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Identify User's Satisfaction from Platform Using Behavior

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Abstract.. The purpose of this study was to verify a model of user's satisfaction of an e-learning environment based upon platform using behaviors. This is a non-experimental study. The data was collected from system management logs and users satisfaction survey after learning service. Total 314 users were invited in this study. First, theory model was identified. Second, the satisfaction survey results were prepared. Third, the behavior data of each survey subject were prepared. A CFA procedure were conducted to verify whether the data fits into the model. The model fit is positive with $\chi 2$ = 2.06, p-value=.151, df= 1, RMSEA=.058. The proposed two-factor theory model with simple structure fit the data. The love e-learning and satisfaction of e-learning factors are significantly supporting the hypothesis of a relationship between the factors. The findings suggested that identifying satisfaction from behavior is possible.

1 Introduction

1.1 E-learning Platform

E-learning is becoming an increasingly large part of higher education (Anderson, 2014, Duck and Parente, 2014, Kim, 2011).

Over 7.1 million college and university students took at least one online course by the end of the fall 2012 semester in the United States (Allen and Seaman, 2014). More than 71% of US colleges and universities offered online courses in 2012(Allen and Seaman, 2013) and one-third of higher education students took at least one online course in 2012 (Allen and Seaman, 2014).

1.2 Problem Statement

For managing an information system, there is always a need to understand user's behavior on system service. In an open learning environment, how can an information service provider keeping their users on using service is an important problem.

The purpose of this study was to identify whether an open ceremony affects on-line learning platform account keeping behavior.

2 Literature review

2.1 Massive Open Online Courses

According to the U.S. Department of Education Distance Learning Report (Bakia et al., 2012), the benefits of e-learning are: a) to broaden access to the educational resources, b) to personalize learning, c) to provide flexibility in time and location for students, and d) to reduce school-based facilities' costs. However, the benefits of e-learning also bring some challenges into the field of education.

First, the retention rates in e-learning courses are 10-25% less than those for traditional face-to-face classes(Ali and Leeds, 2009, Angelina et al., 2007, Lee and Choi, 2013) in higher education. In other words, over one half of distance students may dropout of their education as a result of online courses (Duck and Parente, 2014). Second, students who take online courses for the first time tend to feel lonely and socially isolated not only because previously, tend to focus more on computer or Internet skills, technology accessibility, and general learner characteristics such as attitude toward online education or personal learning preferences (Bernard et al., 2004).

E-learning has been described as technology-based learning (Ali and Leeds, 2009, Kim, 2011), web-based learning (Bakia et al., 2012), network- and computer-based learning (Angelina et al., 2007), or "instructional environments supported by the Internet" (Bakia et al., 2012). Although each researcher uses different terms to describe the phenomenon of e-learning, the common element in all of the research is that learners need to be

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familiar with using computer technology and the Internet to take online courses.

3 Methodology

3.1 Model Hypotheses

Structural equation modeling (SEM) is a collection of statistical techniques that allow a set of relationships between one or more IVs, either continuous or discrete, and one or more DVs, either continuous or discrete, to be examined. Both IVs and DVs can be either factors or measured variables. Structural equation modeling is also referred to as causal modeling, causal analysis, simultaneous equation modeling, analysis of covariance structures, path analysis, or confirmatory factor analysis (CFA). The latter two are actually special types of SEM.

One interesting feature of the analysis is that survival time (the DV) often is unknown for a number of cases at the conclusion of the study. Some of the cases are still in the study but have not yet failed: some employees have not yet left, some components are still functioning, some patients are still apparently well, or some patients are still living. For other cases, the outcome is simply unknown because they have withdrawn from the study or are for some reason lost to follow-up. Cases whose DV values—survival time— are unknown for whatever reason are referred to as censored.

SEM allows questions to be answered that involve multiple regression analyses of factors. Several conventions are used in developing SEM diagrams. Measured variables, also called observed variables, indicators, or manifest variables, are represented by squares or rectangles.

Factors have two or more indicators and are also called latent variables, constructs, or unobserved variables. Factors are represented by circles or ovals in path diagrams. Relationships between variables are indicated by lines; lack of a line connecting variables implies that no direct relationship has been hypothesized. Lines have either one or two arrows. A line with one arrow represents a hypothesized direct relationship between two variables, and the variable with the arrow pointing to it is the DV. A line with an arrow at both ends indicates an unanalyzed relationship, simply a covariance between the two variables with no implied direction of effect.

Parameters (path coefficients, variances, and covariances of IVs) are estimated to create an estimated population covariance matrix. If the model is good, the parameter estimates will produce an estimated matrix that is close to the sample covariance matrix. “Closeness” is evaluated primarily with the chi- square test statistic and fit indices.

3.2 Covariance Algebra

Within the family of survival- analysis techniques, different procedures are used depending on the nature of the data and the kinds of questions that are of greatest interest.

The idea behind SEM is that the hypothesized model has a set of underlying parameters which correspond to (1) the regression coefficients, and (2) the variances and covariances of the independent variables in the model (Bentler, 1995). These parameters are estimated from the sample data to be a “best guess” about population values. The estimated parameters are then combined by means of covariance algebra to produce an estimated population covariance matrix. This estimated population covariance matrix is compared with the sample covariance matrix and, ideally, the difference is very small and not statistically significant.

Covariance algebra is a helpful tool in calculating variances and covariances in SEM models; however, matrix methods are generally employed because covariance algebra becomes extremely tedious as models become increasingly complex. Covariance algebra is useful to demonstrate how parameter estimates are combined to produce an estimated population covariance matrix for a small example.

The three basic rules in covariance algebra appear below where c is a constant and Xi is a random variable:

1. COV(c,X1)=0
2. COV(cX1, X2)=cCOV(X1,X2)
3. COV(X1 + X2, X3) = COV(X1, X3) + COV(X2,X3)

In SEM, as in multiple regression, we assume that the residuals do not correlate with each other or with other variables in the models. In this model, both degree of motivation (Y1) and exam score (Y2) are DVs. Recall that a DV in SEM is any variable with a single- headed arrow pointing toward it. Treatment group (X1) with no single-headed arrows pointing to it is an IV. To specify the model, a separate equation is written for each DV.

3.3 Model Hypotheses

The data set contains four continuous measured variables:

Hours, the number of a participant has learning on-line.

Course, the number of a participant has taken from the e-learning service.

Plat.Sa, a Likert scale measure of degree of the satisfaction of the platform.

Cou.Sa, a Likert scale measure of degree of the satisfaction of the course.

The hypothesized model for these data is diagrammed in Figure 1. Latent variables are represented with oval and measured variables are represented with squares. A line with an arrow indicates a hypothesized direct relationship between the variables.

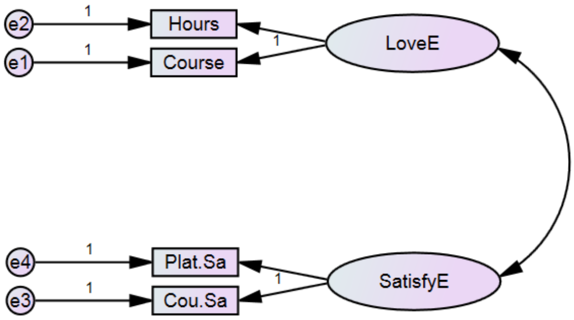

Figure 1. Hypothesized model for the study

4 Findings

In this session, the findings would be reported in descriptive statistics, CFA model, estimates of CFA model, and model fits summary.

For the model fits summary, three sets of model fit index are reported. Those are CMIN, RMSEA, and RMR & GFI.

4.1 Descriptive Statistics

In Table 1., the descriptive statistics of variables were listed. The mean value of course is 9.22. The mean value of hours is 19.45.

The mean course satisfaction is 4.49. The mean platform satisfaction is 4.51. The sample number is 314.

Table 1. N, Minimum, Maximum, Mean, & Std. Deviation of Variables

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
course_num	314	6	10	9.22	.869
hours	314	12	22	19.45	2.853
CourseSa	314	3	5	4.49	.599
PlatformSa	314	3	5	4.51	.636
Valid N (listwise)	314				

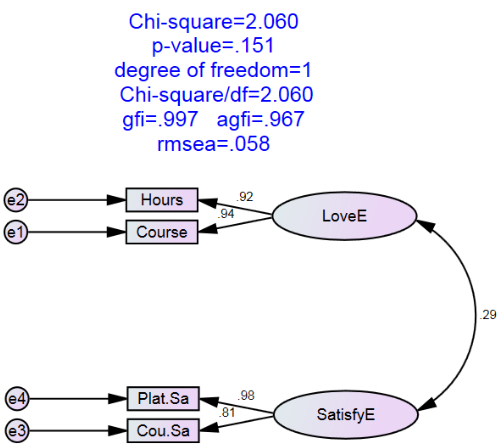

Figure 2. CFA Model of this study

All variables in the model are listed here, classified as either observed or unobserved, and as either endogenous or exogenous. A summary table shows the number of variables in each category, as well as the total number of variables in the model.

In Table 2, parameters of the proposed model were listed. This table shows the numbers of model parameters that fall into various categories.

The columns of the table are:

- **Weights**: regression weights
- **Covariances**: self explanatory
- **Variances**: self explanatory
- **Means**: self explanatory
- **Intercepts**: self explanatory

The rows of the table are:

- **Fixed**: parameters whose values are fixed at a constant value
- **Labeled**: parameters that are labeled
- **Unlabeled**: parameters that are neither fixed nor labeled. Such parameters are free to take on any value. (Labeled parameters can also be free -- a parameter that has been associated with a unique label is free to take on any value.)

Table 2. Parameter Summary

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	6	0	0	0	0	6
Labeled	0	0	0	0	0	0
Unlabeled	2	1	6	0	0	9
Total	8	1	6	0	0	15

4.2 CFA model

The first hypothesis, that the model fits the data, has been evaluated and supported. The model fit is positive with $\chi 2$ = 2.06, p-value=.151, df= 1, RMSEA=.058. The proposed two-factor theory model with simple structure fit the data.

4.3 Estimates of CFA Model

Estimates of the following model parameters:

- Regression weights
- Variances of exogenous variables
- Covariances among exogenous variables
- Means of exogenous variables
- Intercepts for predicting endogenous variables

Estimates of the following quantities also appear here when requested.

- Squared multiple correlations
- Correlations among the exogenous variables
- Standardized regression weights

In Table 3, the regression weights were listed and all indicators are significant.

Table 3. Regression weights

			Estimate	S.E.	C.R.	P	Label
course_num	<---	LoveE	1				
hours	<---	LoveE	3.212	0.346	9.282	***	par_1
CourseSa	<---	SatisfyE	1				
PlatformSa	<---	SatisfyE	1.29	0.198	6.519	***	par_2

In Table 4, the standardized regression weights were listed.

Table 4. Standardized Regression Weights

			Estimate
course_num	<---	LoveE	0.945
hours	<---	LoveE	0.924
CourseSa	<---	SatisfyE	0.807
PlatformSa	<---	SatisfyE	0.982

In Table 5, the covariance between two factors was listed.

Table 5. Covariances of Model

			Estimate	S.E.	C.R.	P	Label
LoveE	<-->	SatisfyE	0.114	0.03	3.826	***	par_3

4.4 Model Fit Summary

4.4.1 CMIN

In Table 6, the model is fit since the p value > .05. The CMIN is 2.060. The CMON/DF is 2.06. The model is acceptable fit.

Table 6. Model Fit of CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	9	2.060	1	.151	2.060
Saturated model	10	.000	0		
Independence model	4	785.138	6	.000	130.856

4.4.2 RMSEA

In Table 7, the RMSEA is .058. The value indicates close approximate fit.

Table 7. Model Fit of RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.058	.000	.174	.301
Independence model	.644	.606	.683	.000

4.4.3 RMR & GFI

In Table 8, the RMR is 0.008. The range of the RMR is calculated based upon the scales of each indicator. The SRMR of 0 indicates perfect fit. The GFI is 0.997. The GFI value suggests a good fit model.

Table 8. Model Fit of RMR & GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0.008	0.997	0.967	0.1
Saturated model	0	1		
Independence model	0.716	0.552	0.253	0.331

5 Conclusions

The purpose of this study was to verify a model of user's satisfaction of an e-learning environment based upon platform using behaviors. This is a non-experimental study.

The data was collected from system management logs and users satisfaction survey after learning service. Total 314 users were invited in this study. First, theory model was identified. Second, the satisfaction survey results were prepared. Third, the behavior data of each survey subject were prepared. A CFA procedure were conducted to verify whether the data fits into the model.

The model fit is positive with $\chi 2$ = 2.06, p-value=.151, df= 1, RMSEA=.058. The proposed two-factor theory model with simple structure fit the data. The love e-learning and satisfaction of e-learning factors are significantly supporting the hypothesis of a relationship between the factors. The findings suggested that identifying satisfaction from behavior is possible.

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