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A Practical Guide To Factorial Validity Using PLS-Graph: Tutorial And Annotated Example

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A PRACTICAL GUIDE TO FACTORIAL VALIDITY USING PLS-GRAPH: TUTORIAL AND ANNOTATED EXAMPLE

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ABSTRACT

This tutorial explains in detail what factorial validity is and how to run its various aspects in PLS. The tutorial is written as a teaching aid for doctoral seminars that may cover PLS and for researchers interested in learning PLS. An annotated example with data is provided as an additional tool to assist the reader in reconstructing the detailed example.

Keywords: PLS, factorial validity, convergent validity, discriminant validity, confirmatory factor analysis, AVE.

I. INTRODUCTION

Since we first published our tutorial "Structural Equation Modeling Techniques and Regression: Guidelines for Research Practice" in *Communications of AIS* [Gefen et al. 2000] and its follow-up "Validation Guidelines for IS Positivist Research" [Straub et al., 2004], we have received many emails about the practicalities of running PLS (Partial Least Squares) and LISREL. In consultation with the editor of *CAIS*, we are publishing this addendum to the *Guidelines*. The objective of this particular short guide is to describe how to run factorial validity and how to examine it through PLS. Specifically, the tutorial discusses and demonstrates convergent and discriminant validity, including the AVE analysis. This tutorial is aimed at researchers aiming to adopt PLS-Graph but still unaware of how to actually assess factorial validity through it.

II. THEORETICAL BACKGROUND

Factorial validity is important in the context of establishing the validity of latent constructs. Latent constructs, also known as latent variables, are research abstractions that cannot be measured directly, variables such as beliefs and perceptions. Quantitative positivist researchers assume that while some variables such as gender and age can be measured directly and with little error, a major difficulty arises with surrogates where the abstraction is removed from objective reality.[1]

[1] See http://dstraub.cis.gsu.edu:88/quant/ for greater detail.

Because such abstractions cannot easily be measured through direct means, agreed-upon practice dictates that they be measured indirectly through several items in a research instrument [Anderson and Gerbing, 1988, Bagozzi, 1977, Campbell and Fiske, 1959, Churchill, 1979]. Each measurement item, i.e., each actual scale item on an instrument, is thus assumed to reflect one and only one latent variable. This property of the scale, having each of its measurement items relate to it better than to any others, is known as unidimensionality. Unidimensionality is discussed in detail by Gerbing and Anderson [1988] and is delineated in another *CAIS* tutorial [Gefen 2003]. Unidimensionality cannot be measured with PLS but is assumed to be there *a priori* [Gefen, 2003, Gerbing and Anderson, 1988].

However, two elements of factorial validity can and must be examined in PLS, as they must be with latent variables in general [Churchill, 1979, Gerbing and Anderson, 1988]. The two elements, convergent validity and discriminant validity, are components of a larger scientific measurement concept known as construct validity [Straub et al., 2004]. These two validities capture some of the aspects of the goodness of fit of the measurement model, i.e., how well the measurement items relate to the constructs. When factorial validity is acceptable, it means each measurement item correlates strongly with the one construct it is related to, while correlating weakly or not significantly with all other constructs. Typically, because of the way factorial validity is established in PLS, this pattern of factorial validity is divided into convergent validity and discriminant validity. Convergent validity is shown when each measurement item correlates strongly with its assumed theoretical construct, while discriminant validity is shown when each measurement item correlates weakly with all other constructs except for the one to which it is theoretically associated.

In first generation regression models, factorial validity was most frequently assessed with an Exploratory Factor Analysis, or EFA.[2] Several estimation methods can be used in an EFA. The objective of all these methods is generally the same, however. This objective is:

- To establish that the measurement items converge into the appropriate number of theoretical factors,
- That each item loads with a high coefficient on only one factor, and
- That this one factor is the same factor for all the measurement items that supposedly relate to the same latent construct [SPSS, 2003].

As a rule of thumb, a measurement item loads highly if its loading coefficient is above .60 and does not load highly if the coefficient is below .40 [Hair et al., 1998]. Technically, an EFA identifies the underlying latent variables, or factors, that explain the pattern of correlations within a set of measurement items. Once this data reduction identifies a small number of factors that explain most of the variance in the measurement items, the loading pattern of these measurement items is determined and revealed in the statistical output. The number of factors that is selected by default is the number of factors with an eigenvalue exceeding 1.0. Sometimes, more or fewer factors are selected by the researcher based on a scree test or on theory [Hair et al., 1998].

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[2] In EFA, the number of factors is not stated in advance by the researcher. The computer program, such as SPSS or SAS, calculates the relationships between all the measurement items, placing those most closely related (highly correlated) into factors, which are then matched to the researcher's theoretically posited constructs. A researcher can also specify a certain number of factors to be extracted within EFA and rotate the matrix. An EFA involves two statistical stages. In the first stage the factors as extracted. In the optional second stage, the factors are then rotated to provide a better picture of the underlying factors of the measurement items. There are several methods of extracting factors. The most common one that we see in IS studies is a Principal Components Analysis (PCA). An EFA enables specifying the expected number of factors, but although this is a move from being entirely exploratory, it not a confirmatory analysis in the sense of a CFA where the pattern by which measurement items load onto certain factor is specified in advance.

These two steps are typically carried out through a Principal Components Analysis, or PCA, which extracts the factors assuming uncorrelated linear combinations of the measurement items. The loading pattern is then rotated to simplify the interpretation of the results. Typically this rotation is a Varimax rotation which creates orthogonal factors with minimized high loadings of the measurement items on other factors. Another common rotation method is the Direct Oblimin Method which performs a nonorthogonal or oblique rotation [SPSS, 2003]. Nonorthogonal rotations can produce a neater pattern of loading, and so they make the interpretation of the factors easier, but at the cost of increasing multicollinearity because of the loss of orthogonality.[3]

Both EFA and PCA are run via programs like SPSS, which calls this approach “data reduction.” In a sense, researchers are attempting to achieve data reduction in that items that do not load properly are dropped and the instrument thereby “purified” and by reducing the larger number of measurement items into a smaller number of factors [Churchill, 1979]. With the advent of structural equation modeling (SEM) tools, such as PLS and LISREL, an argument for not purifying measures and treating an instrument more holistically has been made [MacCallum and Austin, 2000, Straub et al., 2004], but there is no clear resolution about whether measurement error should be modeled and accounted for or simply eliminated.

PLS FACTORIAL VALIDITY

In contrast to EFA, PLS performs a Confirmatory Factor Analysis (CFA). In a CFA, the pattern of loadings of the measurement items on the latent constructs is specified explicitly in the model. Then, the fit of this pre-specified model is examined to determine its convergent and discriminant validities. This factorial validity deals with whether the pattern of loadings of the measurement items corresponds to the theoretically anticipated factors.[4] The example presented in Section III details how this analysis is performed.

Convergent validity is shown when each of the measurement items loads with a significant t-value on its latent construct. Typically, the p-value of this t-value should be significant at least at the 0.05 alpha protection level.

Discriminant validity is shown when two things happen:

1. The correlation of the latent variable scores with the measurement items needs to show an appropriate pattern of loadings, one in which the measurement items load highly on their theoretically assigned factor and not highly on other factors.

   Established thresholds do not yet exist for loadings to establish convergent and discriminant validity. In fact, comparing a CFA in PLS with a EFA with the same data and model, Gefen et al. [2000] showed that loadings in PLS could be as high as .50 when the same loadings in an EFA are below the .40 threshold. Nonetheless, in our opinion, all the loadings of the measurement items on their assigned latent variables should be an order of magnitude larger than any other loading. For example, if one of the measurement

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[3] Other than the statistical assumptions of independence of antecedent variables (this is why they are called “independent variables,” in fact), there is no inherent scientific reason to prefer orthogonal rotations to oblique rotations. Oblique rotations are, perhaps, more in keeping with the real world where constructs frequently overlap both conceptually and statistically.

[4] The discussion assumes that the measurement items are reflections or “reflective” of the construct, which means that all items should correlate highly with each other. We do not deal with the issue of how to validate an instrument when the items (or sub-constructs) are thought to be “formative.” For all intents and purposes, formative measures are still an open issue in the metrics literature. Initial guidelines on constructing indexes with formative measurement items are discussed by Diamantopoulos and Winklhofer [2001].

items loads with a .70 coefficient on its latent construct, then the loadings of all the measurement items on any latent construct but their own should be below .60.

2. Establishing discriminant validity in PLS also requires an appropriate AVE (Average Variance Extracted) analysis. In an AVE analysis, we test to see if the square root of every AVE (there is one for each latent construct) is much larger than any correlation among any pair of latent constructs. AVE, which is a test of discriminant validity offered through PLS, is calculated as:

$$(\Sigma\lambda_i^2)/((\Sigma\lambda_i^2) + (\Sigma(1-\lambda_i^2))$$

where λ_i is the loading of each measurement item on its corresponding construct.

AVEs are generated automatically using the bootstrap technique by the latest version of PLS-Graph (i.e., version 03.00 build 1126 of 2003). AVE measures the variance captured by a latent construct, that is, the explained variance. For each specific construct, it shows the ratio of the sum of its measurement item variance as extracted by the construct relative to the measurement error attributed to its items. As a rule of thumb, the square root of the AVE of each construct should be much larger than the correlation of the specific construct with any of the other constructs in the model [Chin, 1998a] and should be at least .50 [Fornell and Larcker, 1981a].[5] Unfortunately, guidelines about how much larger the AVE should be than these correlations are not available. Conceptually, the AVE test is equivalent to saying that the correlation of the construct with its measurement items should be larger than its correlation with the other constructs. This comparison harkens back to the tests of correlations in multi-trait multi-method matrices [Campbell and Fiske, 1959], and, indeed, the logic is quite similar.

III. PRACTICAL EXAMPLE

To show how these principles apply in research practice, we next illustrate the testing of factorial validity via PLS. Data used below is from a study that deals with purchasing tickets online and tested via the Technology Acceptance Model (TAM) [Davis, 1989]. The study, Gefen [2003], is useful in this context since it shows how to apply tests of discriminant validity. A subset of the items has been selected for this practical example (Table 1). Basically, as in TAM, the perceived ease of use (PEOU) of an IT, which is the website in this case, affects its perceived usefulness (PU), and both PEOU and PU affect intended use (USE). Although, as in other studies, we do not expect PEOU to have a direct effect on USE (Intention to Use) because PEOU is not of an intrinsic value to the information technology being used [Gefen and Straub, 2000]. USE is represented as the “Buy Tickets” behavioral intention in the figures that follow. The raw data are shown in Appendix I. The raw data were collected from subjects who answered each item on a 1 to 7 Likert scale ranging from Strongly Disagree through Neutral to Strongly Agree.

[5] An alternative and more stringent approach of comparing the AVE with the correlations of the latent constructs is presented by Gefen et al. [2000] and by House et al. [1991] who suggest comparing the AVE, rather than the square root of the AVE, with the correlations. If the AVE is larger than the correlation, then the square root of the AVE will always be larger too. The logic behind Gefen et al.’s [2000] more stringent approach reflects the over-estimation of paths by PLS [Chin et al., 2003].

Table 1. Measurement Items in the Example

Item Wording	*Item Code*
Travelocity.com is easy to use	*PEOU1*
It is easy to become skillful at using Travelocity.com	*PEOU2*
Learning to operate Travelocity.com is easy	*PEOU3*
Travelocity.com is flexible to interact with	*PEOU4*
Travelocity.com improves my performance in flight searching and buying	*PU1*
Travelocity.com enables me to search and buy flights faster	*PU2*
Travelocity.com enhances my effectiveness in flight searching and buying	*PU3*
Travelocity.com makes it easier to search for and purchase flights	*PU4*
I would use my credit card to purchase from Travelocity.com	*USE1*
I would not hesitate to provide information about my habits to Travelocity	*USE2*

ASSESSING FACTORIAL VALIDITY IN PLS

Convergent Validity

To assess factorial validity, we first examine the convergent validity of the scales. To do so, we must first build the PLS-Graph model. The model as run in the example is shown in Figure 1.

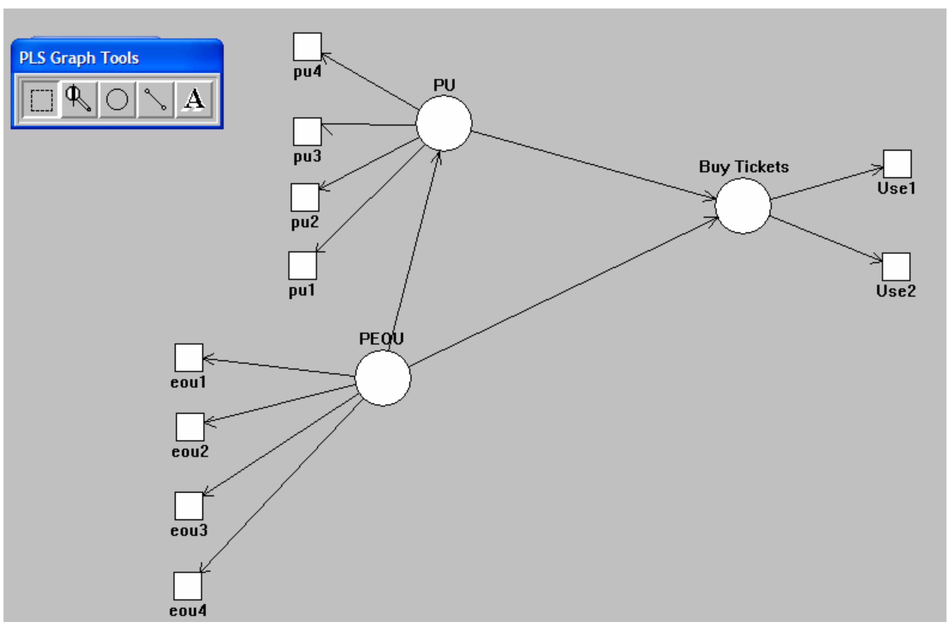


Figure 1. PLS-Graph Model

Next, we generate the t-values with a bootstrap, as shown in Figure 2.[6]

[6] The two options to generate t-values in PLS are bootstrap and jackknife. In this example, we use bootstrap because it also generates the AVEs in the latest version of PLS-Graph.

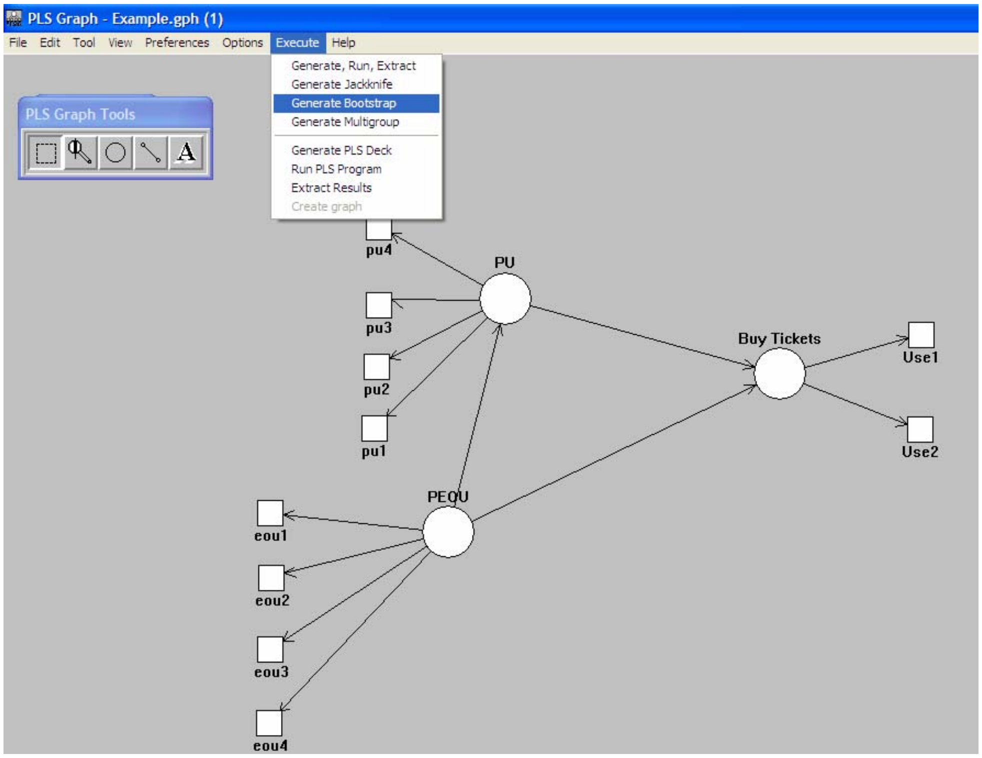


Figure 2 Extracting PLS-Graph Model

The generated t-values are not shown graphically. We need to access the results file to view these results. Carrying this process out involves two steps. First, we must change the requested output to *.out. We select the View menu and click on Show *.out, (Figure 3).

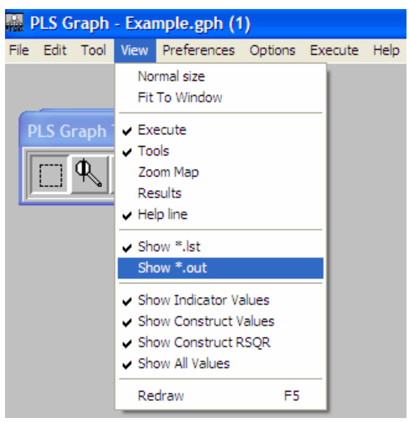


Figure 3. Selecting the View the Out file

And then again in the View menu, select Results, as shown in Figure 4.

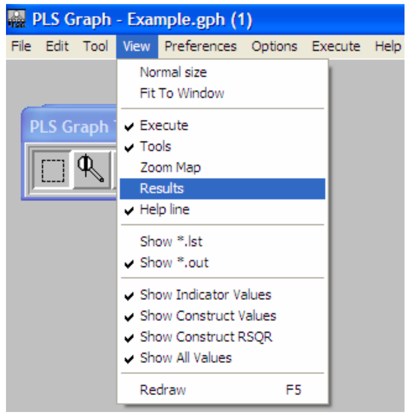


Figure 4. Selecting the Results

This selection opens a Notepad file with the results displayed. Figure 5,shows part of what the file looks like. Convergent validity is shown when the t-values of the Outer Model Loadings are above 1.96. The t-values of the loadings are, in essence, equivalent to t-values in least-squares regressions. Each measurement item is explained by the linear regression of its latent construct and its measurement error.

DISCRIMINANT VALIDITY: PROCEDURE 1

As described in Section II, two procedures are used for assessing discriminant validity:

1. Examine item loadings to construct correlations.

2. Examine the ratio of the square root of the AVE of each construct to the correlations of this construct to all the other constructs.

Outer Model Weights:

===

	Original	Mean of sample	Standard subsamples error	T-Statistic estimate
Buy Tick:				
Use1	0.5278	0.5321	0.0707	7.4690
Use2	0.5782	0.5697	0.0637	9.0817
PU :				
pu1	0.2851	0.2699	0.0337	8.4618
pu2	0.1962	0.2054	0.0354	5.5438
pu3	0.3419	0.3397	0.0290	11.7764
pu4	0.3686	0.3737	0.0419	8.7960
PEOU :				
eou1	0.2921	0.2894	0.0511	5.7192
eou2	0.2993	0.3107	0.0520	5.7600
eou3	0.2654	0.2572	0.0497	5.3444
eou4	0.3414	0.3546	0.0964	3.5410

Outer Model Loadings:

===

	Original	Mean of sample estimate	Standard subsamples error	T-Statistic
Buy Tick:				
(Composite Reliability = 0.899 , AVE = 0.817)				
Use1	0.8945	0.8995	0.0357	25.0546
Use2	0.9130	0.9101	0.0413	22.1054
PU :				
(Composite Reliability = 0.899 , AVE = 0.690)				
pu1	0.8140	0.8024	0.0665	12.2350
pu2	0.7603	0.7632	0.0651	11.6852
pu3	0.8782	0.8794	0.0333	26.3716
pu4	0.8641	0.8698	0.0218	39.5831
PEOU :				
(Composite Reliability = 0.902 , AVE = 0.698)				
eou1	0.8085	0.7823	0.0879	9.1973
eou2	0.8171	0.8035	0.0870	9.3953
eou3	0.8677	0.8524	0.0629	13.7857
eou4	0.8464	0.8406	0.0523	16.1918

Figure 5. Bootstrap Outputs

Extracting the necessary data requires a change to the default output file. To make this change, first select the Output option in the Options menu, as shown in Figure 6, and then request the Latent variable scores, as shown in Figure 7.

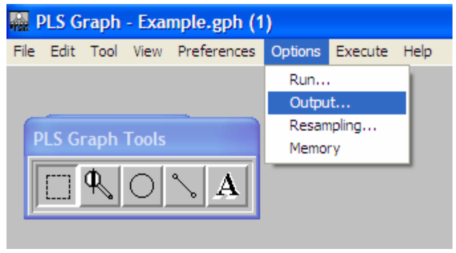


Figure 6. Selecting Set the Output Options

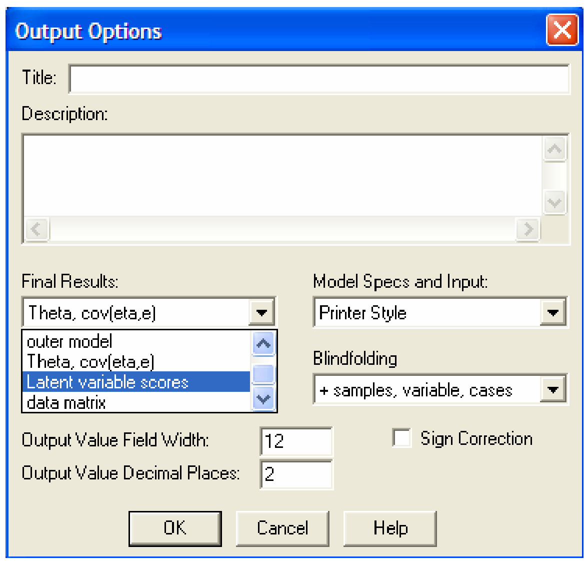


Figure 7. Setting the Output Options

The item loadings on the constructs (latent variables) are calculated based on these scores. Once these scores are generated, we can extract the relevant values, as shown in Figure 8. Figure 8 already shows the graphical results of this extraction. The number above each path from item (in boxes) to latent variable (in circles) is the item loading. The number below each path in brackets is the item weight. The number below each circle is the construct R^2, which is calculated and displayed for each variable that is a dependent variable in the model, in this case, PU and Buy Tickets.

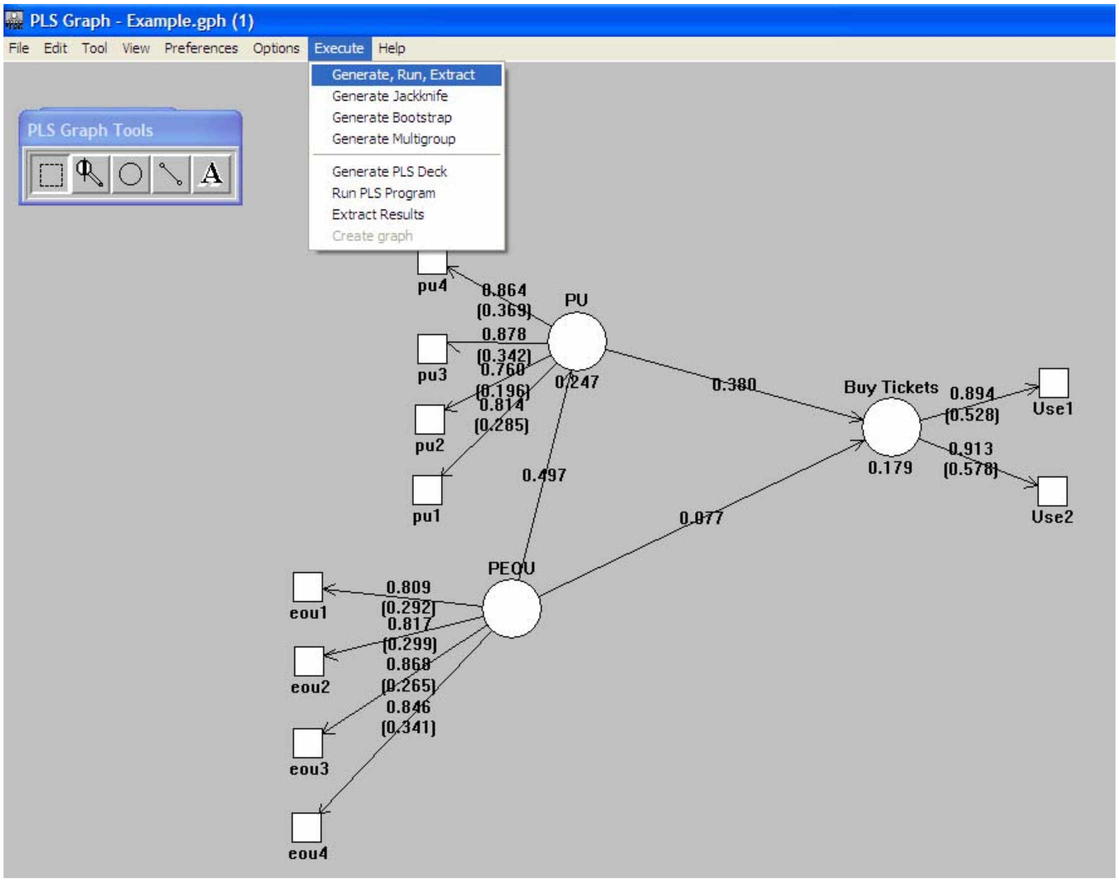


Figure 8. Displaying the PLS-Graph Model

To view the detailed output we must first revert back to the 1st output file by clicking on it in the View menu, as shown in Figure 9.

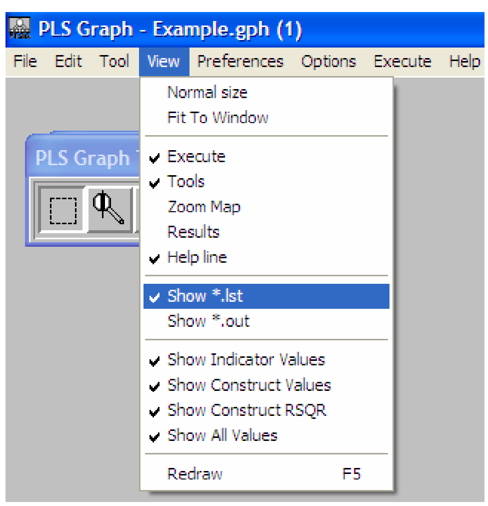


Figure 9: Selecting the View the 1st file

To view the 1st file, select Results in the View menu. The Notepad file will contain several sections, one of these is labeled 'Eta ..Latent variables' (Figure 10). This section appears only because we explicitly requested latent variable scores. The Eta of the first 20 observations, or data points, are shown here. The number of Etas is the number of data points in the data. PLS-Graph copies the label of each construct as the header of each column in the output

Eta .. Latent variables

	Buy Tick	PU	PEOU
c1	1.078	0.982	0.128
c2	1.723	0.462	-0.498
c3	-1.501	-0.111	-1.321
c4	-0.211	0.681	1.220
c5	-0.510	-0.442	0.084
c6	0.433	-0.442	-0.185
c7	-0.856	-1.398	-0.454
c8	0.433	0.299	-0.185
c9	-0.558	-0.579	0.128
c10	-0.211	-0.959	-0.716
c11	0.135	1.556	0.682
c12	-0.259	1.637	0.425
c13	0.874	0.651	1.287
c14	-0.164	-0.225	0.951
c15	-1.501	-1.398	-1.321
c16	-0.211	0.048	0.179
c17	2.022	0.756	-0.739
c18	0.135	0.323	-1.008
c19	-0.809	-0.743	-0.169
c20	0.433	-0.442	-0.185

Figure 10. Eta … Latent Variables

To correlate these latent variable scores with the original items, we copy them, after some minor editing, into SPSS together with the original data in the Appendix, as shown in Figure 11. The arrow shows these scores copied from the PLS output file into an SPSS file.

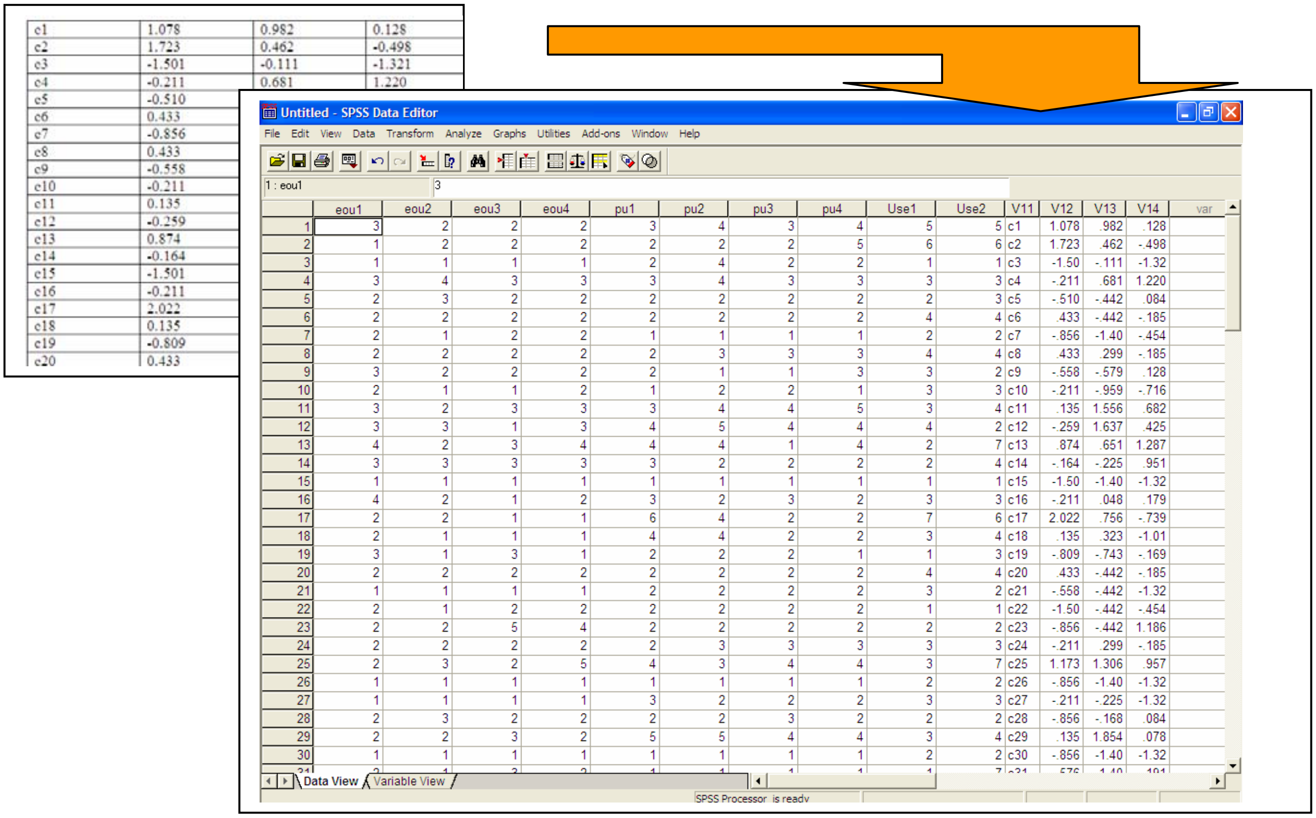
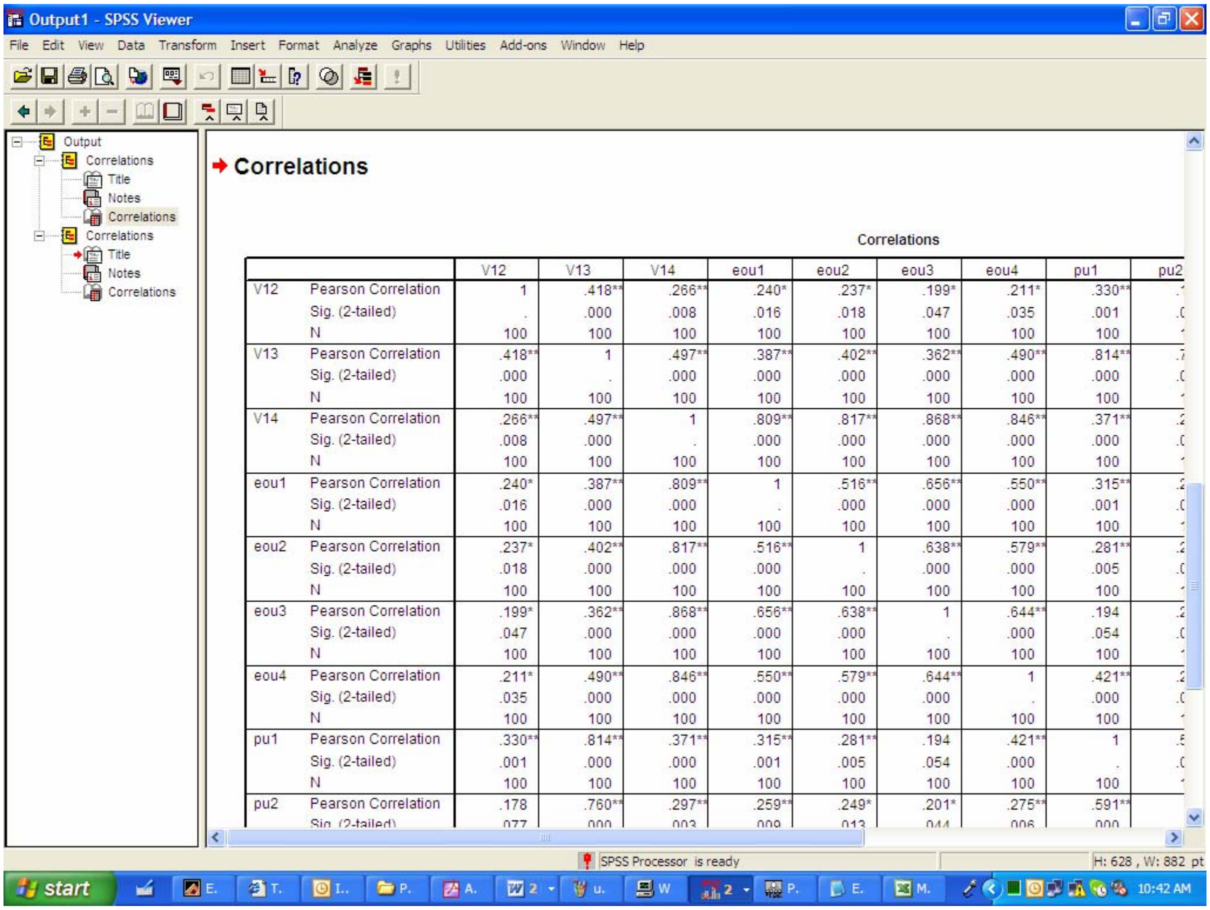


Figure 11. Analyzing Example Data in SPSS with the Latent Variable Scores from PLS

With this step completed, bivariate correlations can be run. If the data is deemed to be interval or ratio data with a normal distribution, then Pearson correlations [Figure 12] are acceptable. If the data could violate distributional assumptions or is ordinal, then use the nonparametric Spearman correlations [SPSS, 2003]. These values will be very close to the Pearson correlations and have only one small disadvantage: their power is slightly lower.[Siegel and Castellan, 1988].[7]

[7] An excellent tutorial on this topic is available at http://www.statsoft.com/textbook/stbasic.html



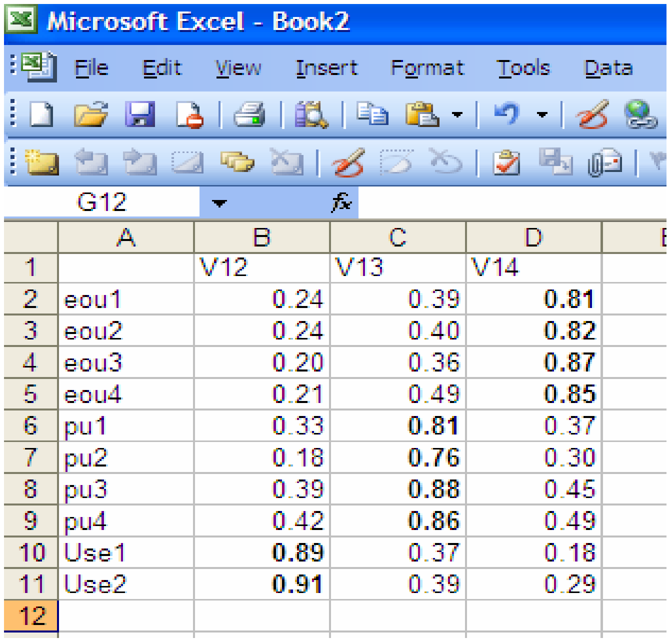
Correlations

Correlations

		V12	V13	V14	eou1	eou2	eou3	eou4	pu1	pu2
V12	Pearson Correlation	1	.418**	.266**	.240*	.237*	.199*	.211*	.330**	
	Sig. (2-tailed)	.	.000	.008	.016	.018	.047	.035	.001	
	N	100	100	100	100	100	100	100	100	
V13	Pearson Correlation	.418**	1	.497**	.387**	.402**	.362**	.490**	.814**	
	Sig. (2-tailed)	.000	.	.000	.000	.000	.000	.000	.000	
	N	100	100	100	100	100	100	100	100	
V14	Pearson Correlation	.266**	.497**	1	.809**	.817**	.868**	.846**	.371**	
	Sig. (2-tailed)	.008	.000	.	.000	.000	.000	.000	.000	
	N	100	100	100	100	100	100	100	100	
eou1	Pearson Correlation	.240*	.387**	.809**	1	.516**	.656**	.550**	.315**	
	Sig. (2-tailed)	.016	.000	.000	.	.000	.000	.000	.001	
	N	100	100	100	100	100	100	100	100	
eou2	Pearson Correlation	.237*	.402**	.817**	.516**	1	.638**	.579**	.281**	
	Sig. (2-tailed)	.018	.000	.000	.000	.	.000	.000	.005	
	N	100	100	100	100	100	100	100	100	
eou3	Pearson Correlation	.199*	.362**	.868**	.656**	.638**	1	.644**	.194	
	Sig. (2-tailed)	.047	.000	.000	.000	.000	.	.000	.054	
	N	100	100	100	100	100	100	100	100	
eou4	Pearson Correlation	.211*	.490**	.846**	.550**	.579**	.644**	1	.421**	
	Sig. (2-tailed)	.035	.000	.000	.000	.000	.000	.	.000	
	N	100	100	100	100	100	100	100	100	
pu1	Pearson Correlation	.330**	.814**	.371**	.315**	.281**	.194	.421**	1	
	Sig. (2-tailed)	.001	.000	.000	.001	.005	.054	.000	.	
	N	100	100	100	100	100	100	100	100	
pu2	Pearson Correlation	.178	.760**	.297**	.259**	.249*	.201*	.275**	.591**	

Figure 12. The Correlations as Produced by SPSS

Next, with some editing in Excel, copy the correlation table produced in SPSS and shown in Figure 12 to produce the correlation table shown in Figure 13. The bold-faced formatting of the numbers was added manually in Figure 13 to emphasize the loading of the measurement items on the constructs to which they are assigned in the CFA.



	A	B	C	D
1		V12	V13	V14
2	eou1	0.24	0.39	**0.81**
3	eou2	0.24	0.40	**0.82**
4	eou3	0.20	0.36	**0.87**
5	eou4	0.21	0.49	**0.85**
6	pu1	0.33	**0.81**	0.37
7	pu2	0.18	**0.76**	0.30
8	pu3	0.39	**0.88**	0.45
9	pu4	0.42	**0.86**	0.49
10	Use1	**0.89**	0.37	0.18
11	Use2	**0.91**	0.39	0.29
12				

Bold face shows loading of the measurement items on the constructs to which they are assigned in the CFA.

Figure 13. Excel Editing of the Correlation Table

Although the loadings might seem high, it is common to have much higher loadings in PLS than in a PCA. To demonstrate this, the same data are also shown here in a PCA where they demonstrate much lower loadings (Figure 14). The high loadings per construct are emphasized in bold font.

	Component		
	1	2	3
eou3	**.894**	.092	.072
eou2	**.784**	.178	.115
eou1	**.782**	.167	.114
eou4	**.771**	.310	.047
pu2	.097	**.856**	-.034
pu1	.159	**.810**	.164
pu3	.261	**.772**	.260
pu4	.337	**.700**	.294
Use1	.030	.186	**.883**
Use2	.186	.144	**.870**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Figure 14. PCA with a Varimax Rotation of the Same Data

DISCRIMINANT VALIDITY: PROCEDURE 2

The second procedure necessary to show discriminant validity is the AVE analysis. The square root of the AVE of each construct needs to be much larger, although there are no guidelines about how much larger, than any correlation between this construct and any other construct. The AVEs were already extracted in the bootstrap shown in Figure 5. We take the square root of each of these and compare them with the construct correlations in the 1st file, shown in Figure 15. In the case of these data, all the square roots are much larger than any correlation, which combined with the correlation of the scores to the items shows a necessary aspect of the discriminant validity of the latent constructs.

Correlations of latent variables

	Buy Tick	PU	PEOU
Buy Tick	1.000		
PU	0.418	1.000	
PEOU	0.266	0.497	1.000

	AVE	SQRT of AVE
Buy Ticket	0.817	0.903881
PU	0.69	0.830662
PEOU	0.698	0.835464

Figure 15. Correlations in the lst file as compared with the Square Root of the AVE

IV. CONCLUSION

In this tutorial supplement to Gefen et al. [2000], we demonstrate the practical side of using PLS-Graph to argue for the factorial validity of constructs. As explained in Straub et al. [2004], factorial validity is a form of construct validity that uses statistical tools that work with factor structures. The purpose of factorial validity is the same as in any examination of the validity of constructs, that is, to show that constructs that are posited to be made up of certain measurement items are, indeed, made up of those items, and not made up of items posited to be part of another construct. In short, these tests show the convergent and discriminant validity of the constructs [Campbell and Fiske, 1959].

IS as a field often selects PLS as a tool of choice along with LISREL and standard regression. It is important, therefore, that quantitative positivist researchers use these tools properly and to their maximal advantage. This paper is designed to contribute to this goal.

ADDITIONAL READING

On PLS in general and guidelines: [Barclay et al., 1995, Chin, 1998a, Chin, 1998b, Fornell and Bookstein, 1982, Fornell and Larcker, 1981a, Fornell and Larcker, 1981b, Gefen et al., 2000]

On Interaction effects in PLS: [Chin et al., 2003]

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APPENDIX 1: THE RAW DATA FILE

eou1	eou2	eou3	eou4	pu1	pu2	pu3	pu4	Use1	Use2
3	2	2	2	3	4	3	4	5	5
1	2	2	2	2	2	2	5	6	6
1	1	1	1	2	4	2	2	1	1
3	4	3	3	3	4	3	3	3	3
2	3	2	2	2	2	2	2	2	3
2	2	2	2	2	2	2	2	4	4
2	1	2	2	1	1	1	1	2	2
2	2	2	2	2	3	3	3	4	4
3	2	2	2	2	1	1	3	3	2
2	1	1	2	1	2	2	1	3	3
3	2	3	3	3	4	4	5	3	4
3	3	1	3	4	5	4	4	4	2
4	2	3	4	4	4	1	4	2	7
3	3	3	3	3	2	2	2	2	4
1	1	1	1	1	1	1	1	1	1
4	2	1	2	3	2	3	2	3	3
2	2	1	1	6	4	2	2	7	6
2	1	1	1	4	4	2	2	3	4
3	1	3	1	2	2	2	1	1	3
2	2	2	2	2	2	2	2	4	4
1	1	1	1	2	2	2	2	3	2
2	1	2	2	2	2	2	2	1	1
2	2	5	4	2	2	2	2	2	2
2	2	2	2	2	3	3	3	3	3
2	3	2	5	4	3	4	4	3	7
1	1	1	1	1	1	1	1	2	2
1	1	1	1	3	2	2	2	3	3
2	3	2	2	2	2	3	2	2	2
2	2	3	2	5	5	4	4	3	4
1	1	1	1	1	1	1	1	2	2
2	1	3	2	1	1	1	1	1	7
1	2	3	3	3	3	3	3	5	4
2	2	2	2	3	4	4	3	7	5
2	2	2	2	1	2	1	1	2	2
3	3	3	3	1	1	1	1	2	2
2	2	2	2	2	1	2	1	1	1
2	2	1	2	2	1	1	1	5	4
1	1	1	1	1	1	2	1	2	2
2	1	3	3	4	3	3	4	2	3
3	4	3	3	2	3	3	2	3	2
1	1	1	1	3	1	1	1	1	1
2	2	2	2	1	3	1	2	3	3
2	2	2	3	3	4	4	3	6	4
2	3	2	2	4	4	4	4	3	3
3	4	3	4	4	3	3	2	3	4
2	1	1	4	5	6	1	1	4	2
1	1	1	1	2	2	2	2	4	4

2	2	2	1	1	2	1	2	1	3
2	2	2	2	2	5	4	2	4	4
1	1	1	2	1	2	2	2	3	4
2	2	1	4	6	2	7	4	7	7
3	3	3	3	1	1	2	4	7	5
3	1	1	1	3	2	3	4	6	7
2	2	2	3	2	2	2	2	2	2
2	2	2	2	2	3	2	3	1	1
1	2	1	1	2	1	1	2	1	1
2	2	2	3	2	4	3	3	2	3
2	2	2	2	2	2	2	3	4	4
1	2	1	1	3	2	3	2	4	5
2	2	2	2	2	1	1	1	1	3
2	2	2	2	2	2	2	2	2	3
2	2	2	2	2	2	2	1	1	4
2	4	4	4	3	3	4	6	3	6
2	2	2	3	5	4	5	4	2	2
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2	2	2	5	7	4	7	5	5	6
1	1	1	1	2	1	2	1	3	2
3	1	1	1	2	2	2	2	6	3
2	2	1	2	3	4	2	2	1	1
2	1	1	2	5	1	1	1	3	3
1	1	1	2	3	2	2	3	3	3
2	1	1	1	1	1	2	1	7	7
2	6	4	3	2	3	3	3	7	7
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3	2	3	3	2	1	2	2	3	3
2	2	2	2	1	1	1	1	3	3
4	4	4	4	3	3	3	4	4	4
7	7	7	7	7	5	7	6	7	7
1	2	1	2	2	1	1	1	5	5
1	6	1	2	3	3	2	2	2	2
3	2	3	3	2	2	2	2	6	3
3	3	2	3	3	1	2	2	1	7
2	2	2	2	1	1	2	2	1	1
2	3	3	3	3	2	2	2	2	4
3	3	3	5	2	2	3	2	2	2
2	2	2	2	3	3	2	4	4	4
1	1	1	1	4	2	1	1	3	4
1	1	1	1	4	4	4	4	2	2
3	4	3	5	5	3	2	5	4	4
1	2	1	2	2	2	1	2	1	2
1	2	2	2	2	2	2	2	6	5
2	2	2	2	2	2	2	2	7	7
3	2	2	3	2	2	3	2	4	4
3	2	2	3	2	3	3	3	2	2
2	2	3	3	4	3	3	2	3	3
2	2	2	6	2	1	2	1	1	2
4	3	3	2	4	4	3	3	1	4

1	3	2	2	3	2	4	3	4	4
1	2	1	3	2	3	2	2	1	3
3	4	3	4	3	1	2	1	3	3

LIST OF ABBREVIATIONS

AVE = Average Variance Extracted

CFA = Confirmatory Factor Analysis

EFA = Exploratory Factor Analysis

PCA = Principal Components Analysis

PEOU,= Perceived Ease of Use, A central component in TAM, the Technology Acceptance Model.

PU = Perceived Usefulness, A central component in TAM, the Technology Acceptance Model.

USE = Intended Use of a new information system. A central component in TAM, the Technology Acceptance Model.

PLS = Partial Least Squares. A structured equation modeling estimation technique which generates estimation of item loadings and path coefficients simultaneously.

PLS-Graph = A software package which applies PLS.

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