate participants to be more cautious with making a prediction to obtain a precise result. This finding suggests managers to create an incentive mechanism to increase the PMS usage. According to our findings, they should design the basic functions of a PMS for hedonic purpose, and the advanced functions for utilitarian sake.

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References

Ahn, T.R., Ryu, S. and Han, I. (2007) 'The impact of Web quality and playfulness on user acceptance of online retailing', *Information and Management*, Vol. 44, No. 3, pp.263–275.

Ajzen, I. (1985) 'From intention to actions: a theory of planned behavior', in Kuhl, J. and Beckmann, J. (Eds.): *Action Control, from Cognition to Behavior*, Springer-Verlag, New York, pp.11–39.

Ajzen, I. (1991) 'The theory of planned behavior', *Organizational behavior and Human Decision Process*, Vol. 50, No. 2, pp.170–211.

Anderson, R.E. and Srinivasan, S.S. (2003) 'E-satisfaction and e-loyalty: a contingency framework', *Psychology and Marketing*, Vol. 20, No. 2, pp.123–138.

Bandura, A. (1997) *Self-efficacy: The Exercise of Control*, Freeman, New York, NY.

Barki, H. and Hartwick, J. (1994) Measuring user participation, user involvement, and user attitude', *MIS Quarterly*, Vol. 18, No. 1, pp.59–82.

Barry, J.M. (2005) 'The Story of influenza: 1918 revisited: lessons and suggestions for further inquiry', in Knobler, S.L., Mack, A., Mahmoud, A. and Lemon, S.M. (Eds.): *The Threat of Pandemic Influenza: Are We Ready? Workshop Summary*, The National Academies Press, Washington DC, pp.60, 61.

Batra, R. and Ahtola, O.T. (1990) 'Measuring the hedonic and utilitarian sources of consumer attitudes', *Marketing Letters*, Vol. 2, No. 2, pp.159–170.

Berg, J.E. and Rietz, T.A. (2003) 'Prediction markets as decision support systems', *Information Systems Frontiers*, Vol. 5, No. 1, pp.79–93.

Berg, J.E., Forsythe, R. and Rietz, T.A. (1997) 'What makes markets predict well? Evidence from the Iowa electronic markets', in Albers, W., Güth, W., Hammerstein, P., Moldovanu, B. and Damme, E. (Eds.): *Understanding Strategic Interaction: Essays in Honor of Reinhard Selten*, Springer, New York, pp.444–463.

Berg, J.E., Forsythe, R., Nelson, F.D. and Rietz, T.A. (2001) 'Results from a dozen years of election futures markets research', in Plot, C. and Smith, V. (Eds.): *Handbook of Experimental Economic Results*, Elsevier, Amsterdam, pp.742–751.

Berg, J.E., Nelson, F.D. and Rietz, T.A. (2008) 'Prediction market accuracy in the long run', *International Journal of Forecasting*, Vol. 24, No. 2, pp.285–300.

Bhattacherjee, A. (2001) 'Understanding information systems continuance: an expectation-confirmation model', *MIS Quarterly*, Vol. 25, No. 3, pp.351–370.

Bhattacherjee, A. and Premkumar, G. (2004) 'Understanding changes in belief and attitude toward information technology usage: a theoretical model and longitudinal test', *MIS Quarterly*, Vol. 28, No. 2, pp.229–254.

Bruggelambert, G. (2004) 'Information and efficiency in political stock markets: using computerized markets to predict election results', *Applied Economics*, Vol. 36, No. 7, pp.753–768.

Camerer, C.F. (1998) 'Can asset markets be manipulated? A field experiment with racetrack betting', *Journal of Political Economy*, Vol. 106, No. 3, pp.457–482.

Chen, K-Y. and Plott, C.R. (2002) *Information Aggregation Mechanisms: Concept, Design and Implementation for a Sales Forecasting Problem*, Caltech Social Science Working Paper No. 1131, California Institute of Technology, Pasadena.

Chen, M.K., Ingersoll, J.E. and Kaplan, E.H. (2008) 'Modeling a presidential prediction market', *Management Science*, Vol. 54, No. 8, pp.1381–1394.

Childers, T.L., Carr, C.L., Peck, J. and Carson, S. (2001) 'Hedonic and utilitarian motivations for online retail shopping behavior', *Journal of Retailing*, Vol. 77, No. 4, pp.511–535.

Chin, W.W. (1998) 'Commentary: issues and opinion on structural equation modeling', *MIS Quarterly*, Vol. 22, No. 1, pp.7–16.

Chin, W.W., Marcolin, B.L. and Newsted, P.R. (2003) 'A partial least squares latent variable modeling approach for measuring interaction effect: results from a Monte Carlo simulation study and an electronic mail emotion/adoption study', *Information Systems Research*, Vol. 14, No. 2, pp.189–217.

Coles, P.A., Lakhani, K.R. and McAfee, A.P. (2007) *Prediction Markets at Google*, Harvard Business School Case 607-088, 30 May, Cambridge, MA.

Compeau, D.R. and Higgins, C.A. (1995) 'Application of social cognitive theory to training for computer skill', *Information Systems Research*, Vol. 6, No. 2, pp.118–143.

Conner, M. and Armitage, C.J. (1998) 'Extending the theory of planned behavior: a review and avenues for further research', *Journal of Applied Social Psychology*, Vol. 28, No. 15, pp.1429–1464.

Cowgill, B., Wolfers, J. and Zitzewitz, E. (2009) *Using Prediction Market Prices to Track Information Flows: Evidence from Google*, Available at http://www.bocowgill.com/GooglePredictionMarketPaper.pdf (Accessed 28 May, 2011).

Cronin, J.J., Brady, M.K. and Hult, G.T.M. (2000) 'Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments', *Journal of Retailing*, Vol. 76, No. 2, pp.193–218.

Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, Vol. 13, No. 3, pp.319–340.

Davis, F.D. (1993) 'User acceptance of information technology: system characteristics, user perceptions and behavioral impacts', *International Journal of Man-Machine Studies*, Vol. 38, No. 3, pp.475–487.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992) 'Extrinsic and intrinsic motivation to use computers in the workplace', *Journal of Applied Social Psychology*, Vol. 22, No. 14, pp.1111–1132.

DeLone W.H. and McLean, E.R. (2003) 'The DeLone and McLean model of information systems success: a ten-year update', *Journal of Management Information Systems*, Vol. 19, No. 4, pp.9–30.

DeLone, W.H. and McLean, E.R. (1992) 'Information systems success: the quest for the dependent variable', *Information Systems Research*, Vol. 3, No. 1, pp.60–95.

Fishbein, M. and Ajzen, I. (1975) *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA.

Fornell, C. and Larcker, D.F. (1981) 'Structural equation models with unobservable variables and measurement error: algebra and statistics', *Journal of Marketing Research*, Vol. 18, No. 1, pp.382–388.

Forsythe, R., Nelson, F., Neumann, G.R. and Wright, J. (1992) 'Anatomy of an experimental political stock market', *American Economic Review*, Vol. 82, No. 5, pp.1142–1161.

Forsythe, R., Rietz, T.A. and Ross, T.W. (1999) 'Wishes, expectations and actions: a survey on price formation in election stock markets', *Journal of Economic Behavior and Organization*, Vol. 39, No. 1, pp.83–110.

Foutz, N.Z. and Jank, W. (2007) *The Wisdom of Crowds: Pre-release Forecasting via Functional Shape Analysis of the Online Virtual Stock Market*, Available at http://ssrn.com/abstract=1432444 (Accessed 1 December, 2009).

Gefen, D. (2000) 'E-commerce: the role of familiarity and trust', *Omega-International Journal of Management Science*, Vol. 28, No. 6, pp.725–737.

Ginsberg, J., Mohebbi, M.H., Patel, R.S., Brammer, L., Smolinski, M.S. and Brilliant, L. (2009) 'Detecting influenza epidemics using search engine query data', *Nature*, Vol. 457, No. 7232, pp.1012–1015.

Goel, S., Pennock, D., Reeves, D. and Yu, C. (2008) 'Yoopick: a combinatorial sports prediction market', *Proceedings of the Twenty-Third AAAI Conference on Artificial Intelligence*, AAAI Press, Chicago, Illinois, pp.1880–1881.

Gronroos, C. (1982) *Strategic Management and Marketing in the Service Sector*, Swedish School of Economics and Business Administration, Helsinki, Finland.

Gruca, T.S. (2000) 'The IEM movie box office market integrating marketing and finance using electronic markets', *Journal of Marketing Education*, Vol. 22, No. 1, pp.5–14.

Gruca, T.S., Berg, J. and Cipriano, M. (2003) 'The effect of electronic markets on forecasts of new product success', *Information Systems Frontiers*, Vol. 5, No. 1, pp.95–105.

Gruca, T.S., Berg, J.E. and Cipriano, M. (2005) 'Consensus and differences of opinion in electronic prediction markets', *Electronic Markets*, Vol. 15, No. 1, pp.13–22.

Guo, Z., Fang, F. and Whinston, A.B. (2006) Supply chain information sharing in a macro prediction market', *Decision Support Systems*, Vol. 42, No. 3, pp.1944–1958.

Hahn, R.W. and Tetlock, P.C. (2005) 'Using information markets to improve decision making', *Harvard Journal of Law and Public Policy*, Vol. 29, No. 1, pp.213–289.

Hanson, R. (2003) 'Combinatorial information market design', *Information Systems Frontiers*, Vol. 5, No. 1, pp.107–119.

Hanson, R. (2007a) 'Logarithmic market scoring rules for modular combinatorial information aggregation', *The Journal of Prediction Markets*, Vol. 1, No. 1, pp.3–15.

Hanson, R. (2007b) 'The policy analysis market: a thwarted experiment in the use of prediction markets for public policy', *Innovations: Technology, Governance, Globalization*, Vol. 2, No. 3, pp.73–88.

Harman, H.H. (1976) *Modern Factor Analysis*, University of Chicago Press, Chicago.

Hayek, F.A. (1945) 'The use of knowledge in society', *American Economic Review*, Vol. 35, No. 4, pp.519–530.

Hellier, P.K., Geursen, G.M., Carr, R.A. and Rickard, J.A. (2003) 'Customer repurchase intention: a general structural equation model', *European Journal of Marketing*, Vol. 37, No. 11, pp.1762–1800.

Hirschman, E.C. and Holbrook, M.B. (1982) 'Hedonic consumption: emerging concepts, methods and propositions', *Journal of Marketing*, Vol. 46, No. 3, pp.92–101.

Ho, T-H. and Chen, K-Y. (2007) 'New product blockbusters: the magic and science of prediction markets', *California Management Review*, Vol. 50, No. 1, pp.144–158.

Hopman, J.W. (2007) 'Using forecasting markets to manage demand risk', *Intel Technology Journal*, Vol. 11, No. 2, pp.127–135.

Inklingmarkets Website (2012) Available at http://inklingmarkets.com/ (Access 29 March, 2012).

Kambil, A. and Van Heck, E. (2002) *Making Markets: How Firms Can Design and Profit from Online Auctions and Exchanges*, Harvard Business School Press, Cambridge, MA.

Karahanna, E., Straub, D.W. and Chervany, N.L. (1999) 'Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs', *MIS Quarterly*, Vol. 23, No. 2, pp.183–213.

King, R. (2006) 'Workers, place your bets. *Bussiness Week*, Available at http://www.businessweek.com/technology/content/aug2006/tc20060803_012437.htm (Accessed 3 August, 2006).

Kwon, N. and Onwuegbuzie, A.J. (2005) 'Modeling the factors affecting individuals' use of community networks: a theoretical explanation of community-based information and communication technology use', *Journal of the American Society for Information Science and Technology*, Vol. 56, No. 14, pp.1525–1543.

LaBarbera, P.A. and Mazursky, D. (1983) 'A longitudinal assessment of consumer satisfaction/dissatisfaction: the dynamic aspect of the cognitive process', *Journal of Marketing Research*, Vol. 20, No. 4, pp.393–404.

LaComb, C.A., Barnett, J.A. and Pan, Q. (2007) 'The imagination market', *Information Systems Frontiers*, Vol. 9, Nos. 2–3, pp.245–256.

Ledyard, J.O. (2006) 'Designing information markets for policy analysis', in Hahn, R. and Tetlock, P. (Eds.): *Information Markets: A New Way of Making Decisions*, AEI Press, Washington DC, pp.37–66.

Lee, M-C. (2010) 'Explaining and predicting users' continuance intention toward e-learning: an extension of the expectation-confirmation model', *Computer and Education*, Vol. 54, No. 2, pp.506–516.

Lewis, B.R. and Soureli, M. (2006) 'The antecedents of consumer loyalty in retail banking', *Journal of Consumer Behaviour*, Vol. 5, No. 1, pp.15–31.

Lewis, R.C. and Booms, B.H. (1983) 'The marketing aspects of service quality', in Berry, L.L., Shostack, G.L. and Upah, G. (Eds.): *Emerging Perspectives in Services Marketing*, American Marketing Association, Chicago, pp.99–107.

Liu, C. and Arnett, K.P. (2000) 'Exploring the factors associated with web site success in the context of electronic commerce', *Information and Management*, Vol. 38, No. 1, pp.23–33.

Luckner, S., Schroder, J. and Slamka, C. (2007) 'On the forecast accuracy of sports prediction markets', in Gimpel, H., Jennings, N.R., Kersten, G.E., Ockenfels, A. and Weinhardt, C. (Eds.): *Negotiation, Auctions, and Market Engineering*, Springer-Verlag, Berlin, Heidelberg, pp.227–234.

Luckner, S., Weinhardt, C. and Studer, R. (2006) 'Predictive power of markets: a comparison of two sports forecasting exchanges', in Dreier, T., Studer, R. and Weinhardt, C. (Eds.): *Information Management and Market Engineering*, Karlsruhe University Press, Karlsruhe, pp.187–195.

Luhmann, N. (1988) Familiarity, confidence, trust: problems and alternatives', in Gambetta, D. (Ed.): *Trust: Making and Breaking Cooperative Relations*, Basil Blackwell, New York, pp.94–107.

MacKenzie, D. (2009) 'Deadly new flu virus in US and Mexico may go pandemic', *NewScientist*, Available at http://www.newscientist.com/article/dn17025-deadly-new-flu-virus-in-us-and-mexico-may-go-pandemic.html (Accessed 20 July, 2012).

Magni, M., Tayor, M.S. and Venkatesh, V. (2010) 'To play or not to play: a cross-temporal investigation using hedonic and instrumental perspective to explain user-intentions to explore a technology', *International Journal of Human-Computer Studie*s, Vol. 68, No. 9, pp.572–588.

Manski, C.F. (2006) 'Interpreting the predictions of Prediction markets', *Economics Letters*, Vol. 91, No. 3, pp.425–429.

Marakas, G.M., Yi, M.Y. and Johnson, R.D. (1998) 'The multiple and multifaceted character of computer self-efficacy: toward clarification of the construct and an integrative framework for research', *Information Systems Research*, Vol. 9, No. 2, pp.126–163.

Mathieson, K. (1991) 'Predicting user intention: comparing the technology acceptance model with the theory of planned behavior', *Information Systems Research*, Vol. 2, No. 3, pp.173–191.

Notani, A.S. (1998) 'Moderators of perceived behavioral control's predictiveness in the theory of planned behavior: a meta-analysis', *Journal of Consumer Psychology*, Vol. 7, No. 3, pp.247–271.

Oliven, K. and Rietz, T.A. (2004) 'Suckers are born but markets are made: individual rationality, arbitrage, and market efficiency on an electronic futures market', *Management Science*, Vol. 50, No. 3, pp.336–351.

Oliver, R.L. (1980) 'A cognitive model of the antecedents and consequences of satisfaction decisions', *Journal of Marketing Research*, Vol. 17, No. 4, pp.460- 469.

Overby, J.W. and Lee, E-J. (2006) 'The effect of utilitarian and hedonic online shopping value on consumer preference and intentions', *Journal of Business Research*, Vol. 53, No. 10, pp.1160–1166.

Parasuraman, A., Ziethaml, V.A. and Berry, L.L. (1988) 'SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality', *Journal of Retailing*, Vol. 64, No. 1, pp.12–40.

Pavlou, P.A. and Fygenson, M. (2006) 'Understanding and predicting electronic commerce adoption: an extension of the theory of planned behavior', *MIS Quarterly*, Vol. 30, No. 1, pp.115–143.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003) 'Common method biases in behavioral research: a critical review of the literature and recommended remedies', *Journal of Applied Psychology*, Vol. 88, No. 5, pp.879–903.

Polgreen, P.M., Nelson, F.D. and Neumann, G.R. (2006) 'Using prediction markets to forecast trend in infectious diseases', *Microbe Magazine*, Vol. 1, No. 10, pp.459–465.

Polgreen, P.M., Nelson, F.D. and Neumann, G.R. (2007) 'Use of prediction markets to forecast infectious disease activity', *Clinical Infectious Diseases*, Vol. 44, No. 2, pp.272–279.

Rajakovich, D. and Vladimirov, V. (2009) 'Prediction markets as a medic forecasting tool: demand for hospital services', *Journal of Prediction Markets*, Vol. 3, No. 2, pp.78–106.

Rhode, P.W. and Strumpf, K.S. (2009) 'Manipulating political stock markets: a field experiment and a century of observational data, Available at: http://www.unc.edu/~cigar/papers/ManipNBER.pdf (Accessed 28 May, 2011).

Roca, J.C., Chiu, C-M. and Martinez, F.J. (2006) Understanding e-learning continuance intention: an extension of the technology acceptance model', *International Journal of Human-Computer Studies*, Vol. 64, No. 8, pp.683–696.

Rosenbloom, E.S. and Notz, W. (2006) 'Statistical tests of real-money versus play money prediction markets', *Electronic Markets*, Vol. 16, No. 1, pp.63–69.

Seddon, P.B. (1997) 'A respecification and extension of the DeLone and McLean model of IS success', *Information Systems Research*, Vol. 8, No. 3, pp.240–253.

Servan-Schreiber, E., Wolfers, J., Pennock, D.M. and Galebach, B. (2004) 'Prediction markets: does money matter?', *Electronic Markets*, Vol. 14, No. 3, pp.243–251.

Smith, V.L. (1982) 'Microeconomic systems as an experimental science', *American Economic Review*, Vol. 72, No. 5, pp.923–955.

Snowberg, E., Wolfers, J. and Zitzewitz, E. (2007) 'Partisan impacts on the economy: evidence from information markets and close elections', *The Quarterly Journal of Economics*, Vol. 122, No. 2, pp.807–829.

Spann, M. and Skiera, B. (2003) 'Internet-based virtual stock markets for business forecasting', *Management science*, Vol. 49, No. 10, pp.1310–1326.

Spann, M. and Skiera, B. (2009) 'Sports forecasting: a comparison of the forecast accuracy of prediction markets, betting odds and tipsters', *Journal of Forecasting*, Vol. 28, No. 1, pp.55–72.

Spreng, R.A., MacKenzie, S.B. and Olshavsky, R.W. (1996) 'A reexamination of the determinants of customer satisfaction', *Journal of Marketing*, Vol. 60, No. 3, pp.15–32.

Sprenger, T., Bolster, P. and Venkateswaran, A. (2007) 'Conditional prediction markets as corporate decision support systems – an experimental comparison with group deliberations', *Journal of Prediction Markets*, Vol. 1, No. 3, pp.189–208.

Stoel, L., Wickliffe, V. and Lee, K.H. (2004) 'Attribute beliefs and spending as antecedents to shopping value', *Journal of Business Research*, Vol. 57, No. 10, pp.1067–1073.

Sutton, S. (1998) 'Predicting and explaining intentions and behavior: how well are we doing?', *Journal of Applied Social Psychology*, Vol. 28, No. 15, pp.1317–1338.

Szajna, B. (1996) Empirical evaluation of the revised technology acceptance model', *Management Science*, Vol. 42, No. 1, pp.85–92.

Taylor, S. and Todd, P.A. (1995) 'Understanding information technology usage: a test of competing models', *Information Systems Research*, Vol. 6, No. 2, pp.144–176.

To, P-L., Liao, C. and Lin, T-H. (2007) 'Shopping motivations on internet: a study based on utilitarian and hedonic value', *Technovation*, Vol. 27, No. 12, pp.774–787.

Walker, D.A. (2006) 'Predicting presidential election results', *Applied Economics*, Vol. 38, No. 5, pp.483–490.

Wixom, B.H. and Todd, P.A. (2005) 'A theoretical integration of user satisfaction and technology acceptance', *Information Systems Research*, Vol. 16, No. 1, pp.85–102.

Wolfers, J. and Zitzewitz, E. (2006) *Prediction Markets in Theory and Practice*, NBER Working Paper No. 12083, Available at http://www.nber.org/papers/w12083

Xu, C., Ryan, S., Prybutok, V. and Wen, C. (2012) 'It is not for fun: an examination of social network site usage', *Information and Management*, Vol. 49, No. 5, pp.210–217.

Yang, Z. and Peterson, R.T. (2004) 'Customer perceived value, satisfaction and loyalty: the role of switching costs', *Psychology and Marketing*, Vol. 21, No. 10, pp.799–822.

Zeithaml, V.A., Berry, L.L. and Parasuraman, A. (1996) 'The behavioral consequences of service quality', *Journal of Marketing*, Vol. 60, No. 2, pp.31–46.