Psychology, **2010, 1: 22-26**
doi:10.4236/psych.2010.11004 Published Online April 2010 (http://www.SciRP.org/journal/psych)

Analysis of Psychological Health and Life Qualities of Internet Addicts Using Structural Equation Model*

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Received January 6th, 2010; revised January 28th, 2010; accepted January 29th, 2010.

ABSTRACT

Internet addiction disorder has become a serious social problem, and aroused great concern from the public and specialists. In this paper, the psychological states of internet addicts are measured by some famous mental scales, and their life qualities are investigated by some questionnaires. Structural Equations Model (SEM) is used to analyze the relationship between the psychological health and life qualities of internet addicts. Meanwhile, a definite linear algorithm of SEM is proposed which is useful for psychological analysis.

Keywords: *Psychological Health, Life Quality, Internet Addict, SEM Algorithm*

1. Introduction

Internet addiction disorder (IAD), or, more broadly, Internet overuse, problematic computer use or pathological computer use, is excessive computer use that interferes with daily life. IAD was originally proposed as a disorder in a satirical hoax by Ivan Goldberg in 1995 [1]. He took pathological gambling as diagnosed by the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) as his model for the description of IAD [2]. It is not however included in the current DSM as of 2009. IAD receives coverage in the press, and possible future classification as a psychological disorder continues to be debated and researched.

Goldberg converted Internet Addiction Disorder (IAD) into Pathological Computer Use (PCU). However, the basic contents of these two are the same. This paper used the concept of Internet Addiction.

Following Goldberg, people find their work could be in trouble because of Internet addiction, as well as social relationship, family relationship, finance, psychology and so on. Young (1996) discovered the emergence of a new clinical disorder by Internet addiction [3]. Kraut (1998) analyzed the Internet paradox: a social technology that reduces social involvement and psychological well-being [4]. Shaw (2002) analyzes the relationship between Internet communication and depression, loneliness, self-esteem, and perceived social support [5].

As the research go deep, mathematical models are used to describe Internet addiction. Weiser (2001) builds a cognitive-behavior model of pathological Internet addiction (PIU). Zhang (2006) use Structural Equation Model (SEM) to analyze the relationship of motives, behaviors of Internet addiction and related social-psychological health. Wen (2008) builds appropriate standardized estimates for moderating effects in Structural Equation Models.

Indeed, SEM is very useful to investigate the personality characteristic and life satisfaction of adults who have Internet addiction, and reveal the relationships between them, and the potential factor of Internet addiction. It will provide basis to intervene the people with Internet addiction.

But there are some problems in calculation of SEM because SEM is a indefinite equation. In this paper we build a SEM for Internet addiction, meanwhile we offer a definite linear algorithm for SEM which is useful for any SEM.

2. The Index System of Psychological Health in Internet Addiction

The researches of Internet addiction vary from person to person. Different people choose different scales. This

*The research was supported by the National Natural Science Foundation of China (30570611, 60773210).

paper takes Young [3] ten questionnaires to inquiry Internet addiction. There are many personality scales. Chinese Minnesota Multiphasic Personality Inventory (MMPI) which consists of ten indexes, including hypochondriasis, depression, hysteria, psychopathic deviate, masculinity feminity, paranoia, psychasthenia, schizophrenia, hypomania and social introversion, is took to test personality characteristic in this paper. Edward Dienner's Life Satisfaction Scale is also adopted to test life satisfaction, it comprises five questions.

The correlation between the above factors has been given a clear description in some articles. These three factors interact, and can be all affected by people's basic circs. We make an index system. People's basic circs, including sex, age, profession, education level, can be as independent variables; meanwhile, we choose three dependent variables which are Internet addiction, personality characteristic and life satisfaction. Independent variable and three dependent variables are latent variables. Each latent variable has certain kinds of explicit variables which are called manifest variables. The related dependent variables are showed in **Figure 1**.

3. Structural Equation Model

Structural Equation Model (SEM) is a fast-growing branch in the filed of applied statistics, widely used in psychology, sociology and other fields. This paper is the application of SEM to analyze social-psychological of Internet addiction.

There are two kinds of equations in SEM. One is the equations of the measurement model (outer model) between the latent variables and the manifest variables, we call Measurement Equations. The other is the equation of the structural model (inner model) among the latent variables, we call Structural Equations. In our model, there are 5 latent variables (ξ_1, ξ_2, $\eta_1 \sim \eta_3$) and 5 path relationships. The path coefficients from the exogenous latent variables ξ_i to the endogenous latent variables η_j are λ_{ji}, and the path coefficients among the endogenous latent variables η_{ij} are β_{ij}.

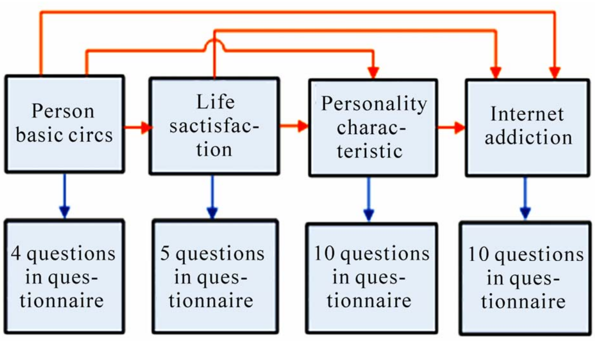

Figure 1. The basic index of dependent variables

Structural Equation Model can also be seen as the summary of secondary indicators. The latent variables ξ_1, ξ_2, $\eta_1 \sim \eta_3$ are the first-level index, they are virtual without direct observation values. Manifest variables are the second-level index, with practical observation values. The model in this paper, manifest variables can be acquired directly by questionnaire.

The Structural Equations are relationships among the latent variables. The Structural Equations can be expressed as follows

$$\begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 & 0 \\ 0 & \beta_{42} & \beta_{43} & 0 \end{pmatrix} \begin{pmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{pmatrix} + \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \end{pmatrix} \xi_1 + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{pmatrix} \tag{1}$$

Under normal circumstances, the form of Structural Equation coefficients may be different from the Equation (1) except for the diagonal line with 0. We use vector and matrix to describe the Structural Equations. Let $\xi' = (\xi_1', \cdots, \xi_k')$, $\eta' = (\eta_1', \cdots, \eta_m')$. The coefficient matrix of η is denoted as a $m \times m$ matrix B, and the coefficient matrix of ξ is denoted as a $m \times k$ matrix Γ. The residual vector is $\varepsilon_\eta' = (\varepsilon_1', \cdots, \varepsilon_m')$. The Structural Equation (1) can be expressed as:

$$\eta = B\eta + \Gamma\xi + \varepsilon_\eta \tag{2}$$

The Measurement Equations are relationships between the latent variables and the manifest variables. Suppose there are k exogenous latent variables and m endogenous latent variables. The manifest variables corresponding to the exogenous latent variable ξ_t are denoted as x_{tj}, $t = 1, \cdots, k$; $j = 1, \cdots, K(t)$, where $K(t)$ is the number of manifest variables corresponding to the exogenous latent variable ξ_t. The manifest variables corresponding to the endogenous variable η_i are denoted as y_{ij}, $i = 1, \cdots, m$, $j = 1, \cdots, L(i)$, where $L(i)$ is the number of manifest variables corresponding to the exogenous latent variable η_i.

The Measurement Equations can be expressed as the relationship from the manifest variables to the latent variables:

$$\xi_t = \sum_{j=1}^{K(t)} \psi_{tj} x_{tj} + \varepsilon_{xt}, \quad t = 1, \cdots, k \tag{3}$$

$$\eta_i = \sum_{j=1}^{L(i)} \omega_{ij}\, y_{ij} + \varepsilon_{yi}\,, \quad i = 1,\cdots,m \tag{4}$$

where ψ_{tj}, ω_{ij} are the path coefficients, and ε with subscript is a random error.

The Measurement Equations can also be expressed as the relationship from the latent variables to the manifest variables:

$$\begin{pmatrix} x_{t1} \\ \vdots \\ x_{tK(t)} \end{pmatrix} = \begin{pmatrix} \upsilon_{t1} \\ \vdots \\ \upsilon_{tK(t)} \end{pmatrix} \xi_t + \begin{pmatrix} \varepsilon_{xt1} \\ \vdots \\ \varepsilon_{xtK(t)} \end{pmatrix}, \quad t = 1,\cdots,k \tag{5}$$

$$\begin{pmatrix} y_{i1} \\ \vdots \\ y_{iL(i)} \end{pmatrix} = \begin{pmatrix} \lambda_{i1} \\ \vdots \\ \lambda_{iL(i)} \end{pmatrix} \eta_i + \begin{pmatrix} \varepsilon_{yi1} \\ \vdots \\ \varepsilon_{yiL(i)} \end{pmatrix}, \quad i = 1,\cdots,m \tag{6}$$

where $\upsilon_{tj}, \lambda_{ij}$ are the loading coefficients, and ε with subscript is still a random error.

Denoting manifest vectors as $x_t' = (x_{t1}',\cdots,x_{tK(t)}')$, $y_i' = (y_{i1}',\cdots,y_{iL(i)}')$, and denoting coefficients as $\psi_t' = (\psi_{t1},\cdots,\psi_{tK(t)})$, $\omega_i' = (\omega_{i1},\cdots,\omega_{iL(i)})$, then the Measurement Equation (3) can be expressed as:

$$\xi_t = \psi_t' x_t + \varepsilon_{xt}, \; t = 1,\cdots,k \tag{7}$$

And (4) can be expressed as:

$$\eta_i = \omega_i' y_i + \varepsilon_{yi}, \; i = 1,\cdots,m \tag{8}$$

Then the Equations (2,7,8) can be written as

$$SEM^+ \quad \begin{cases} \eta = B\eta + \Gamma\xi + \varepsilon_\eta \\ \xi_t = \psi_t' x_t + \varepsilon_{xt}, \; t = 1,\cdots,k \\ \eta_i = \omega_i' y_i + \varepsilon_{yi}, \; i = 1,\cdots,m \end{cases} \tag{9}$$

We call SEM^+ the Structural Equation Model with positive observation.

Letting $\upsilon_t' = (\upsilon_{t1},\cdots,\upsilon_{tK(t)})$, $\lambda_i' = (\lambda_{i1},\cdots,\lambda_{iL(i)})$, then the Measurement Equation (5) can be expressed as:

$$x_t = \upsilon_t \xi_t + \varepsilon_{xt}\,, \quad t = 1,\cdots,k \tag{10}$$

And (6) can be expressed as:

$$y_i = \lambda_i \eta_i + \varepsilon_{yi}\,, \quad i = 1,\cdots,m \tag{11}$$

We combine the Equations (2,10,11) as:

$$SEM^- \quad \begin{cases} \eta = B\eta + \Gamma\xi + \varepsilon_\eta \\ x_t = \upsilon_t \xi_t + \varepsilon_{xt}, \; t = 1,\cdots,k \\ y_i = \lambda_i \eta_i + \varepsilon_{yi}, \; i = 1,\cdots,m \end{cases} \tag{12}$$

And call SEM^- the Structural Equation Model with converse observation. The difference between SEM^+ and SEM^- is that the causalities between the latent variables and the manifest variables are converse.

4. LSE by the Modular Constraint of Structural Vector

If the observation equations of SEM are analyzed carefully, we can discover the way to use the least squares method between each structural variable and its corresponding observation variables, and obtain the least squares solution of structural variable by the modular constraint least square (MCLS) solution. The MCLS algorithm is as follows (the specific process can be seen in reference [10]).

Algorithm 1. The modular constraint least square solution of SEM

Step 1. In SEM^-, suppose that ξ_t, η_i all are unit vectors, and calculate the least square estimates of the loading coefficients between the latent variable and its manifest variables:

$$\hat{\upsilon}_{tj}^2 = x_{tj} x_{tj}'\,, \quad j = 1,\cdots,K(t)\,, \quad t = 1,\cdots,k \tag{13}$$

$$\hat{\lambda}_{ij}^2 = y_{ij} y_{ij}'\,, \quad j = 1,\cdots,L(i)\,, \quad i = 1,\cdots,m \tag{14}$$

Step 2. In SEM^-, calculate the least square estimates of latent variable by making use of $\hat{\upsilon}_{ij}, \hat{\lambda}_{ij}$:

$$\hat{\xi}_{ts} = \frac{\hat{\upsilon}_t' X_{ts}}{\hat{\upsilon}_t \hat{\upsilon}_t'}, \quad \hat{\eta}_{is} = \frac{\hat{\lambda}_i' Y_{is}}{\hat{\lambda}_i \hat{\lambda}_i'} \tag{15}$$

where $s = 1,\cdots,N$, $t = 1,\cdots,k$, $i = 1,\cdots,m$, and X_{ts}, Y_{is} are the transverse vectors of the observation data matrix $X_{ts}' = (x_{t1s},\cdots,x_{tK(t)s})$, $Y_{is}' = (x_{i1s},\cdots,x_{iL(i)s})$.

Step 3. In SEM^+ (or (3,4)), make use of $\hat{\xi}_t, \hat{\eta}_i$ obtained in Step 2 to calculate regression coefficients ψ_{tj}, ω_{ij} according to a common linear regression method.

Step 4. In SEM^+ (or (2)), make use of $\hat{\xi}_t, \hat{\eta}_i$ obtained in Step 2 to calculate the estimates of coefficient matrices B, Γ.

Notice that (2) is a common linear regression equation system, we can use Two Step Least Square to calculate it.

5. Definite Linear Algorithm with Prescription Constraint

Obviously, the solutions of SEM^+ or SEM^- are not unique, and they may differ by a multiple. Therefore, in the Structural Equation (1) or (2), if each latent variable is multiplied by the same multiple, its coefficient solution is the same. Taking note of this, the solution of Structural Equations is irrelevant to the modular length of the latent variable. However, it is not reasonable to assume that the modular length of each latent variable is 1. On the other hand, if each modular length of the latent variable is not the same in the possibly existing optimal solution set, then MCLS is not good. Therefore, we need further consideration.

One reasonable way is to let each latent variable have an undetermined parameter of the modular length and combine the Structural Equation (1) or (2) to find the solution. The square sum of error of this solution includes $m+k$ modular length parameters. Changing these modular length parameters to minimize the square sum of error, we can obtain a reasonable modular length of the latent variable.

Another possible way is to find a more reasonable constraint to replace the modular constraint. After getting MCLS, we can change the modular length of the latent variable in Measurement Equations to make the path coefficient between latent variables and manifest variables satisfy the prescription condition. In Equations (3,4), the prescription conditions are:

$$\sum_{j=1}^{K(t)} \psi_{tj} = 1, \quad \psi_{tj} \ge 0, \quad t = 1, \cdots, k \tag{16}$$

$$\sum_{j=1}^{L(i)} \omega_{ij} = 1, \quad \omega_{ij} \ge 0, \quad i = 1, \cdots, m \tag{17}$$

To compute the prescription condition, we need to consider two cases.

If the corresponding path coefficients of MCLS are non-negative at the beginning, then it is simple. We just need to divide the two sides of the Equations (3, 4) by a constant. This constant should be the sum of the corresponding path coefficients in MCLS. For example, in the Equation (3), if $\sum_{j=1}^{K(t)} \psi_{tj} = c_t$, then the two sides o the Equation (4) are divided by the constant c_t, and $\sum_{j=1}^{K(t)} \psi_{tj} = 1$.

If the corresponding path coefficients of MCLS are negative at the beginning, we cannot copy the method of prescription regression proposed by Fang (1982) [11], because regression endogenous variables are not completely known. Now we know the direction of regression endogenous variables, but the modular length is undetermined. According to the theorem in [11], if the initial regression coefficients have negative ones, whose prescription regression coefficient should be 0. So we can first make ordinary regression about MCLS, where the modular length of endogenous variables is 1. If there are some non-positive terms in the initial regression coefficients, we can get rid of these variables, and thus the corresponding regression coefficient is 0. Then the two sides of the Equations (3,4) can be divided by a constant that should be the sum of the corresponding path coefficients in MCLS, as discussed in the previous paragraph.

Of course we can improve the constraint of the prescription condition. If some regression coefficient is 0, its corresponding variable may be removed from the model, which is not a desired situation. To avoid this, we may change the prescription condition and let $\psi_{tj} \ge \delta$, $\omega_{ij} \ge \delta$, where $\delta > 0$ is decided by user according to practice problem. If some initial regression coefficients are less than δ, they all are changed as δ, and the corresponding exogenous variables with coefficient δ should be moved to the left side of the equation in regression process.

Summarizing the above discussion we can continue to improve the algorithm of MCLS.

Algorithm 2. Improvement on Step 3 of Algorithm 1.

Step $3'$. After getting the estimate of latent variables $\hat{\xi}_t, \hat{\eta}_i$ in Step 2, calculate the summarizing coefficients ψ_{tj}, ω_{ij} by prescription regression, and recalculate the estimates of ξ_t, η_i.

1) Make use of $\hat{\xi}_t, \hat{\eta}_i$ directly in Step 2 and calculate $\hat{\psi}_{tj}, \hat{\omega}_{ij}$ in SEM^+ by common regression.

2) For any t, if there are $\hat{\psi}_{tj} \ge \delta$, ($\delta \ge 0$) for all j, and $\sum_{j=1}^{K(t)} \psi_{tj} = c_t$, then divide both sides of Equation (3) by c_t. Similarly, for any i, if there are $\omega_{ij} \ge \delta$, ($\delta \ge 0$) for all j, and $\sum_{j=1}^{L(i)} \omega_{ij} = c_i$ then divide both sides of Equation (4) by c_i.

After checking all t, i, go to Step 4 in Algorithm 1.

3) For any t, i, if there is some j so that $\hat{\psi}_{tj} < \delta$, or $\omega_{ij} < \delta$, ($\delta \ge 0$), then let the corresponding term be fixed, i.e., $\hat{\psi}_{tj} = \delta$ or $\omega_{ij} = \delta$. After checking all j, go to Step 1 and Step 2 in algorithm 1.

Note that if some regression coefficient is fixed in common regression, the corresponding exogenous variables with its coefficient δ should be moved to the left side of the equation and combined with the endogenous variable to regression. After regression the corresponding exogenous variable with its coefficient δ should be moved to the right side of the equation.

This model and definite algorithm is helpful to researchers who study Internet addiction. More detailed proof of algorithm and data examples can be found in website http://public.whut.edu.cn/slx/English/.

6. Acknowledgment

The authors would like to express sincerely thanks to the referees and editors for their valuable comments.

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