# 行政院國家科學委員會專題研究計畫 成果報告

## 以期望理論分析愛荷華賭博作業之檢定力
## 研究成果報告(精簡版)

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計 畫 主 持 人：鄭中平

計畫參與人員：博士班研究生-兼任助理人員：陳淑萍

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# 行政院國家科學委員會專題研究計劃報告

# 以期望理論分析愛荷華賭博作業之檢定力

# On the Power of Expectancy-Valence Model Based Analysis of Iowa Gambling Task

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主持人：鄭中平　　政治大學心理學系

**cpcheng@nccu.edu.tw**

摘要

愛荷華賭博作業是一個廣泛用來偵測可能決策缺失的認知作業。透過以期望理論對愛荷華賭博作業進行認知模擬，期望理論的參數分別對應了愛荷華賭博作業心理歷程的不同影響成分。當比較兩個群體在愛荷華賭博作業上的歷程時，典型的分析方式是二階段的。第一階段先以個別受試為單位估計參數，第二階段則對此參數進行平均數的比較。本計畫首先修正原始的期望模型，將個別受試參數視為由一分配中抽出，亦即，考慮參數的隨機效果，並推導此時的估計方式。

由於不同群體的決策歷程差異可能是許多心理學研究興趣所在，偵測群體差異的檢定力議題不容忽視。本計畫目的並以蒙地卡羅法比較兩階段與一階段分析的檢定力，初步發現修正後模式之檢定力較高。

關鍵詞：愛荷華賭博作業、隨機效果、混合效果

# Abstract

Iowa Gambling Task is a cognitive task designed for exploring the possible decision making deficit. By modeling this task, parameters of the expectancy-valence model are correspondent the components of psychological processes underlying the Iowa gambling task. When comparing psychological process of different groups of participants in the Iowa Gambling Task, the typical analysis is two-staged. The first stage is to estimate the parameters individually. The second stage is to compare the parameters from different groups. In the study, we modified the original Expectancy-Valence model such that parameters of different participants in the same group are considered to be normal distributed. By doing so, comparison of parameters from participants of different groups can be made in one stage. For the difference of decision making processes of different populations may be the main concern of many psychological studies, power to detect the difference cannot be overlooked. We also compared the powers of two-stage and one-stage analyses by Monte Carlo method.

# Introduction

The study proposes to extend the expectancy-valence (EV) learning model (Busemeyer & Stout, 2002) by incorporating subject-specific random effects to account for individual differences in performing the Iowa Gambling Task (Bechara, Damasio, Damasio & Anderson, 1994). The extended model permits all participants' performance to be analyzed simultaneously. Compared with fitting the EV model to individual IGT performance, an analysis based on the proposed model gains statistical power, for instance, in detecting group difference in IGT. Given that the task has been widely used to examine deficits in many areas of human decision making under uncertainty, the improved ability of the extended model to detect empirical differences in the IGT performance represents an important methodological advance.

IGT is designed to simulate real-life decision making process. At each trial of IGT, the participant is required to choose one card out of four decks of cards each of which is associated with different amount of (monetary) gain or loss. Feedback on the amount of gain or loss is provided after the choice is made. Two of the four decks of cards are associated with a large constant gain but with a negative expected gain in the long run; on the other hand, the other two decks of cards are associated with a lower constant gain, but with a positive expected value in the long run. The participant is, therefore, confronted with a tradeoff between immediate versus long term gains.

Typically, normal participants start off by choosing the decks with immediate gains before shifting their preference to the decks with long term gains after a few trials. In contrast, participants with decision making deficits tend not to change their choices throughout the course of trials even with feedback. IGT has been found to be useful in differentiating young and healthy subjects from other target groups such as elders (Wood, Busemeyer, Koling, Cox & Davis, 2005), substance abusers (Busemeyer et al, 2007; Stout, Busemeyer, Lin Grant & Bonson, 2004; Verdejo-Garcia et al., 2007; Yechiam, Busemeyer, Stout & Bechara, 2005), patients with Huntington's and/or Parkinson disease (Busemeyer & Stout, 2002), and patients with damage of orbital frontal cortex (Busemeyer, Stout & Finn, 2007).

In analyzing the trial by trial choices among the four decks for an individual participant, the EV model assumes that the decision maker integrates gains and losses before and at any given trial in IGT to form an expectancy valence for that trial on which probabilities of the next trial depend.

To account for participants' performance in the task, parameters of the EV model may be interpreted in correspondence to the components of psychological processes underlying the task. These model parameter estimates can then be used to compare healthy young adults against other target groups. For example, Busemeyer & Stout (2002) found higher learning rate parameter estimates for the Huntington group than that in healthy group; Yechiam et al. (2005) analyzed IGT data obtained from 10 different populations of participants based on the EV model, and mapped parameter estimates derived from each of the groups in the space of parameters.

Comparison of model parameter estimates on a map may reveal differences of decision making processes of distinct groups which is unattainable from the analysis of percentages of decks chosen alone. It may well be that the differences of parameter estimates between groups is the main concern of the empirical studies undertaken. Thus, the ability of a model to detect group difference in IGT must be considered.

Traditionally, the analysis of IGT based on the EV model is a two-stage process. First, estimates of model parameters are obtained, separately, from fitting the EV model to data from each individual.

The values (usually the central locations) of these individual parameter estimates then serve as raw data for comparing group differences via standard parametric statistical procedures such as the Student's t-test or analysis of variance.

The two-stage process of analyzing the IGT data is clearly inefficient since, for example, information contained in the standard errors of parameter estimates is ignored in the second comparison stage. Here, instead of analyzing IGT data in two stages, we propose a mixed-effects expectancy valence model by incorporating both subject-specific random effect parameters and group-specific fixed-effect parameters so that parameter estimation and group comparison can be achieved within a single statistical framework. By pooling information from groups of individuals, the mixed-effects EV model gains statistical power for detecting group differences when such differences exist in the populations.

Mixed Effects Expectancy-Valence Model

The mixed-effects EV model is specified as follows:

$$v_t = (1-w_i)*G_t + w_i * L_t \tag{1}$$

$$Ev_{t,k} = (1-a_i)Ev_{t-1,k} + a_i * v_t \quad \text{if} \quad D_{t,k} = 1 \tag{2}$$

$$p_{t+1,k} = \frac{\exp(Ev_{t,k} * (\mathrm{t}/10)^{c_i})}{\sum_{j=1}^{4} \exp(Ev_{t,j} * (\mathrm{t}/10)^{c_i})} \tag{3}$$

where $v_t$ is the valence at trial t, $w_i$ is the attention weight for the ith individual, $G_t$ and $L_t$ indicate gain and loss at trial t. $Ev_{t,k}$ denotes the expectancy-valence of choosing deck k at trail t, $a_i$ is the learning rate for the ith individual. The indicator variable $D_{t,k}$ is one if at trial t the deck k is chosen, otherwise $D_{t,k} = 0$. $p_{t,k}$ denotes the probability of choosing deck k at trail t, and $c_i$ is the sensitivity of ith individual ‘s choice behavior to expectancy-valence.

Equation (1), (2), (3) are identical to the original formulation of the EV model (Busemeyer & Stout, 2002) except the model parameters: *w*, which is the attention weight parameter, indicating a decision maker’s attention to loss relative to gain, *a*, which represents the rate at which expectance valence is updated, and *c,* which specifies the sensitivity of the choice probability to expectancy, are assumed to be subject-specific random effects and are indexed by *i*, for the ith participant.

In order to stabilize numerical routines and facilitate computation during parameter estimation, equation (3) is reparameterized with $c_i^{'} = 10^{c_i}$:

$$p_{t+1,k} = \frac{\exp(Ev_{t,k} * c_i^{'\log_{10} t - 1})}{\sum_{j=1}^{4} \exp(Ev_{t,j} * c_i^{'\log_{10} t - 1})} \tag{4}$$

We further assume that the random-effect parameters are sampled from independent and identically distributed multivariate normal distributions whose mean vector and covariance matrix are specified as follows:

$$(w_i, a_i, c_i^{'}) \sim N((w_0 + w_1 X, a_0 + a_1 X, c_0^{'} + c_1^{'} X), \begin{pmatrix} \sigma_{ww} & & \\ \sigma_{aw} & \sigma_{aa} & \\ \sigma_{c'w} & \sigma_{c'a} & \sigma_{c'c'} \end{pmatrix})$$

where *X* is a design matrix with fixed covariates. For example, with only two distinct groups of participants, the group membership is coded by an indicator *X*, resulting in the between-group difference being represent through model parameters $w_1$, $a_1$, and $c_1^{'}$. $\sigma_{ww}$, $\sigma_{aa}$ and $\sigma_{c'c'}$ indicate variances of parameters of *w*, *a*, and *c*' respectively. Covariance between two parameters is denoted by $\sigma_{XY}$ whose subscripts indicate the parameters.

## Estimation

<u>Parameter Estimation of the EV Model</u>

Buesmeyer and Stout (2002) estimated parameters of the EV model by the maximum likelihood method with Nelder-Mead simplex optimization (O'Neill, 1971). In fitting the original EV model to IGT data, our experience showed that the parameters estimated by the simplex method were very susceptive to their start values. In particular, the sensitivity parameter *c* is the exponent of a power function which, in turn, is exponentiated; tiny differences in the amplitude of *c* can produce wildly different choice probabilities. Replacing *c* with *c*', we found most optimization routines such as simplex, conjugate-gradient optimization and double dogleg optimization (SAS, 2004) converge to a single value when different starting values were set for parameters during modeling fitting. In addition, the latter two methods appeared to be computationally faster than simplex optimization.

We note that the EV model can be seen as a nonlinear regression model. Equations (1)-(3) can be reformulated as a single equation (since equation (2) is recursively specified):

$$p_{t+1,k} = \frac{\exp(\sum_{l=1}^{t} D_{l,k} * a_i * (1-a_i)^{\sum_{m=1}^{t} D_{m,k} - 1 - \sum_{m=1}^{l} D_{m,k}} * ((1-w_i) * G_t + w_i * L_t) * c_i^{' \log_{10} l - 1})}{\sum_{j=1}^{4} \exp(\sum_{l=1}^{t} D_{l,j} * a_i * (1-a_i)^{\sum_{m=1}^{t} D_{m,j} - 1 - \sum_{m=1}^{l} D_{m,j}} * ((1-w_i) * G_t + w_i * L_t) * c_i^{' \log_{10} l - 1}))}$$

$$= f(G_1, G_2, ......, G_t, L_1, L_2, ..., L_t, D_{1,k}, D_{2,k}, ..., D_{t,k} \mid a_i, w_i, c_i^{'}) .$$

The probability of choosing deck k at trial t + 1 is clearly a nonlinear function of cumulative gains and losses as well as the responses of previous trials. In practice, the parameters can be estimated by nonlinear regression packages such as PROC NLIN (SAS, 2004).

<u>Parameter Estimation of the Mixed-effects EV model</u>

Given that the EV model is a nonlinear regression model, the extended EV model with subject-specific random effect is a nonlinear mixed-effects model (Pinheiro & Bates, 1995). In the study, the NLMIXED procedure (SAS, 2004), which is designed to fit nonlinear mixed models, is used to estimate parameters of the mixed-effects EV model.

For a nonlinear mixed model, estimation of parameters is to maximize an approximation to the likelihood integrated over the random effects (Pinheiro & Bates, 1995; SAS, 2004). Conceptually, we obtain estimates of the nonlinear model from incorporating random effects via integral approximations. In fitting the mixed-effects EV model, we applied the maximum likelihood procedure with conjugate-gradient optimization and adaptive Gaussian quadrature. The reader may consult the article by Sheu, Chen, Su and Wang (2005) on how to implement mixed-effects models in PROC NLMIXED.

## Gender differences in IGT

We investigated gender differences in IGT performance of a sample of 14 male and 14 female Taiwanese college students in IGT using both the original and extended versions of the EV model. Results based on the original EV model are shown on the left of Table 1; no gender differences were found by comparing the three parameter estimates. In contrast, results based on the mixed-effects EV model shown on the right of Table 1; parameter estimates for *w* and *a* were found to be different across genders.

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Insert Table 1 here

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## Discussions

A mixed-effects EV model is proposed to efficiently account for human performance in IGT by extending the standard EV model. Results from the analysis of a small dataset suggested that the extended model was more sensitive at detecting group difference by efficiently pooling information from all individuals. Since IGT has been applied in many target groups to explore differences in the decision making process among these populations, a more general formulation of the EV model proposed here can potentially unify diverse empirical findings within a single statistical framework.

Although the current study focuses on testing for group differences in IGT, other aspects of the decision making process in IGT can also be investigated using the extended mixed-effects EV model. For instance, the extended model can easily be applied to account for the relationship between decision-making ability and personality traits as discussed in Davis, Patte, Tweed & Curtis (2007).

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Table 1

Comparisons of parameter estimates of the two versions of the expectancy-valence model between female (N = 14) and male (N =14) college students

| | Expectancy-Valence model + t test for two independent samples | | | | | | | Mixed-effects expectancy-valence model | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Female | | Male | | Diff | t (26) | 95% CI of Diff | Female | | Male | | Diff | t (25)[b] | 95% CI of Diff |
| | M | SD | M | SD | | | | M | SD | M | SD[a] | | | |
| *w* | .830 | .175 | .840 | .153 | .010 | .154 | (-.118, .137) | .823 | .211 | .854 | .211 | .031 | 2.583* | (.006, .056) |
| *a* | .008 | .005 | .008 | .008 | -.000 | -.015 | (-.005, .005) | .008 | .001 | .004 | .001 | -.003 | -2.329* | (-.006, -.0003)) |
| *c'* | .265 | .363 | .293 | .487 | .028 | .171 | (-.306, .361) | .357 | .828 | .367 | .828 | .010 | .554 | (-.027, .047) |

Note: M and SD is mean and standard deviation of estimates of parameters of individuals. Diff is the mean difference across genders, and 95% CI of Diff is the 95% confidence interval of mean difference.

a Covariance patterns in the mixed-effects EV model are assumed to be the same for both gender.

b To test whether the parameter is different from 0.

* $p < .05$.

# 出國報告

本次計畫中，前往芝加哥，參與 The 38th annual meeting of the Society for Computers in Psychology。該會議主要是關於電腦在心理學中的應用，可以約略分爲兩大類，一類是利用電腦或相關儀器進行心理學實驗，另一類利用電腦的功能，進行模擬或計算。此一會議固定在 Annual Meeting of Psychonomic Society 的同一地點，但在前一天舉行，因此在同一地點，可以連續參加兩個會議。

本次會議中，有研究者開發利用手機進行心理學實驗，並在不同手機中測試，初步發現如果實驗不牽涉精密計時，可以在手機上實驗，如此，可以拓展將來心理學實驗收集資料的管道。此外，著名的檢定力程式 G*Power 開發團隊亦於本會發表第三版。我個人的報告是考慮模擬愛荷華賭局作業的期望價值模型中的隨機效果，利用 SAS \ NLMIXED 模組協助估計。此一會議之論文全文可以直接投到 Psychonomic Society 的 Behavioral Research Method 期刊，因此我也在會前完成，一併投稿，並獲接受。

會議於當天傍晚結束，緊接著的是 Annual Meeting of Psychonomic Society 的開幕演講，本次請到 Daniel Kahneman，隔開開始一連三天，便是 Annual Meeting of Psychonomic Society 的口頭報告。我也聽了若干場次，特別是關於實驗資料的處理，利用貝式的方式從新考慮目前的常用分析方法。本次會議除發表論文外，亦結識若干研究電腦在心理學中應用的學者，交換訊息。