大數據行銷研究
Big Data Marketing Research

Tamkang University
淡江大學

確認性因素分析
(Confirmatory Factor Analysis)

1051BDMR07
MIS EMBA (M2262) (8638)
Thu, 12,13,14 (19:20-22:10) (D409)

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2016-11-11

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2016/09/16	中秋節 (調整放假一天) (Mid-Autumn Festival Holiday)(Day off)
2	2016/09/23	大數據行銷研究課程介紹 (Course Orientation for Big Data Marketing Research)
3	2016/09/30	資料科學與大數據行銷 (Data Science and Big Data Marketing)
4	2016/10/07	大數據行銷分析與研究 (Big Data Marketing Analytics and Research)
5	2016/10/14	測量構念 (Measuring the Construct)
6	2016/10/21	測量與量表 (Measurement and Scaling)

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

7 2016/10/28 大數據行銷個案分析 I
(Case Study on Big Data Marketing I)

8 2016/11/04 探索性因素分析 (Exploratory Factor Analysis)

9 2016/11/11 確認性因素分析 (Confirmatory Factor Analysis)

10 2016/11/18 期中報告 (Midterm Presentation)

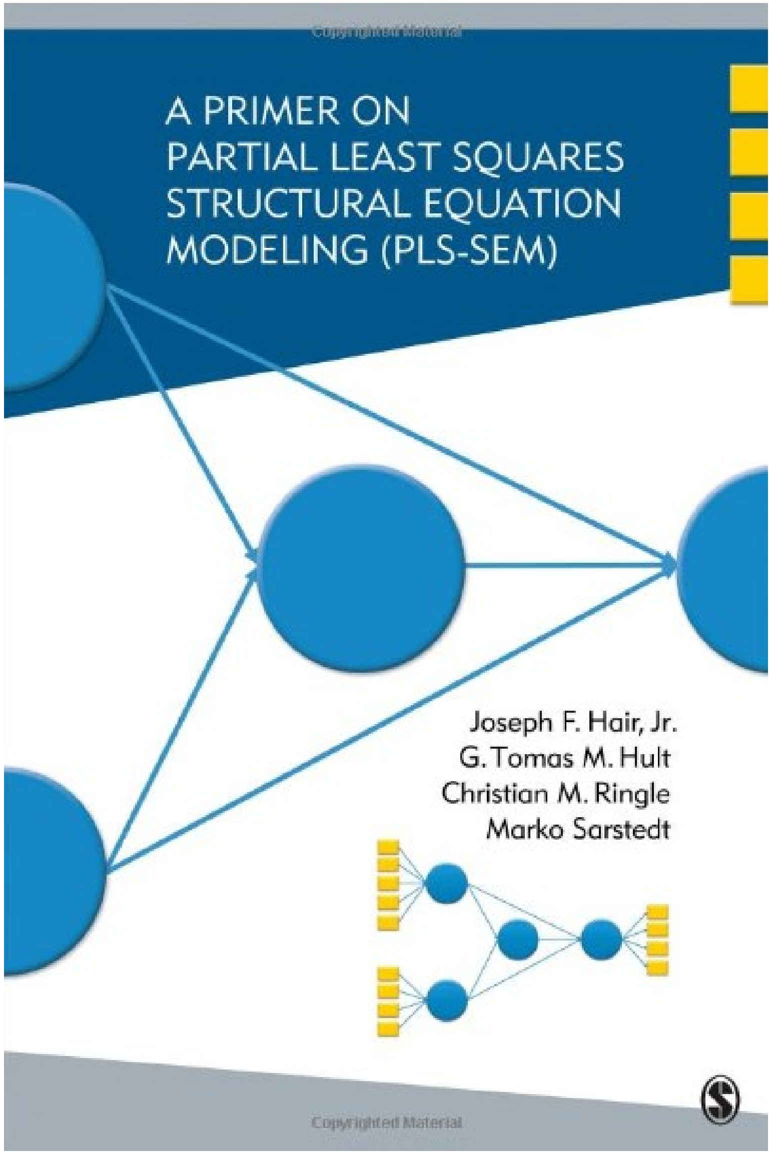
11 2016/11/25 社群運算與大數據分析
(Social Computing and Big Data Analytics)

12 2016/12/02 社會網路分析 (Social Network Analysis)

課程大綱 (Syllabus)

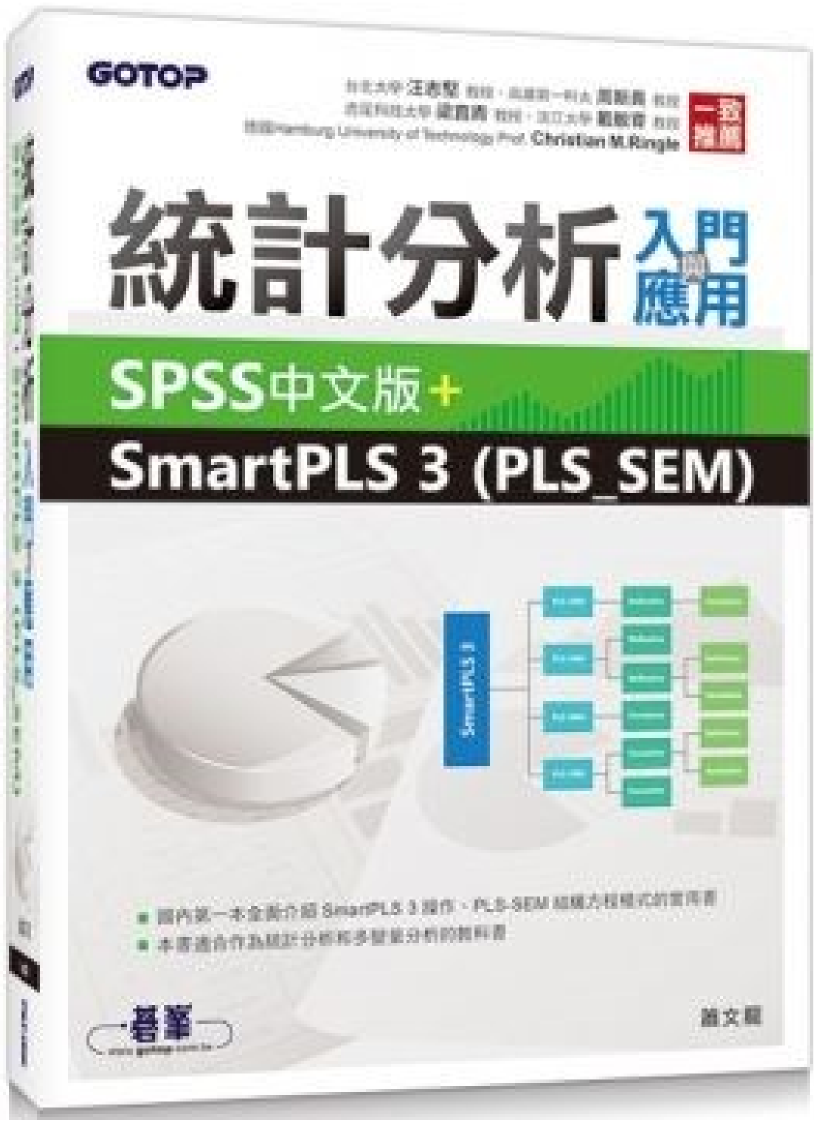
週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2016/12/09	大數據行銷個案分析 II (Case Study on Big Data Marketing II)
14	2016/12/16	社會網絡分析量測與實務 (Measurements and Practices of Social Network Analysis)
15	2016/12/23	大數據情感分析 (Big Data Sentiment Analysis)
16	2016/12/30	金融科技行銷研究 (FinTech Marketing Research)
17	2017/01/06	期末報告 I (Term Project Presentation I)
18	2017/01/13	期末報告 II (Term Project Presentation II)

Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt,
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM),
SAGE, 2013



Source: http://www.amazon.com/Partial-Squares-Structural-Equation-Modeling/dp/1452217440/

蕭文龍 (2016),
統計分析入門與應用：SPSS中文版＋SmartPLS 3（PLS_SEM），
碁峰資訊



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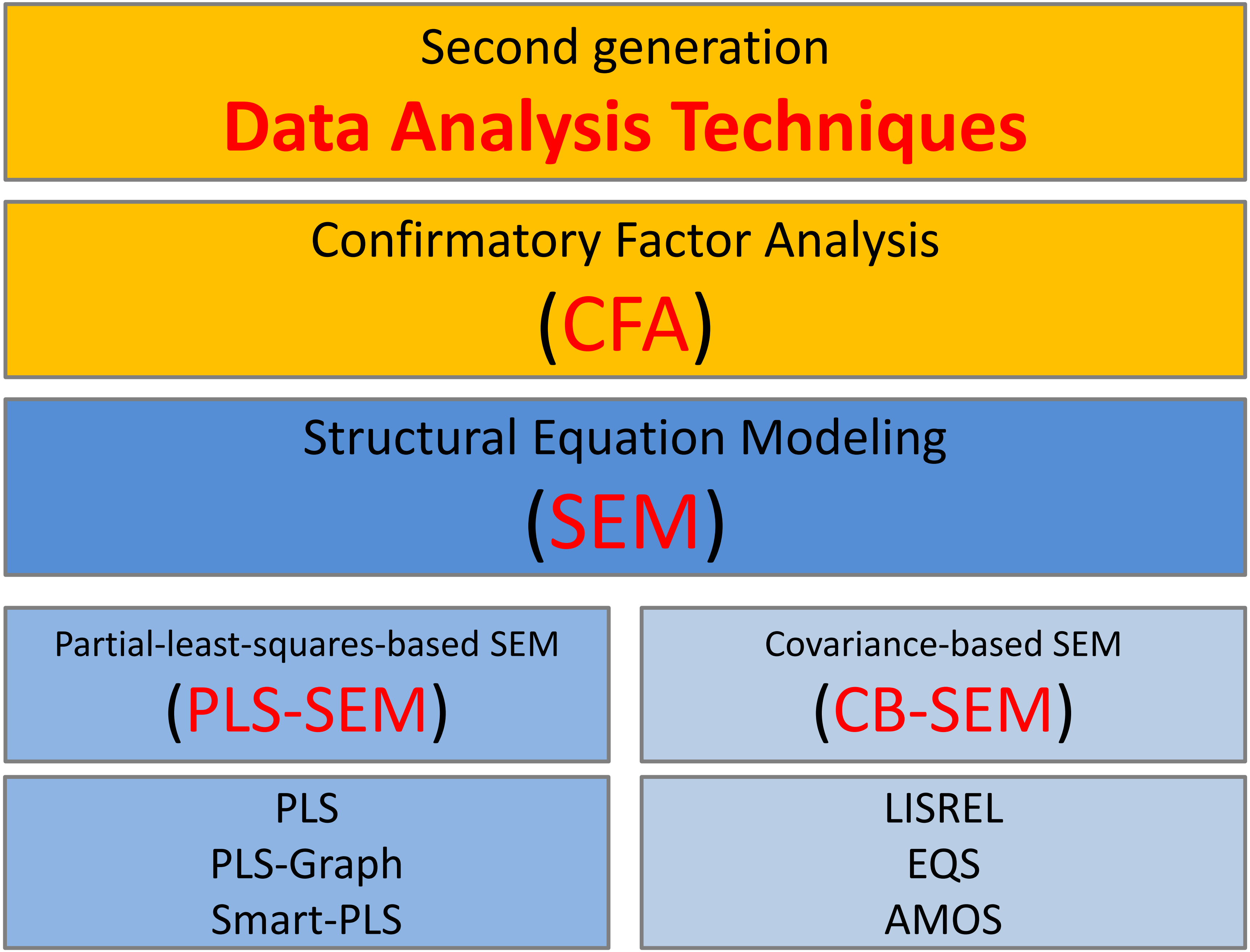


Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Types of Factor Analysis

- Exploratory Factor Analysis (EFA)
  - is used to discover the factor structure of a construct and examine its reliability.
    It is data driven.
- Confirmatory Factor Analysis (CFA)
  - is used to confirm the fit of the hypothesized factor structure to the observed (sample) data.
    It is theory driven.

Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall

Structural Equation Modeling (SEM)

- Structural Equation Modeling (SEM)
  techniques such as
  LISREL and
  Partial Least Squares (PLS)
  are
  second generation data analysis techniques

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Data Analysis Techniques

- Second generation data analysis techniques
  - SEM
    - PLS, LISREL
  - statistical conclusion validity
- First generation statistical tools
  - Regression models:
    - linear regression, LOGIT, ANOVA, and MANOVA

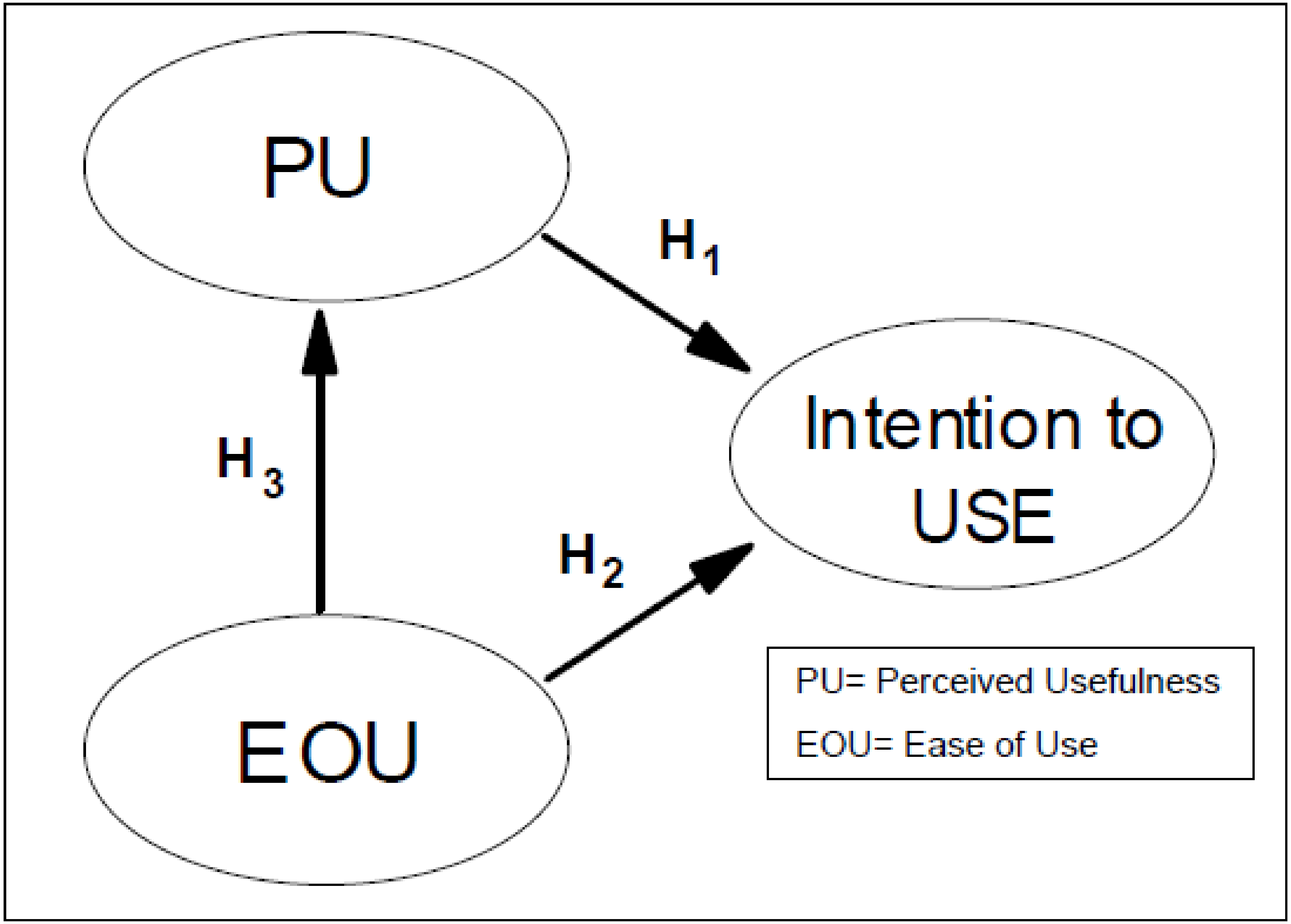
Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

SEM models in the IT literature

- Partial-least-squares-based SEM (PLS-SEM)
  - PLS, PLS-Graph, Smart-PLS
- Covariance-based SEM (CB-SEM)
  - LISREL, EQS, AMOS

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

The TAM Model



Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Structured Equation Modeling (SEM)

- Structural model
  - the assumed causation among a set of dependent and independent constructs
- Measurement model
  - loadings of observed items (measurements) on their expected latent variables (constructs).

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

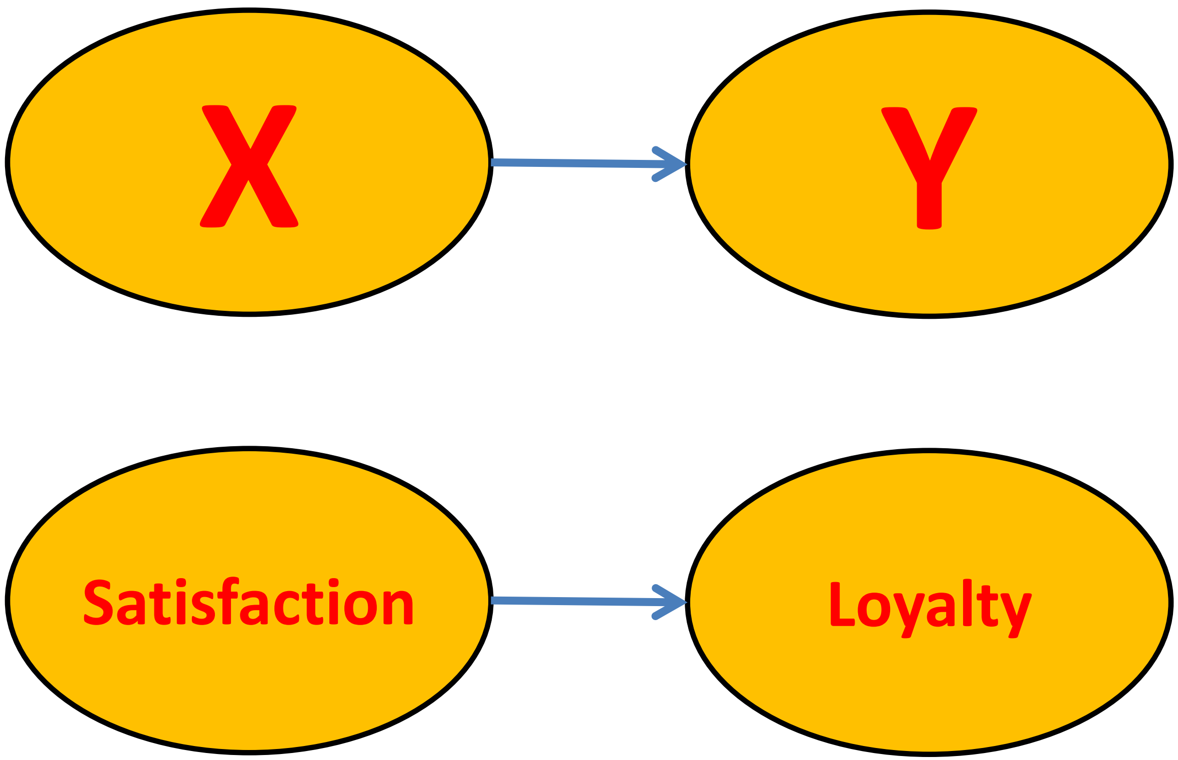
Structured Equation Modeling (SEM)

- The combined analysis of the measurement and the structural model enables:
  - measurement errors of the observed variables to be analyzed as an integral part of the model
  - factor analysis to be combined in one operation with the hypotheses testing
- SEM
  - factor analysis and hypotheses are tested in the same analysis

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Structure Model

Structured Equation Modeling (SEM)
Path Model (Causal Model)

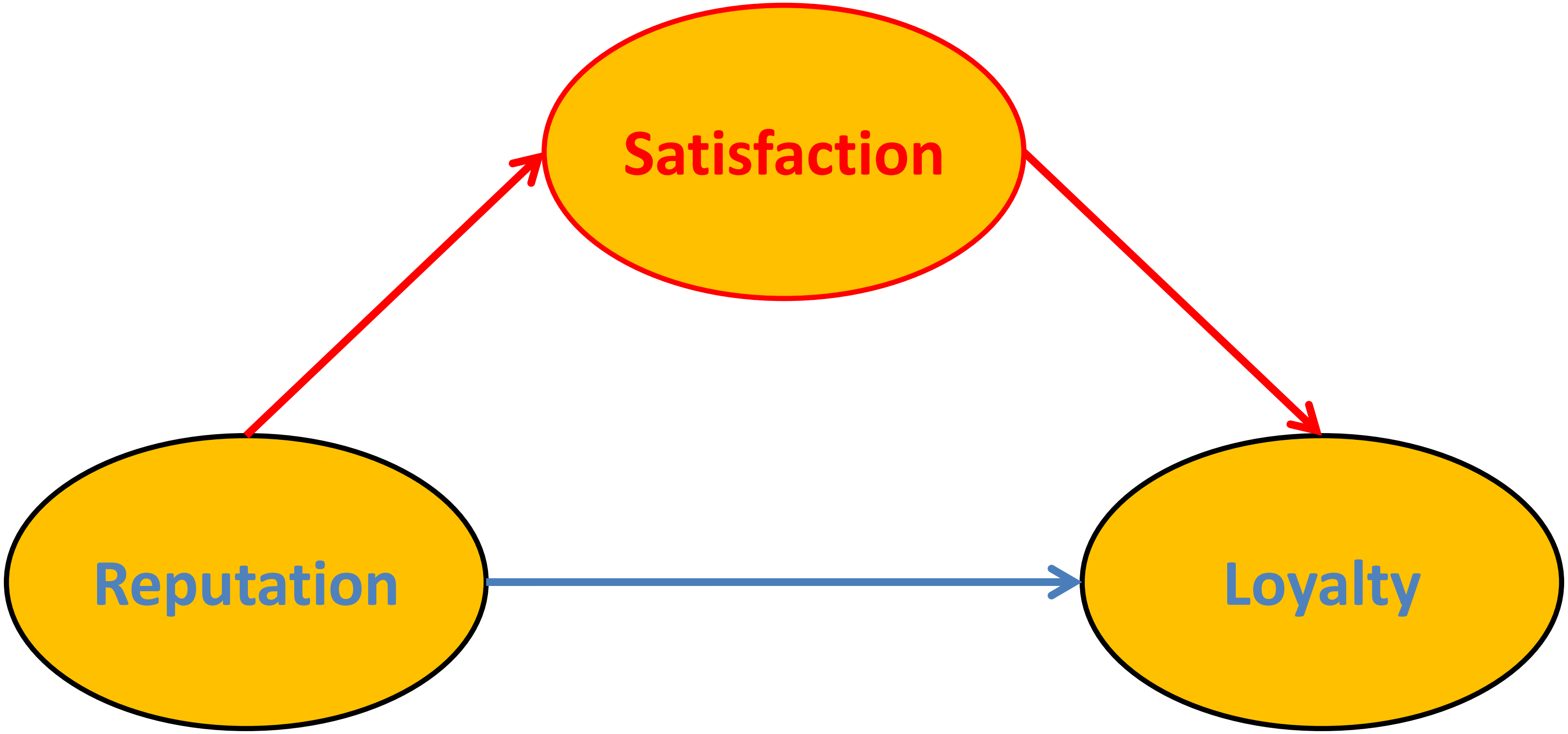


Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013),
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Structured Equation Modeling (SEM)
Path Model and Constructs

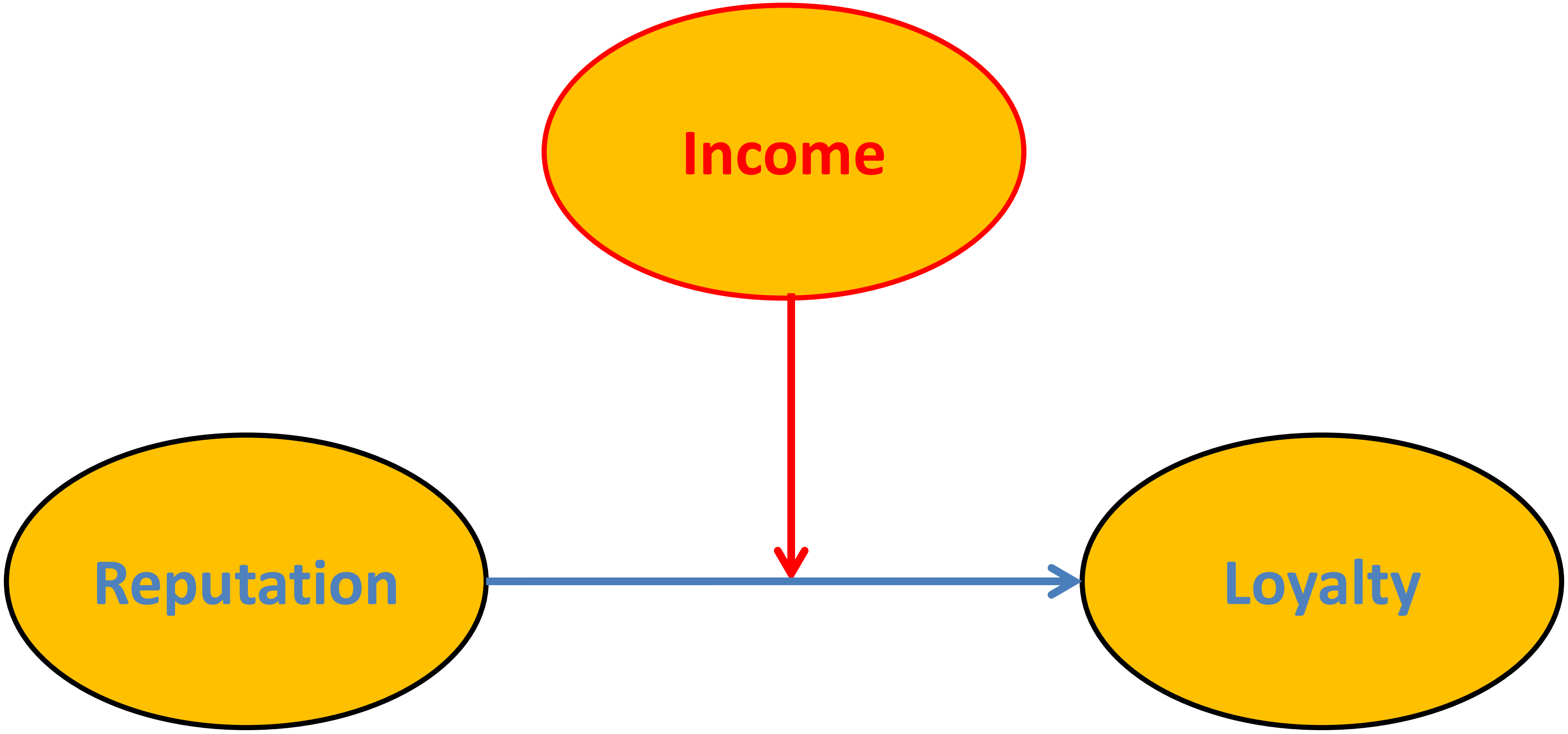
Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013),
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Mediating Effect (Mediator)



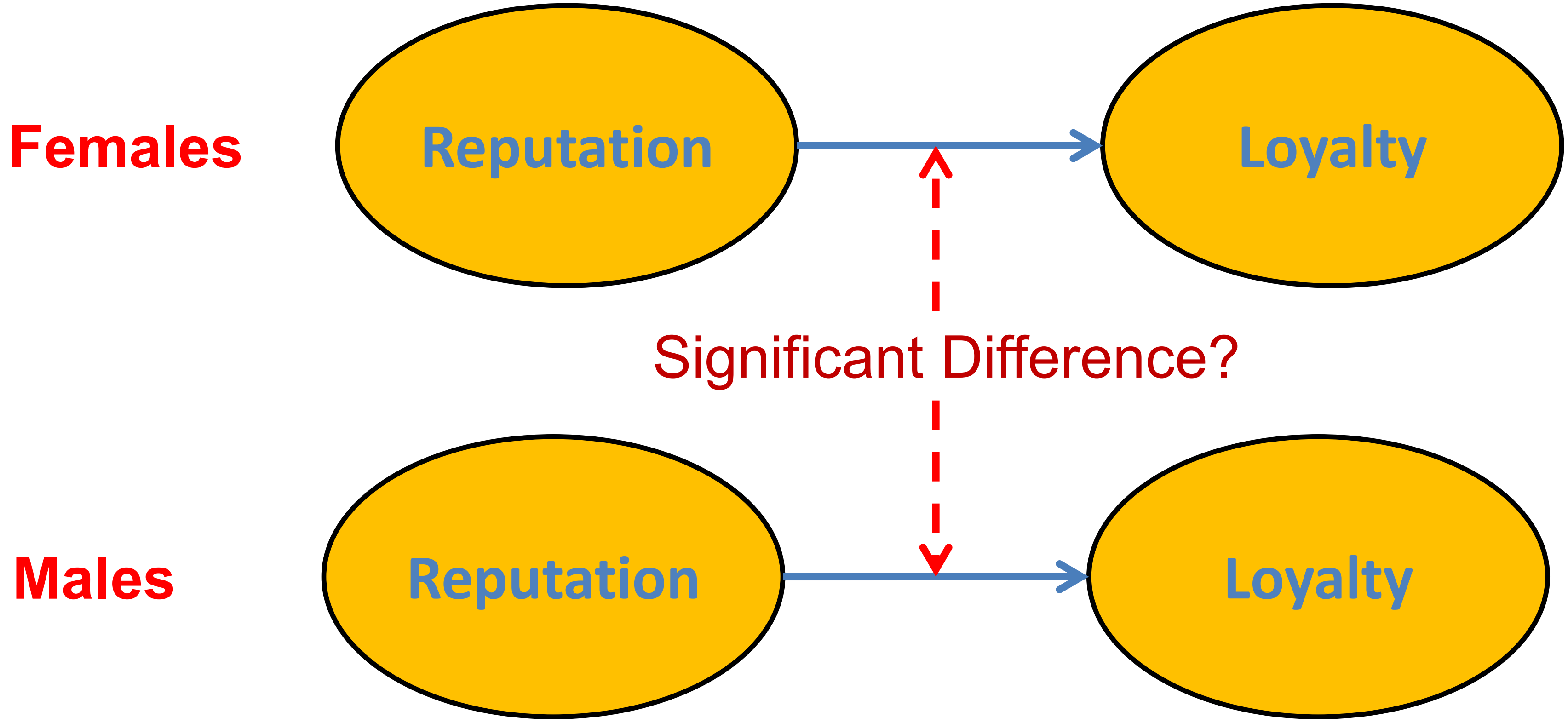
Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Continuous Moderating Effect (Moderator)



Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013),
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

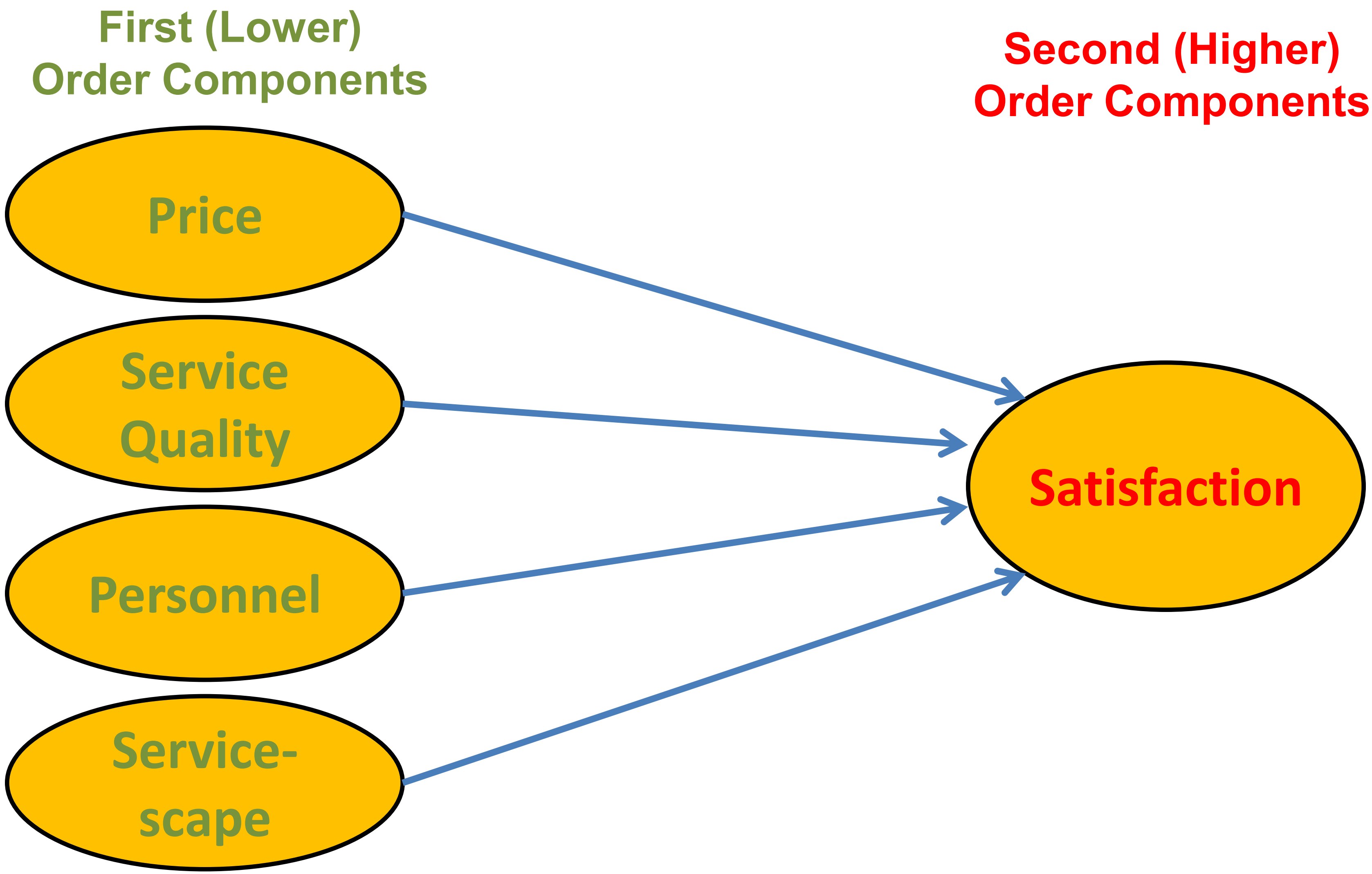
Categorical Moderation Effect (Moderator)



Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Hierarchical Component Model

First Order Construct vs. Second Order Construct

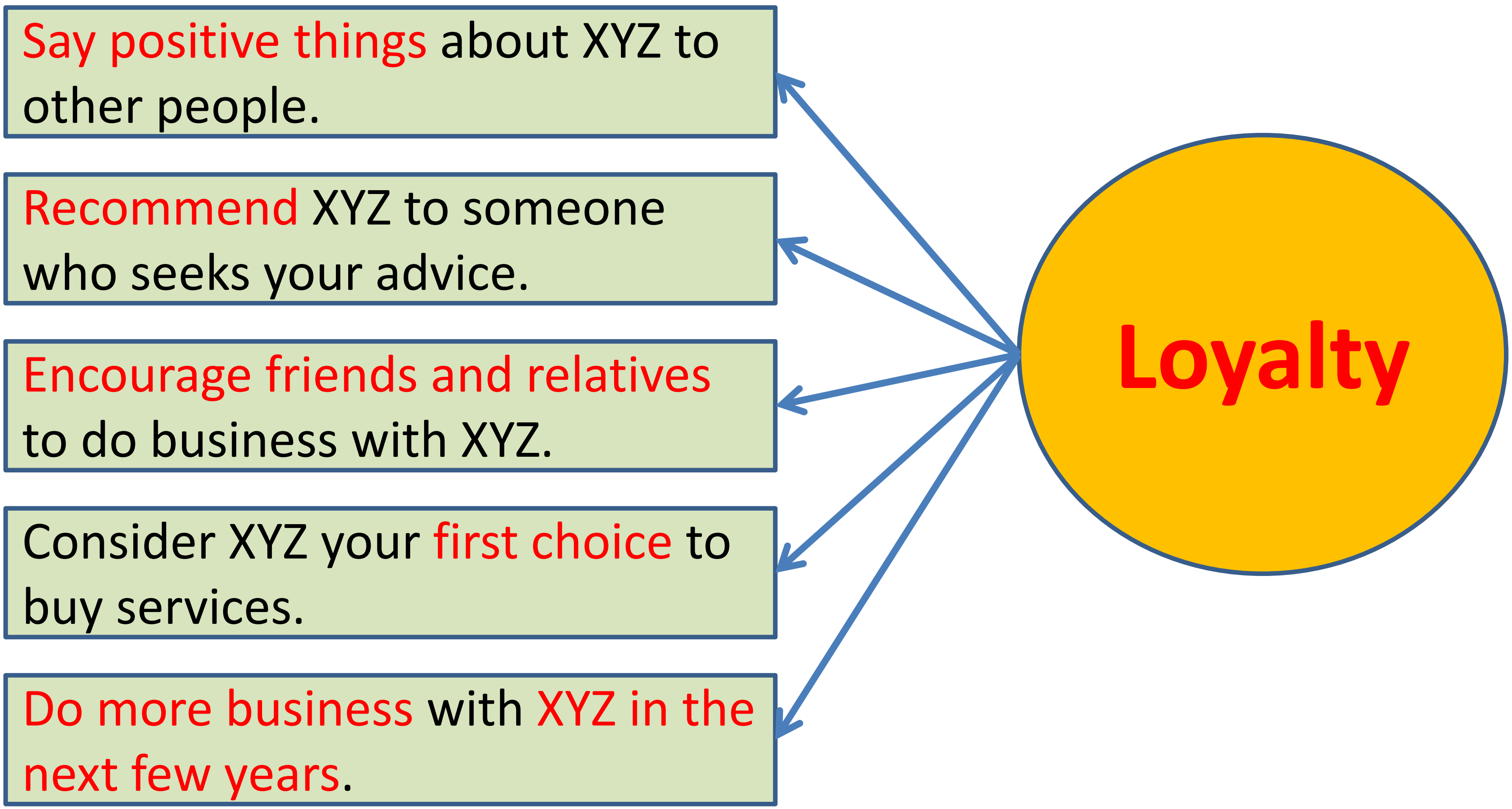


Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013),
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Measurement Model

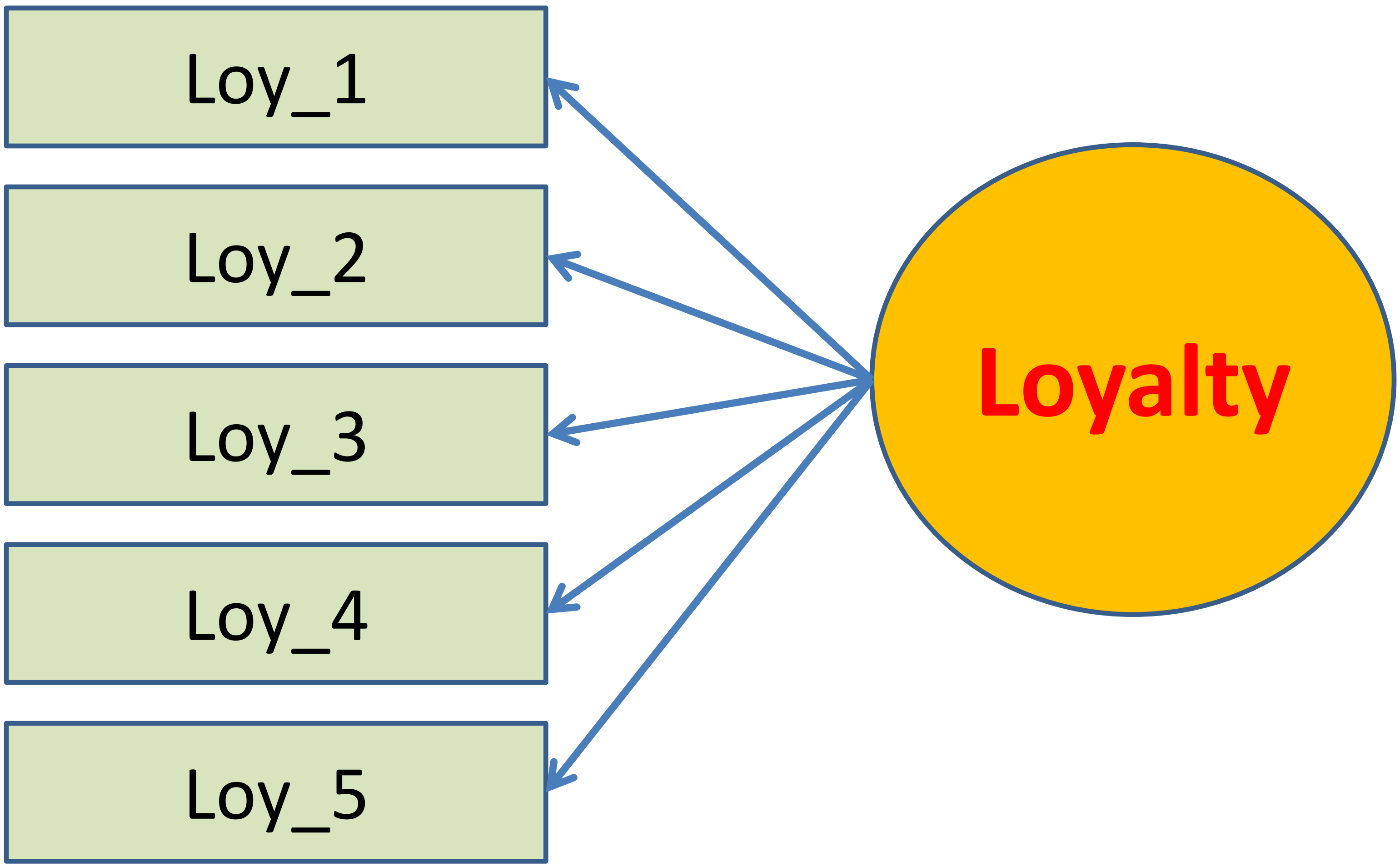
Measuring Loyalty
5 Variables (Items) (5:1)

(Zeithaml, Berry & Parasuraman, 1996)



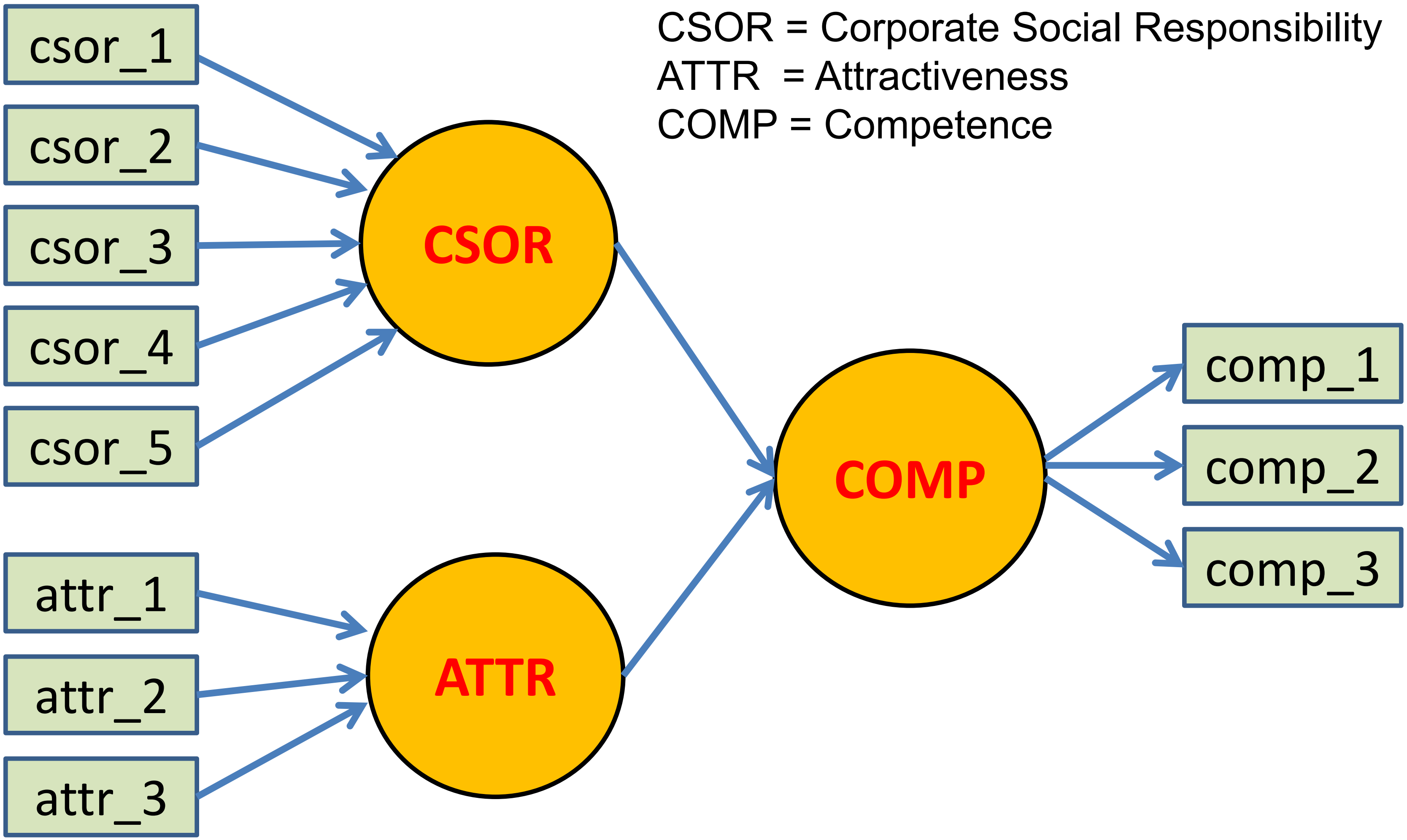
Source: Valarie A. Zeithaml, Leonard L. Berry and A. Parasuraman,
“The Behavioral Consequences of Service Quality,” Journal of Marketing, Vol. 60, No. 2 (Apr., 1996), pp. 31-46

Measurement Model



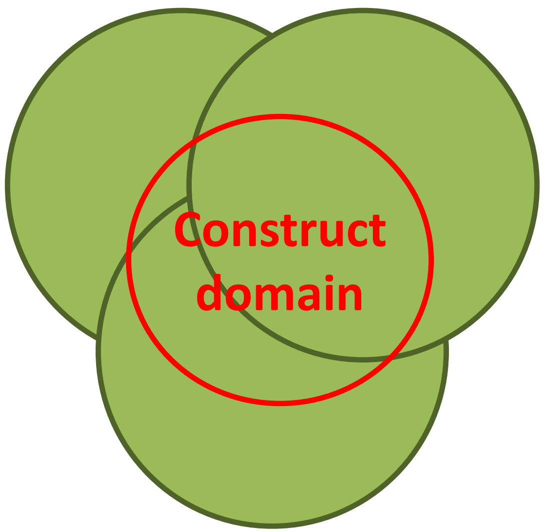
Source: Hair et al. (2009), Multivariate Data Analysis, 7th Edition, Prentice Hall

Example of a Path Model With Three Constructs

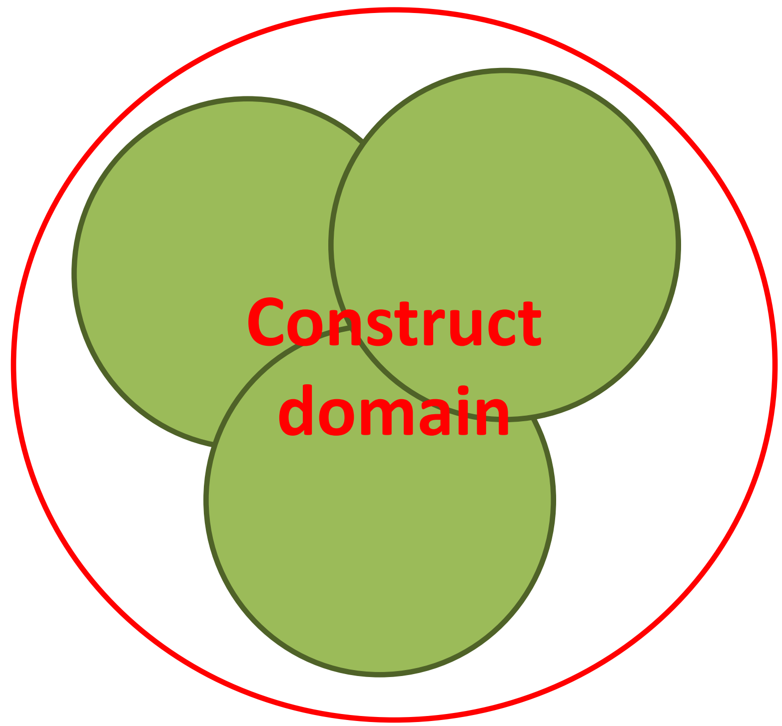


Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Difference Between Reflective and Formative Measures



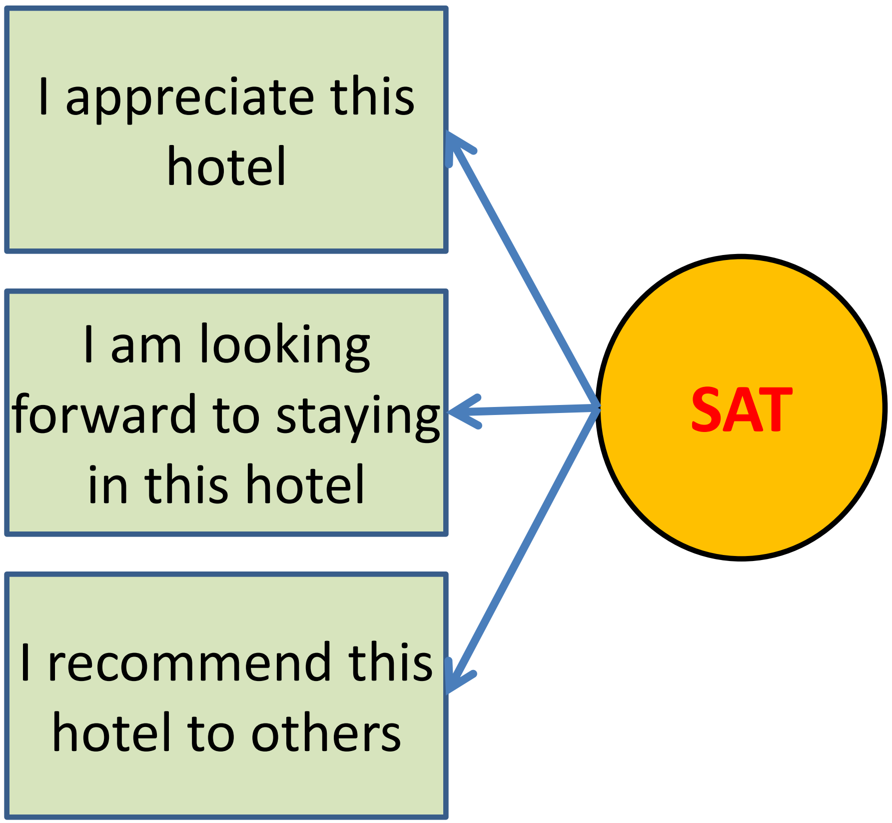
Reflective Measurement Model



Formative Measurement Model

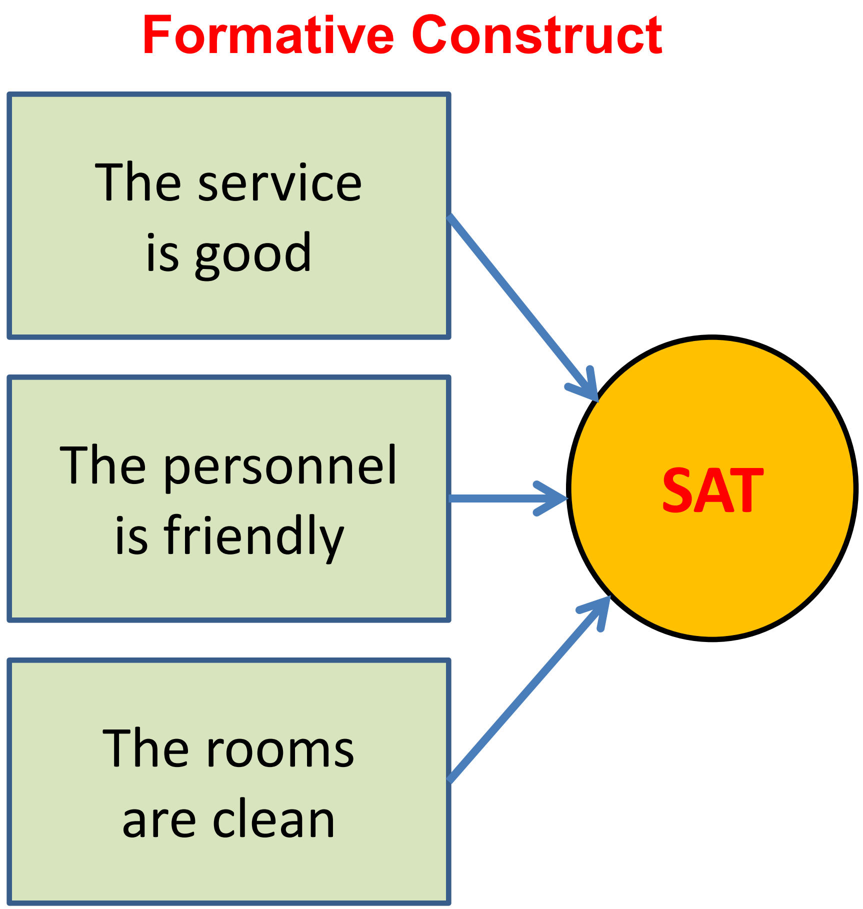
Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Satisfaction as a Reflective Construct



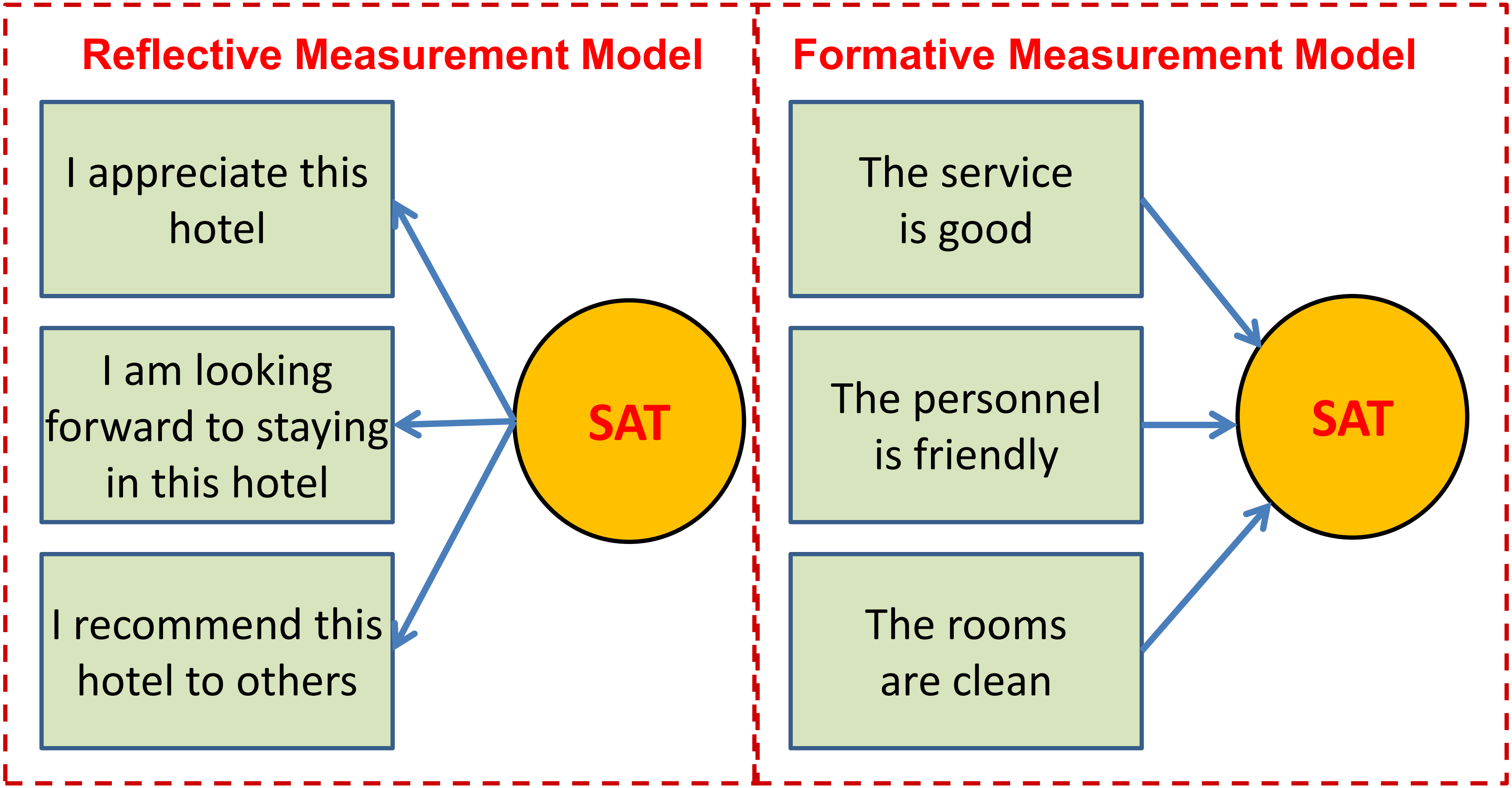
Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Satisfaction as a **Formative Construct**



Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Satisfaction as a Reflective and Formative Construct

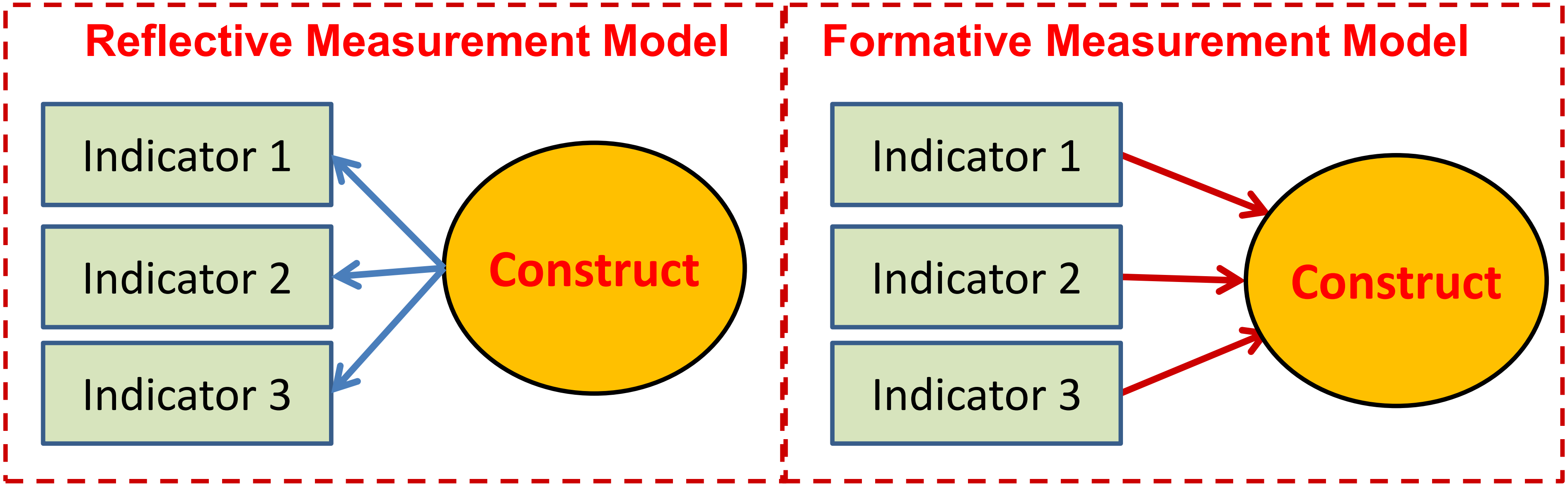


Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Reflective Construct ?
Formative Construct ?

1

Causal priority between the indicator and the construct
From the construct to the indicators: reflective
From the indicators to the construct: formative
Diamantopoulos and Winklhofer (2001)



Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013),
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

2

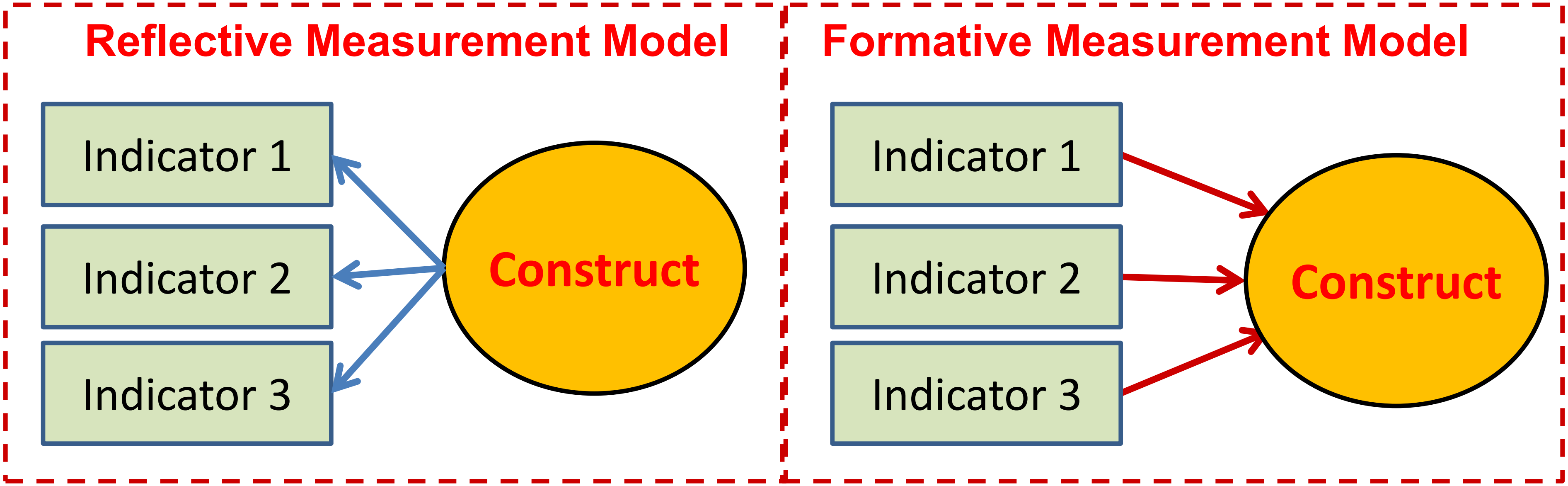
Reflective Construct ?
Formative Construct ?

Is the construct a trait explaining the indicators or rather a combination of the indicator?

If trait: reflective

If combination: formative

Fornell and Bookstein (1982)



Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

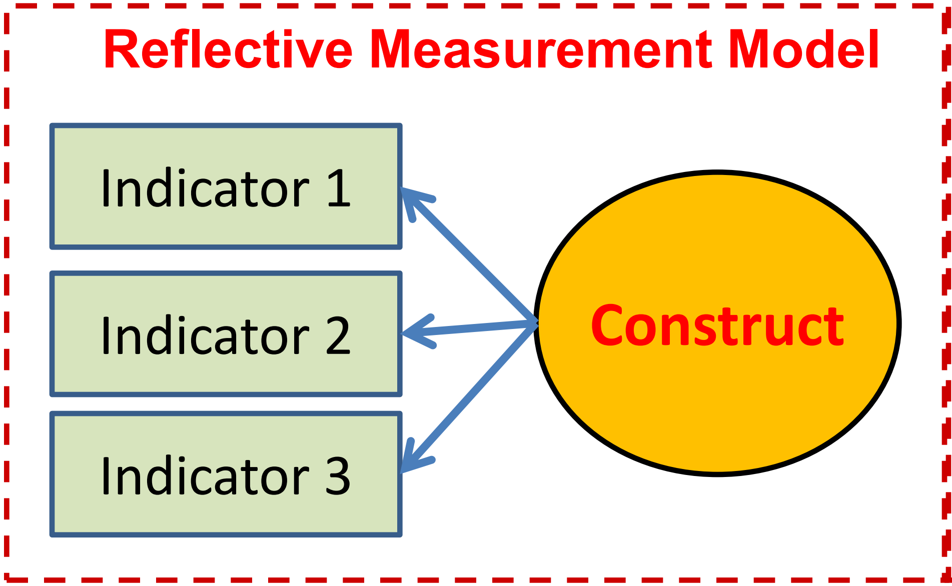
3 Reflective Construct ? Formative Construct ?

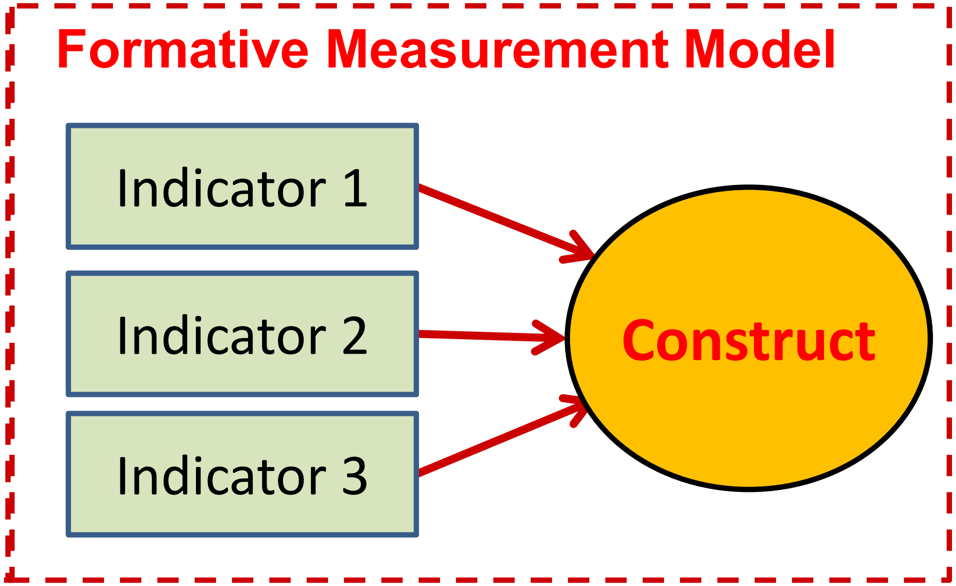
Do the indicators represent consequences or causes of the construct?

If consequences: reflective

If causes: formative

Rossieter (2002)



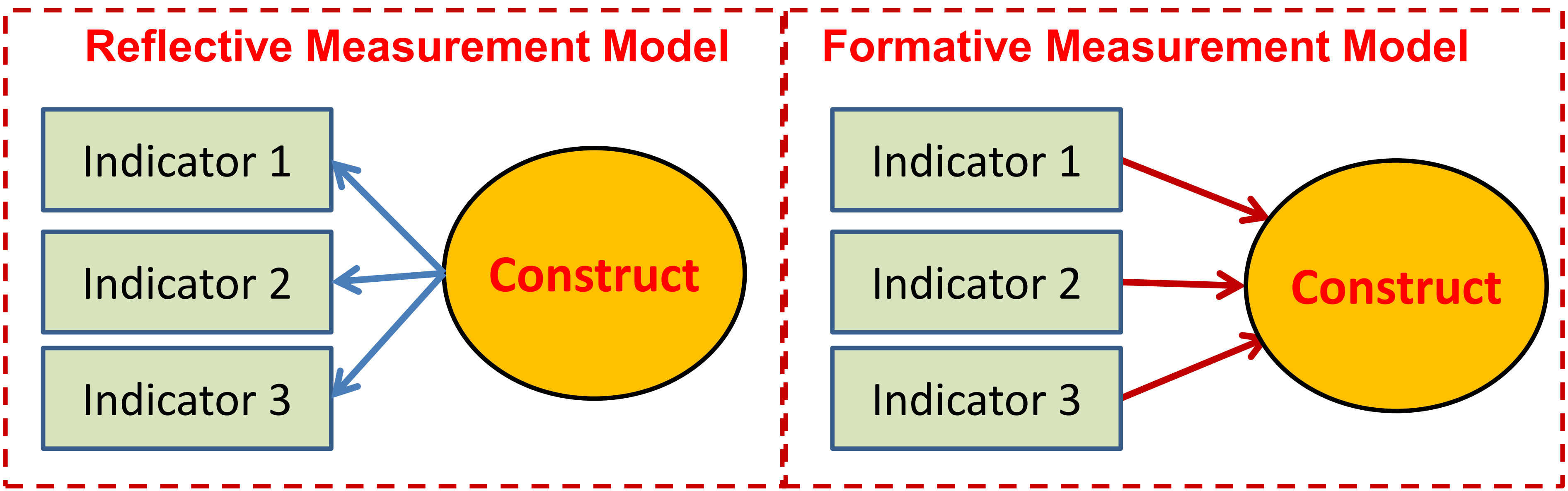


Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

4

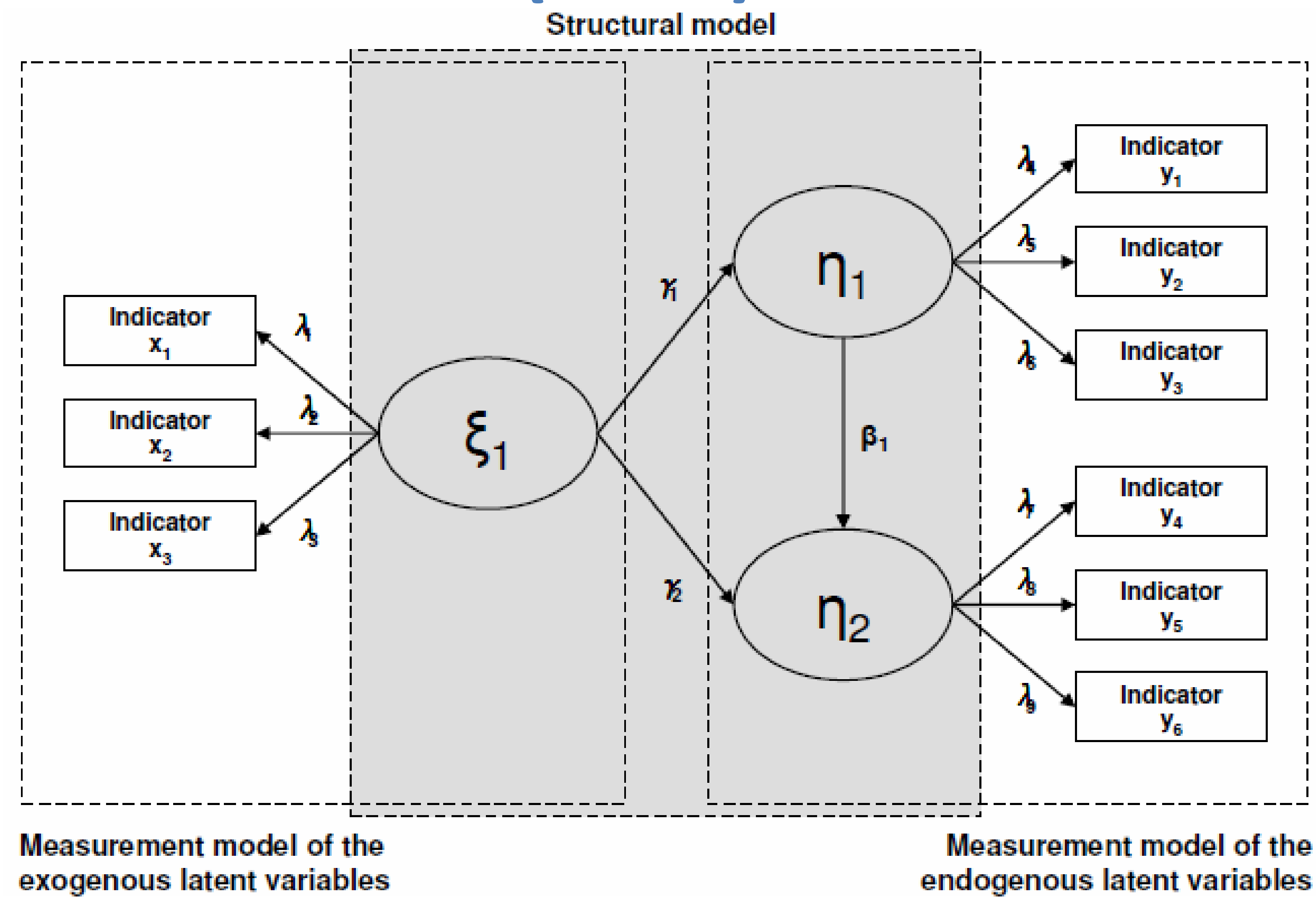
Reflective Construct ?
Formative Construct ?

Are the items mutually interchangeable?
If yes: reflective
If no: formative
Jarvis, MacKenzie, and Podsakoff (2003)



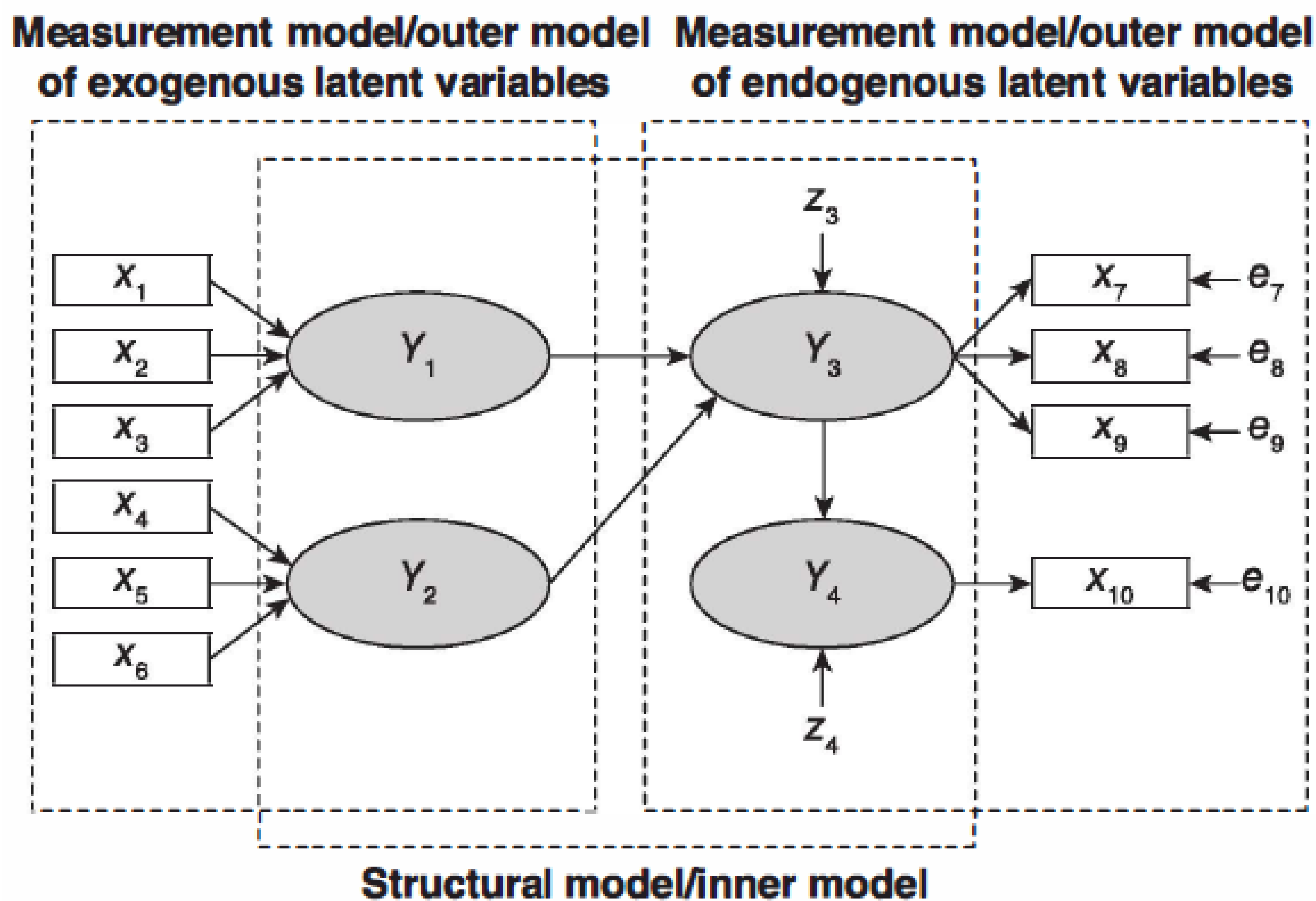
Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013),
A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Structured Equation Modeling (SEM)



Source: Nils Urbach and Frederik Ahlemann (2010) "Structural equation modeling in information systems research using partial least squares, " Journal of Information Technology Theory and Application, 11(2), 5-40.

Structured Equation Modeling (SEM) with Partial Least Squares (PLS)



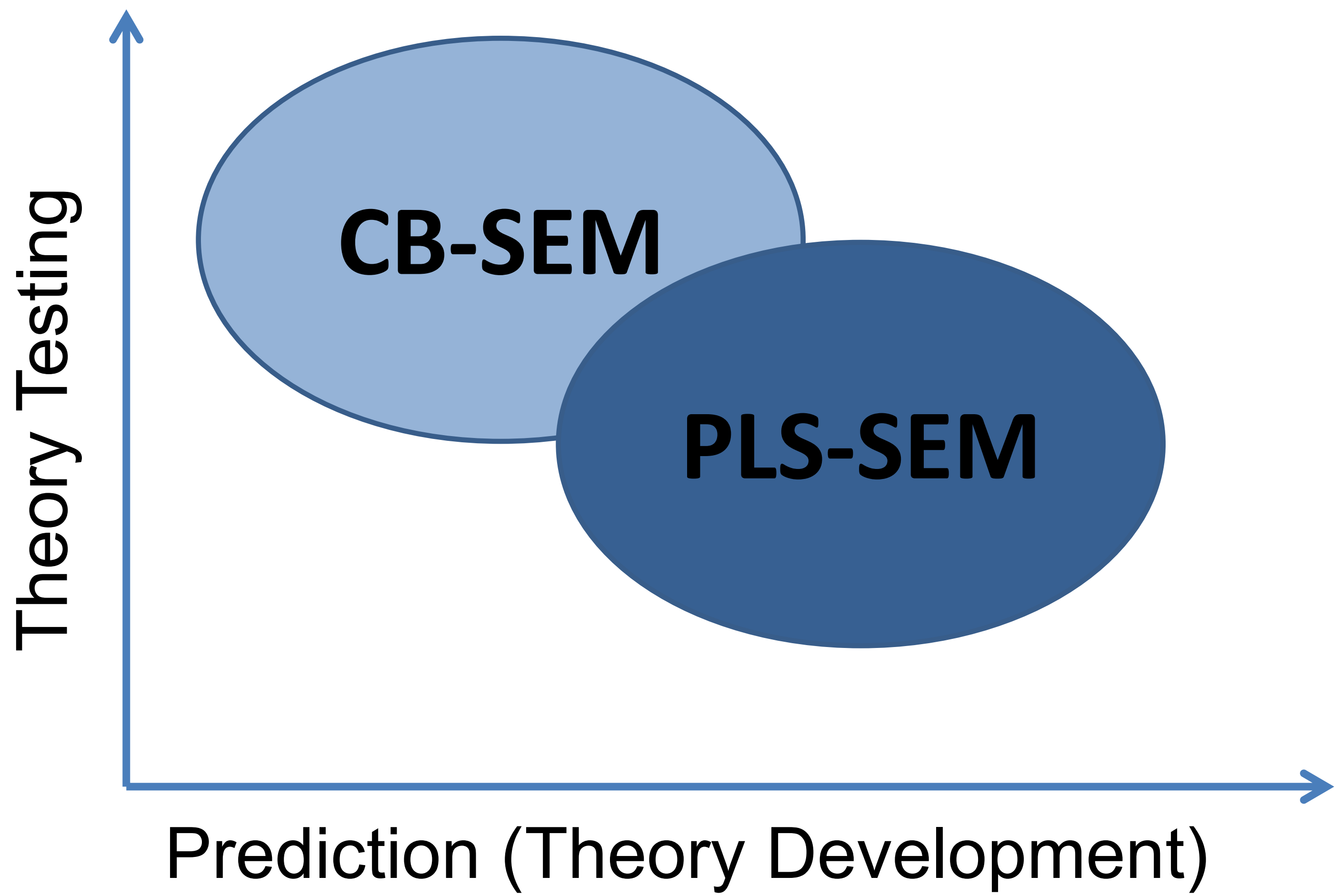
Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Framework for Applying PLS in Structural Equation Modeling

	Problem Definition & Research Design	Theoretical Foundation	Model Construction & Instrument Development	Data Collection	Model Validation	Interpretation
Activities	• Define research question • Develop research methodology • Specify intended external validity • Specify scope and level of analysis	• Literature review	• Develop structural model • Develop measurement models • Develop survey instrument • Pre- and pilot testing	• Distribute survey instrument • Collect return • Quality assessment of collected data	• Validate reflective and formative measurement models • Validate the structural model • Perform Bootstrapping or Jackknifing (significance testing)	• Analyze and interpret the results
Results	• Research question • Statement on external validity • Statement on the scope and level of analysis	• Basic theories • Potential construct definitions • Potential measurement models	• Complete structural model • (Several alternative) measurement models and indicators • Survey instrument	• Raw data	• Acceptable values for all relevant validity measures and/or a well grounded discussion of deviations • A final version of the model with acceptable model parameters	• Confirmed or rejected hypotheses • Conclusions drawn from the final model • Identification of further need for research

Source: Nils Urbach and Frederik Ahlemann (2010) "Structural equation modeling in information systems research using partial least squares," Journal of Information Technology Theory and Application, 11(2), 5-40.

CB-SEM vs. PLS-SEM



Source: Nils Urbach and Frederik Ahlemann (2010) "Structural equation modeling in information systems research using partial least squares, " Journal of Information Technology Theory and Application, 11(2), 5-40.

Exhibit 1.6 Rules of Thumb for Choosing Between PLS-SEM and CB-SEM

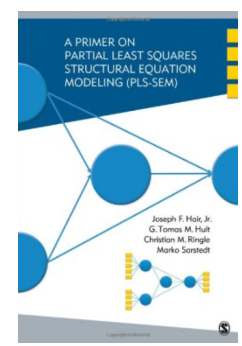
Use PLS-SEM when

- The goal is predicting key target constructs or identifying key "driver" constructs.
- Formatively measured constructs are part of the structural model. Note that formative measures can also be used with CB-SEM, but doing so requires construct specification modifications (e.g., the construct must include both formative and reflective indicators to meet identification requirements).
- The structural model is complex (many constructs and many indicators).
- The sample size is small and/or the data are non-normally distributed.
- The plan is to use latent variable scores in subsequent analyses.

Use CB-SEM when

- The goal is theory testing, theory confirmation, or the comparison of alternative theories.
- Error terms require additional specification, such as the covariation.
- The structural model has non-recursive relationships.
- The research requires a global goodness-of-fit criterion.

Source: Adapted from *The Journal of Marketing Theory and Practice* 19(2) (Spring 2011), 139–151. Copyright © 2011 by M. E. Sharpe, Inc. Used by permission. All Rights Reserved. Not for reproduction.



Source: Joseph F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt (2013), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE

Use of Structural Equation Modeling Tools 1994-1997

SEM Approaches	I&M (n=106)	*ISR* (n=27)	*MISQ* (n=38)	All Three Journals
PLS	2%	19%	11%	7%
LISREL	3%	15%	11%	7%
Other *	3%	11%	3%	4%
Total %	8%	45%	25%	18%

* Other includes SEM techniques such as AMOS and EQS.

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Comparative Analysis between Techniques

Issue	LISREL	PLS	Linear Regression
Objective of Overall Analysis	Show that the null hypothesis of the entire proposed model is plausible, while rejecting path-specific null hypotheses of no effect.	Reject a set of path-specific null hypotheses of no effect.	Reject a set of path-specific null hypotheses of no effect.
Objective of Variance Analysis	Overall model fit, such as insignificant χ^2 or high AGFI.	Variance explanation (high R-square)	Variance explanation (high R-square)
Required Theory Base	Requires sound theory base. Supports confirmatory research.	Does not necessarily require sound theory base. Supports both exploratory and confirmatory research.	Does not necessarily require sound theory base. Supports both exploratory and confirmatory research.
Assumed Distribution	Multivariate normal, if estimation is through ML. Deviations from multivariate normal are supported with other estimation techniques.	Relatively robust to deviations from a multivariate distribution.	Relatively robust to deviations from a multivariate distribution, with established methods of handling non-multivariate distributions.
Required Minimal Sample Size	At least 100-150 cases.	At least 10 times the number of items in the most complex construct.	Supports smaller sample sizes, although a sample of at least 30 is required.

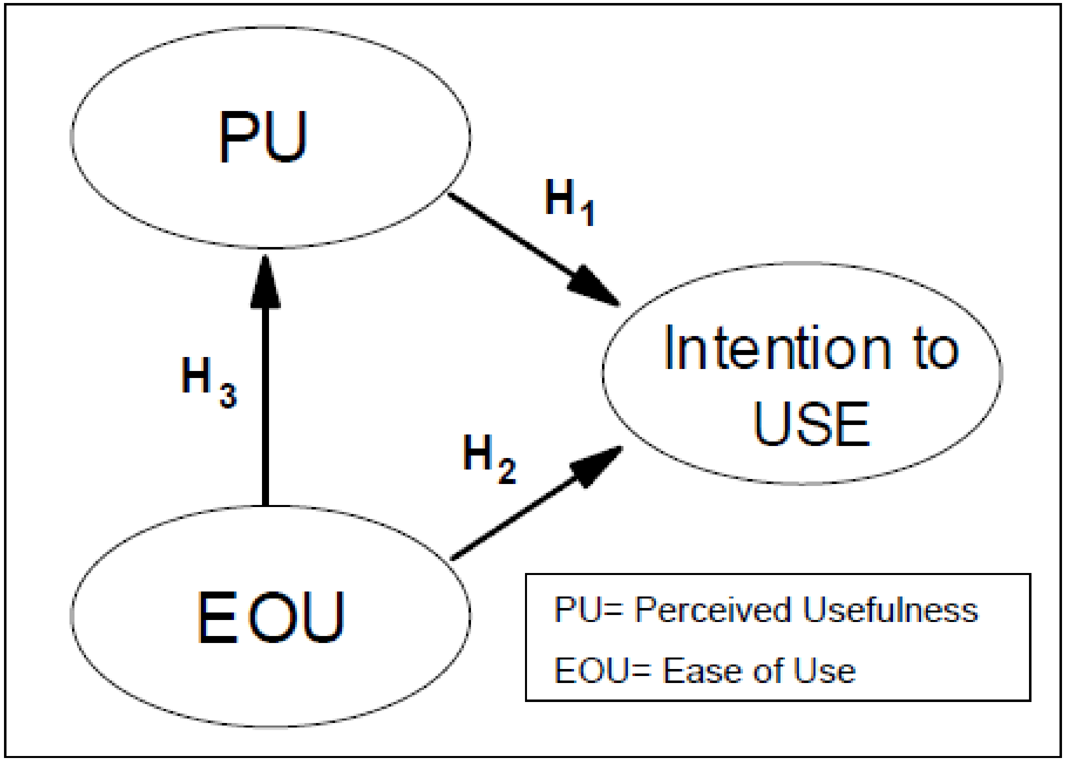
Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Capabilities by Research Approach

Capabilities	LISREL	PLS	Regression
Maps paths to many dependent (latent or observed) variables in the same research model and analyze all the paths simultaneously rather than one at a time.	Supported	Supported	Not supported
Maps specific and error variance of the observed variables into the research model.	Supported	Not supported	Not supported
Maps reflective observed variables	Supported	Supported	Supported
Maps formative observed variables	Not supported	Supported	Not supported
Permits rigorous analysis of all the variance components of each observed variable (common, specific, and error) as an integral part of assessing the structural model.	Supported	Not supported	Not supported
Allows setting of non-common variance of an observed variable to a given value in the research model.	Supported	Not supported	Supported by adjusting the correlation matrix.
Analyzes all the paths, both measurement and structural, in one analysis.	Supported	Supported	Not supported
Can perform a confirmatory factor analysis	Supported	Supported	Not supported
Provides a statistic to compare alternative confirmatory factor analyses models	Supported	Not supported	Not supported

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

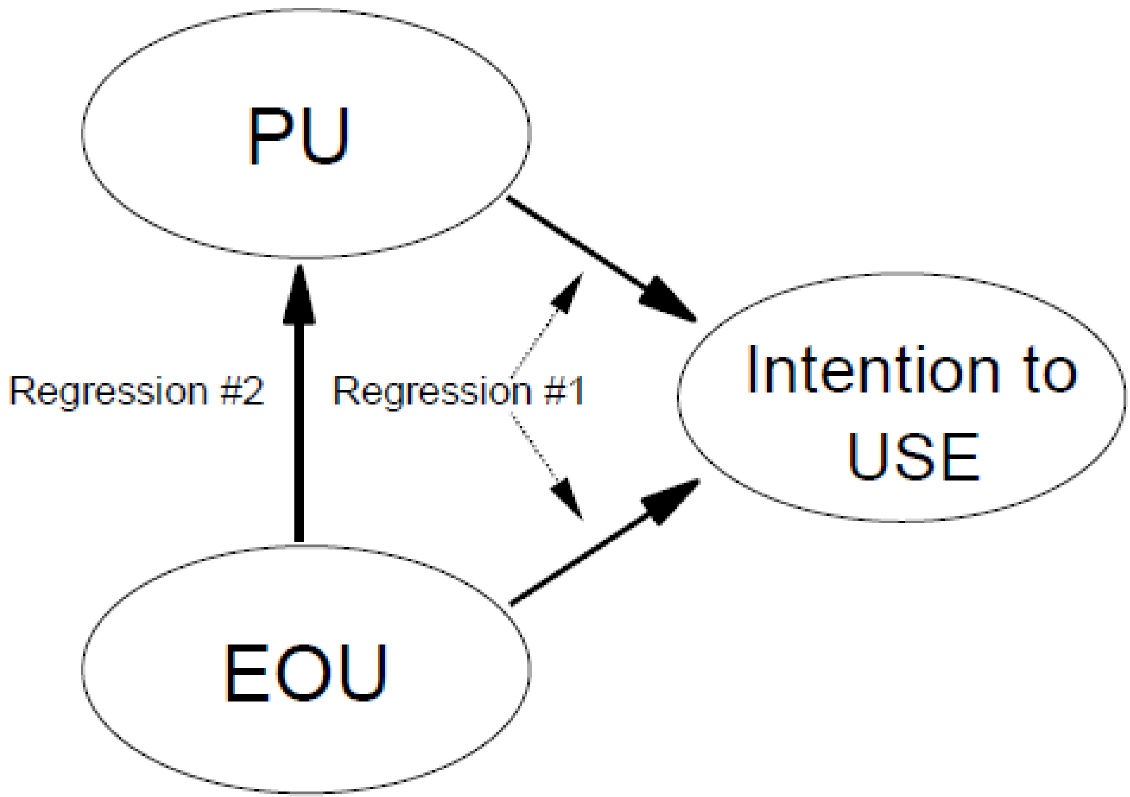
TAM Model and Hypothesis



	Hypothesis
H_1	PU will impact the system outcome construct, Intention to Use the System.
H_2	EOU will impact the system outcome construct, Intention to Use the System.
H_3	EOU will impact PU.

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

TAM Causal Path Findings via Linear Regression Analysis



	DV	F (R^2)	IV	Coefficient (T-value)
Regression #1	Intention to Use	23.80** (.24)	PU	.41 (4.45**)
			EOU	.10 (1.07)
Regression #2	PU	124.01** (.44)	EOU	.66 (11.14**)

** = Significant at the .01 level

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

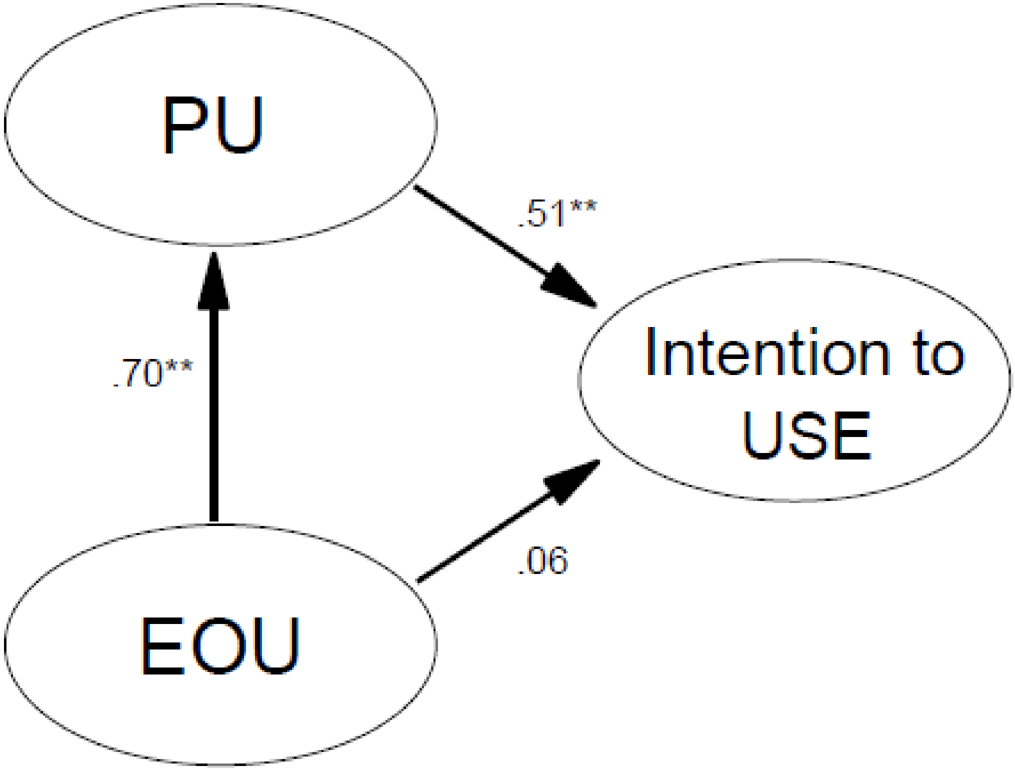
Factor Analysis and Reliabilities for Example Dataset

		Factors			Cronbach's α
Construct	Item	*1*	*2*	*3*	
Perceived Usefulness (PU)	PU1	**.543**	.277	.185	.91
	PU2	**.771**	.178	.053	
	PU3	**.827**	.315	.185	
	PU4	**.800**	.268	.234	
	PU5	**.762**	.352	.236	
	PU6	**.844**	.437	.290	
Perceived Ease-of-Use (EOU)	EOU1	.265	**.751**	.109	.93
	EOU2	.217	**.774**	.150	
	EOU3	.270	**.853**	.103	
	EOU4	.303	**.787**	.105	
	EOU5	.248	**.831**	.179	
	EOU6	.242	**.859**	.152	
Intention To Use (IUSE)	IUSE1	.183	.147	**.849**	.80
	IUSE2	.224	.062	**.835**	
	IUSE3	.139	.226	**.754**	

Rotation Method: Varimax with Kaiser Normalization (Rotation converged in 6 iterations)

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

TAM Standardized Causal Path Findings via LISREL Analysis



LISREL Fit Indices
$X^2 = 160.17$
df = 87
AGFI = .84
RMR = .047

Link	Coefficient (T-value)	SMC
PU -> Intended Use	.51 (3.94**)	.30
EOU -> Intended Use	.06 (.48)	
EOU -> PU	.70 (7.05**)	.48

** = Significant at the .01 level

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

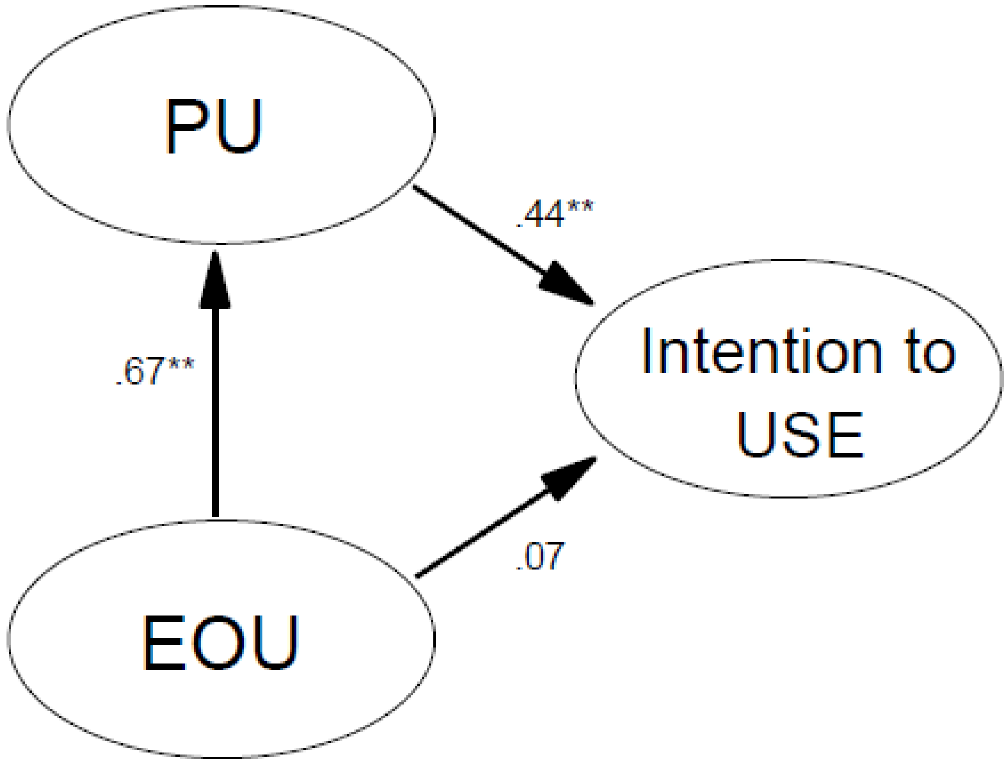
Standardized Loadings and Reliabilities in LISREL Analysis

		Latent Construct Loading (and Error)			Reliability Coefficient
Construct	Item	*PU*	*EOU*	*IUSE*	
Perceived Usefulness (PU)	PU1 PU2 PU3 PU4 PU5 PU6	0.99 (.50) 1.10 (.39)** 0.93 (.45)** 1.07 (.26)** 1.10 (.29)** 1.11 (.24)**			.95
Perceived Ease-of-Use (EOU)	EOU1 EOU2 EOU3 EOU4 EOU5 EOU6		0.78 (.45) 0.95 (.38)** 0.92 (.25)** 0.99 (.31)** 1.00 (.27)** 0.94 (.21)**		.94
Intention To Use (IUSE)	IUSE1 IUSE2 IUSE3			1.36 (.34) 2.17 (.38)** 1.15 (.53)**	.95

The first item loading in each latent variable is fixed at 1.00 and does not have a t- value.
** Significant at the .01 level

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

TAM Causal Path Findings via PLS Analysis



Link	Coefficient (T-value)	R^2
PU -> Intended Use	.44 (3.69**)	.24
EOU -> Intended Use	.07 (.12)	
EOU -> PU	.67 (10.20**)	.44

** = Significant at the .01 level

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Loadings in PLS Analysis

		Latent Construct		
Construct	**Item**	***PU***	***EOU***	***IUSE***
Perceived Usefulness (PU)	PU1	**.776****	.613	.405
	PU2	**.828****	.498	.407
	PU3	**.789****	.448	.302
	PU4	**.886****	.558	.353
	PU5	**.862****	.591	.451
	PU6	**.879****	.562	.406
Perceived Ease-of-Use (EOU)	EOU1	.534	**.802****	.323
	EOU2	.557	**.839****	.338
	EOU3	.467	**.886****	.260
	EOU4	.562	**.843****	.289
	EOU5	.542	**.865****	.304
	EOU6	.508	**.889****	.288
Intention To Use (IUSE)	IUSE1	.350	.270	**.868****
	IUSE2	.380	.234	**.858****
	IUSE3	.336	.280	**.814****

N.B. A reliability statistic not automatically produced in PLS.
** Significant at the .01 level

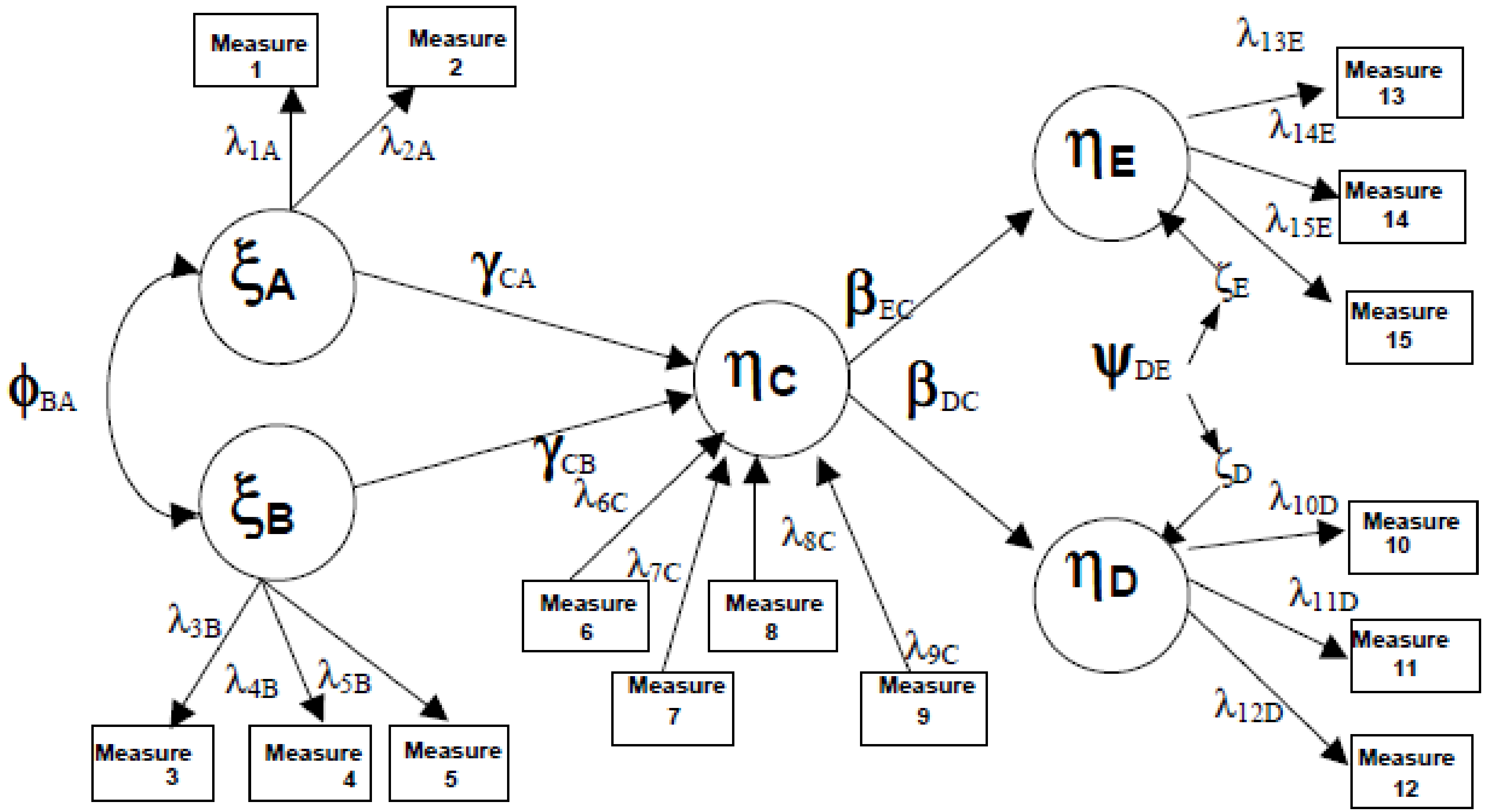
Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

AVE and Correlation Among Constructs in PLS Analysis

AVE/ Correlation	IUSE	PU	EOU
IUSE	.721		
PU	.468	.742	
EOU	.359	.632	.738

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Generic Theoretical Network with Constructs and Measures



Exogenous Latent Variables A and B *Endogenous Latent Variables C, D, and E*

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Number of Covariance-based SEM Articles Reporting SEM Statistics in IS Research

Statistics	*I&M* (n=6)	*ISR* (n=7)	*MISQ* (n=5)	All Journals (n=18)
GFI reported	3 (50%)	3 (43%)	1 (20%)	7 (39%)
Of GFI reported, number > 0.90	1 (33%)	2 (67%)	1 (100%)	4 (57%)
AGFI reported	2 (33%)	2 (29%)	1 (20%)	5 (28%)
Of AGFI reported, number > 0.80	1 (50%)	2 (100%)	1 (100%)	4 (80%)
RMR reported	2 (33%)	4 (57%)	2 (40%)	8 (44%)
Of RMR reported, number < 0.05	0 (0%)	1 (25%)	1 (50%)	2 (25%)
χ^2 insignificance reported	3 (50%)	2 (29%)	0 (0%)	5 (28%)
Of χ^2 insig. reported, number > .05	3 (100%)	1 (50%)	0 (0%)	4 (80%)
Ratio χ^2 / df reported	5 (83%)	6 (86%)	4 (80%)	15 (83%)
Of ratio χ^2 / df reported, number < 3	5 (100%)	5 (83%)	2 (50%)	12 (80%)
SMC	2 (33%)	3 (43%)	2 (40%)	7 (39%)
NFI reported	3 (50%)	3 (43%)	3 (60%)	9 (50%)
Of NFI reported, number > .90	2 (67%)	3 (100%)	3 (100%)	8 (89%)
CFI reported	3 (50%)	2 (29%)	1 (20%)	6 (33%)
T-values or significance of paths	4 (67%)	6 (86%)	4 (80%)	14 (78%)
Construct Reliability reported	5 (83%)	7 (100%)	4 (80%)	16 (89%)
Use of Nested Models	4 (67%)	6 (86%)	3 (60%)	13 (72%)

Notes: Rows in gray should receive special attention when reporting results
11 articles used LISREL, 6 EQS, and 1 AMOS

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Number of PLS Studies Reporting PLS Statistics in IS Research
(Rows in gray should receive special attention when reporting results)

PLS Statistics	*I&M* (n=2)	*ISR* (n=5)	*MISQ* (n=4)	All Journals (n=11)
R^2 reported	2 (100%)	5 (100%)	4 (100%)	11 (100%)
AVE reported	2 (100%)	5 (100%)	3 (75%)	10 (91%)
T-values or significance of paths	2 (100%)	5 (100%)	4 (100%)	11 (100%)
Construct Reliability reported	2 (100%)	4 (80%)	3 (75%)	9 (82%)
Use of Nested Models	0 (0%)	0 (0%)	0 (0%)	0 (0%)

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Structure Model

In LISREL terminology, the structural model contains the following:

- exogenous latent constructs called Xi or Ksi (ξ), depending on the dictionary used.
- endogenous latent constructs called Eta (η).
- paths connecting ξ to η represented statistically as Gamma (γ) coefficients.
- paths connecting one η to another are designated Beta (β).
- shared correlation matrix among ξ ; called Phi (ϕ).
- shared correlation matrix among the error terms of the η called Psi (ψ).
- the error terms themselves are known as ζ (Zeta).

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Structure Model

To illustrate, IUSE and PU would be considered to be endogenous constructs in the TAM running example used earlier. Both are predicted by one or more other variables, or latent constructs. EOU, however, would be considered to be an exogenous latent construct in that no other variable in this particular model predicts it. The causal path PU (ξ_1) $\Rightarrow$ IUSE (ξ_2) was estimated as a β coefficient. The causal path EOU (η_1) $\Rightarrow$ PU (ξ_1) was estimated as a γ coefficient.[9]

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Measurement Model

In addition, the measurement model consists of:

- X and Y variables, which are observations or the actual data collected. X and Y are the measures of the exogenous and endogenous constructs, respectively. Each X should load onto one ξ, and each Y should load onto one η.
- Lambda X (λ_X) representing the path between an observed variable X and its ξ, i.e., the item loading on its latent variable.
- Theta Delta (Θ_δ) representing the error variance associated with this X item, i.e., the variance not reflecting its latent variable ξ.
- Lambda Y (λ_Y) representing the path between an observed variable Y and its η, i.e., the item loading on its latent variable.
- Theta Epsilon (Θ_ε) representing the error variance associated with this Y item, i.e., the variance not reflecting its latent variable η.

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

SEM

The holistic analysis that SEM is capable of performing is carried out via one of two distinct statistical techniques:

1. covariance analysis
   – employed in LISREL, EQS and AMOS
2. partial least squares
   – employed in PLS and PLS-Graph

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Comparative Analysis Based on Statistics Provided by SEM

Statistics	LISREL	PLS	Regression
Analysis of overall model fit	Provided	Provided	Provided
Analysis of individual causation paths	Provided	Provided	Provided
Analysis of individual item loading paths	Provided	Provided	Not provided
Analysis of residual non-common error	Provided	Not Provided	Not provided
Type of variance examined	1. Common 2. Specific 3. Error	Common Combined specific and error	Common
Analysis of statistical power	Not available	Available through the f^2 statistic.	Available

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Comparative Analysis Based on Capabilities

Capabilities	LISREL	PLS	Regression
Examines interaction effect on cause-effect paths	Supported	Supported	Supported
Examines interaction effect on item loadings	Supported	Not readily supported	Not supported
Examines interaction effect on non-common variance	Supported	Not readily supported	Not supported
Examines interaction effect on the entire model	Supported	Not readily supported	Not supported
Can cope with relatively small sample size	Problematic	Supported	Supported
Readily examines interaction effect with numerous variable levels	Problematic	Supported	Supported
Can constrain a path to a given value	Supported	Not supported	Not supported
Examines nested models	Supported	Supported	Supported

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Comparative Analysis Based on Capabilities

Capabilities	LISREL	PLS	Regression
Establishment of causation	No	No	No
Possible over-fitting	Problematic	Less problematic	Less problematic
Testing of suspected non-linear effect	Problematic	Problematic	Mitigated by data transformation
Suspected influential outliers	Problematic	Problematic	Mitigated by data transformation
Suspected heteroscedasticity	Problematic	Problematic	Mitigated by data transformation
Suspected polynomial relation	Problematic	Problematic	Mitigated by data transformation

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Heuristics for Statistical Conclusion Validity (Part 1)

Validity	Technique	Heuristic
Construct Validity		
Convergent Validity	CFA used in covariance-based SEM only.	GFI > .90, NFI > .90, AGFI > .80 (or >.90) and an insignificant χ^2, to show unidimensionality. In addition, item loadings should be above .707, to show that over half the variance is captured by the latent construct [Chin, 1998b, Hair et al., 1998, Segars, 1997, Thompson et al., 1995].
Discriminant Validity	CFA used in covariance-based SEM only.	Comparing the χ^2 of the original model with an alternative model where the constructs in question are united as one construct. If the χ^2 is significantly smaller in the original model, discriminant validity has been shown [Segars, 1997].
Convergent & Discriminant Validities	PCA used in PLS can assess factor analysis but not as rigorously as a CFA in LISREL does and without examining unidimensionality	Each construct AVE should be larger than its correlation with other constructs, and each item should load more highly on its assigned construct than on the other constructs.
Reliability		
Internal Consistency	Cronbach's α	Cronbach's αs should be above .60 for exploratory research and above .70 for confirmatory research [Nunnally, 1967, Nunnally, 1978, Nunnally and Bernstein, 1994, Peter, 1979].
	SEM	The internal consistency coefficient should be above .70 [Hair et al., 1998, Thompson et al., 1995].
Unidimensional Reliability	Covariance-based SEM only.	Model comparisons favor unidimensionality with a significantly smaller χ^2 in the proposed measurement model in comparison with alternative measurement models [Segars, 1997].

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Heuristics for Statistical Conclusion Validity (Part 2)

Model Validity		
AGFI	LISREL	AGFI > .80 [Segars and Grover, 1993]
Squared Multiple Correlations	LISREL, PLS	No official guidelines exist, but, clearly, the larger these values, the better
χ^2	LISREL	Insignificant and χ^2 to degrees of freedom ratio of less than 3:1 [Chin and Todd, 1995, Hair et al., 1998]
Residuals	LISREL	RMR <.05 [Hair et al., 1998]
NFI	LISREL	NFI > .90 [Hair et al., 1998]
Path Validity Coefficients	LISREL	The β and γ coefficients must be significant; standardized values should be reported for comparison purposes [Bollen, 1989, Hair et al., 1998, Jöreskog and Sörbom, 1989] .
	PLS	Significant t-values [Thompson et al., 1995].
	Linear Regression	Significant t-values [Thompson et al., 1995].
Nested Models		
	LISREL	A nested model is rejected based on insignificant βs and γs paths and an insignificant change in the χ^2 between the models given the change in degrees of freedom [Anderson and Gerbing, 1988] [Jöreskog and Sörbom, 1989] .
	PLS	A nested model is rejected if it does not yield significant a f^2 [Chin and Todd, 1995].
	Linear Regression	A nested model in a stepwise regression is rejected if it does not yield a significant change in the F statistic (reflected directly in the change in R^2) [Neter et al., 1990].

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

APPENDIX B

INSTRUCTIONS TO SUBJECTS AND INSTRUMENTATION

INSTRUCTIONS:

As part of an ongoing study on Internet use, we would be grateful if you could devote 10 minutes to completing this instrument.

1. Please logon to the Internet and access www.travelocity.com
2. Use the Web-site to search for a flight to Heathrow Airport (London) next month.
3. Then, please fill in the instrument below.

Please circle the appropriate category:

Gender	M , F	
Age group	15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 50-54, 55-59, 60-64, 65-69, above 70	
What language do you speak at home (English, Italian, Hindi, Cantonese, etc.)?		
Have you ever bought products on the World Wide Web		Yes, No
How many times have you used Travelocity.com?		
Have you given your credit card number on the Web?		Yes, No

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

Please indicate your agreement with the next set of statements using the following rating scale:

1	2	3	4	5	6	7
Strongly Agree	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree	Strongly Disagree

Code*	Item	Agree Disagree
EOU1	Travelocity.com is easy to use.	1 2 3 4 5 6 7
EOU2	It is easy to become skillful at using Travelocity.com.	1 2 3 4 5 6 7
EOU3	Learning to operate Travelocity.com is easy .	1 2 3 4 5 6 7
EOU4	Travelocity.com is flexible to interact with .	1 2 3 4 5 6 7
EOU5	My interaction with Travelocity.com is clear and understandable .	1 2 3 4 5 6 7
EOU6	It is easy to interact with Travelocity.com.	1 2 3 4 5 6 7
PU1	Travelocity.com is useful for searching and buying flights .	1 2 3 4 5 6 7
PU2	Travelocity.com improves my performance in flight searching and buying.	1 2 3 4 5 6 7
PU3	Travelocity.com enables me to search and buy flights faster.	1 2 3 4 5 6 7
PU4	Travelocity.com enhances my effectiveness in flight searching and buying.	1 2 3 4 5 6 7
PU5	Travelocity.com makes it easier to search for and purchase flights.	1 2 3 4 5 6 7
PU6	Travelocity.com increases my productivity in searching and purchasing flights.	1 2 3 4 5 6 7
IUSE1	I am very likely to buy books from Travelocity.com.	1 2 3 4 5 6 7
IUSE2	I would use my credit card to purchase from Travelocity.com.	1 2 3 4 5 6 7
IUSE3	I would not hesitate to provide information about my habits to Travelocity.	1 2 3 4 5 6 7

Thank You!

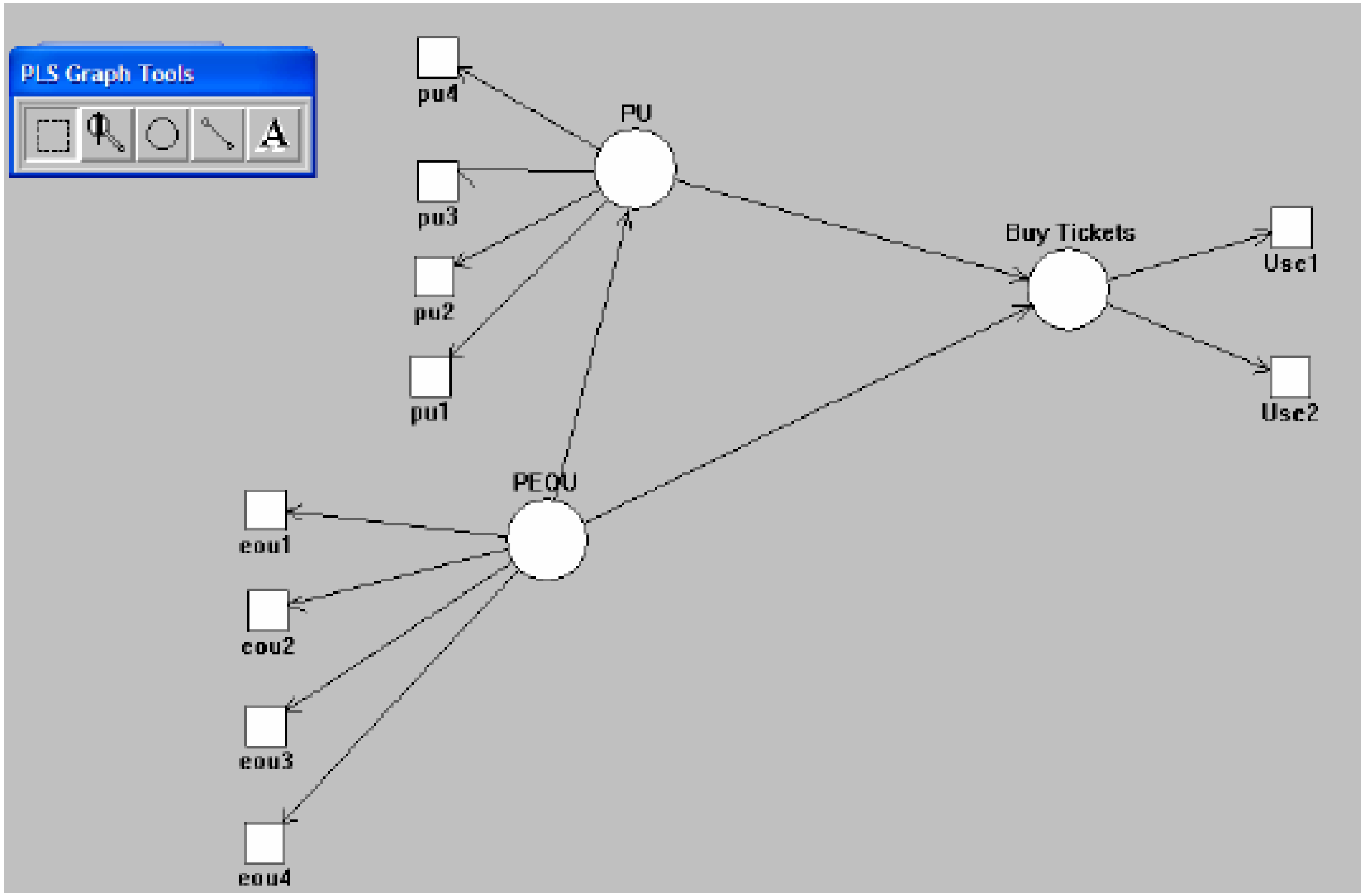
* Students did not receive the item codes****.

Source: Gefen, David; Straub, Detmar; and Boudreau, Marie-Claude (2000)

A Practical Guide To Factorial Validity Using PLS-Graph

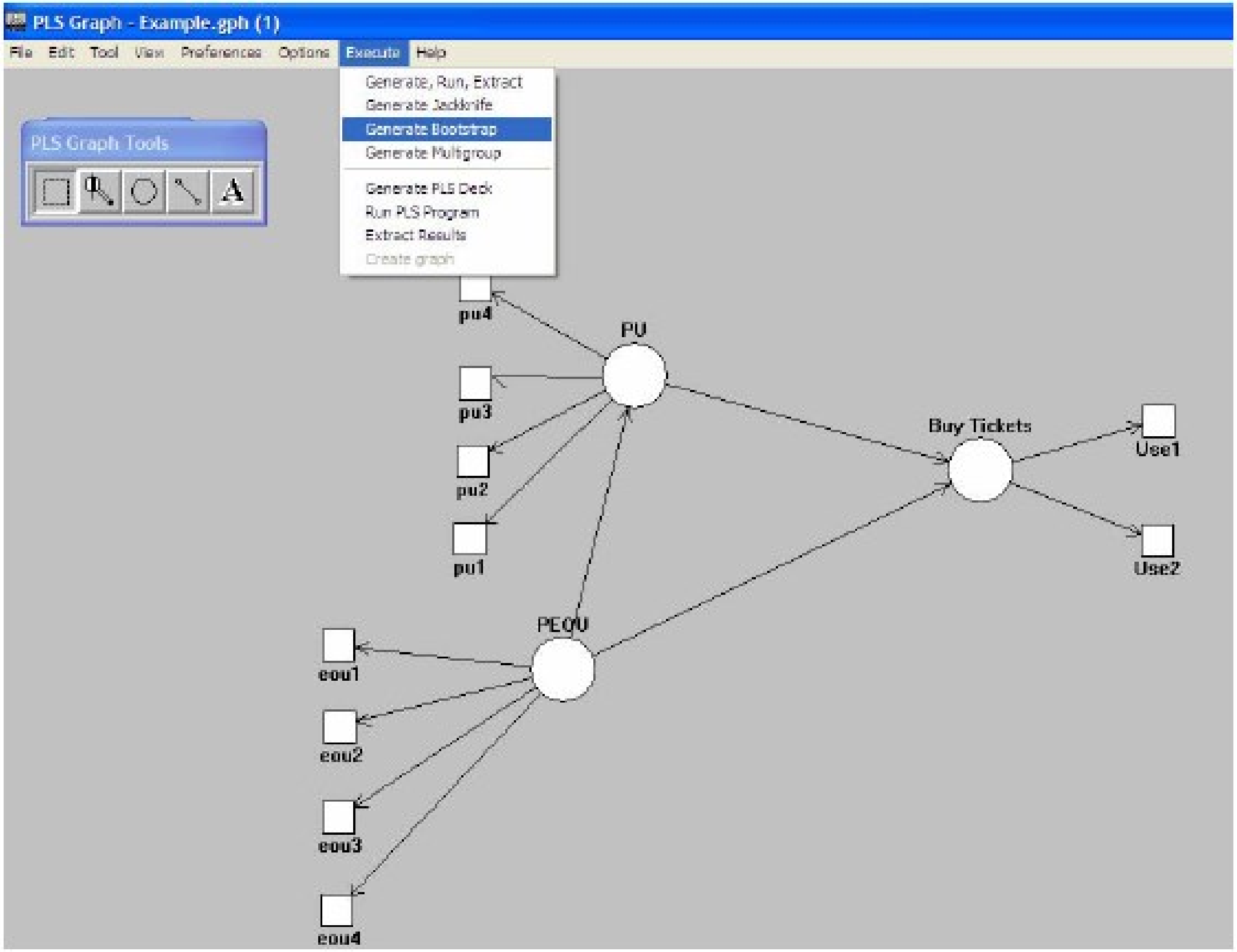
- Gefen, David and Straub, Detmar (2005) "A Practical Guide To Factorial Validity Using PLS-Graph: Tutorial And Annotated Example," Communications of the Association for Information Systems: Vol. 16, Article 5. Available at: http://aisel.aisnet.org/cais/vol16/iss1/5

PLS-Graph Model



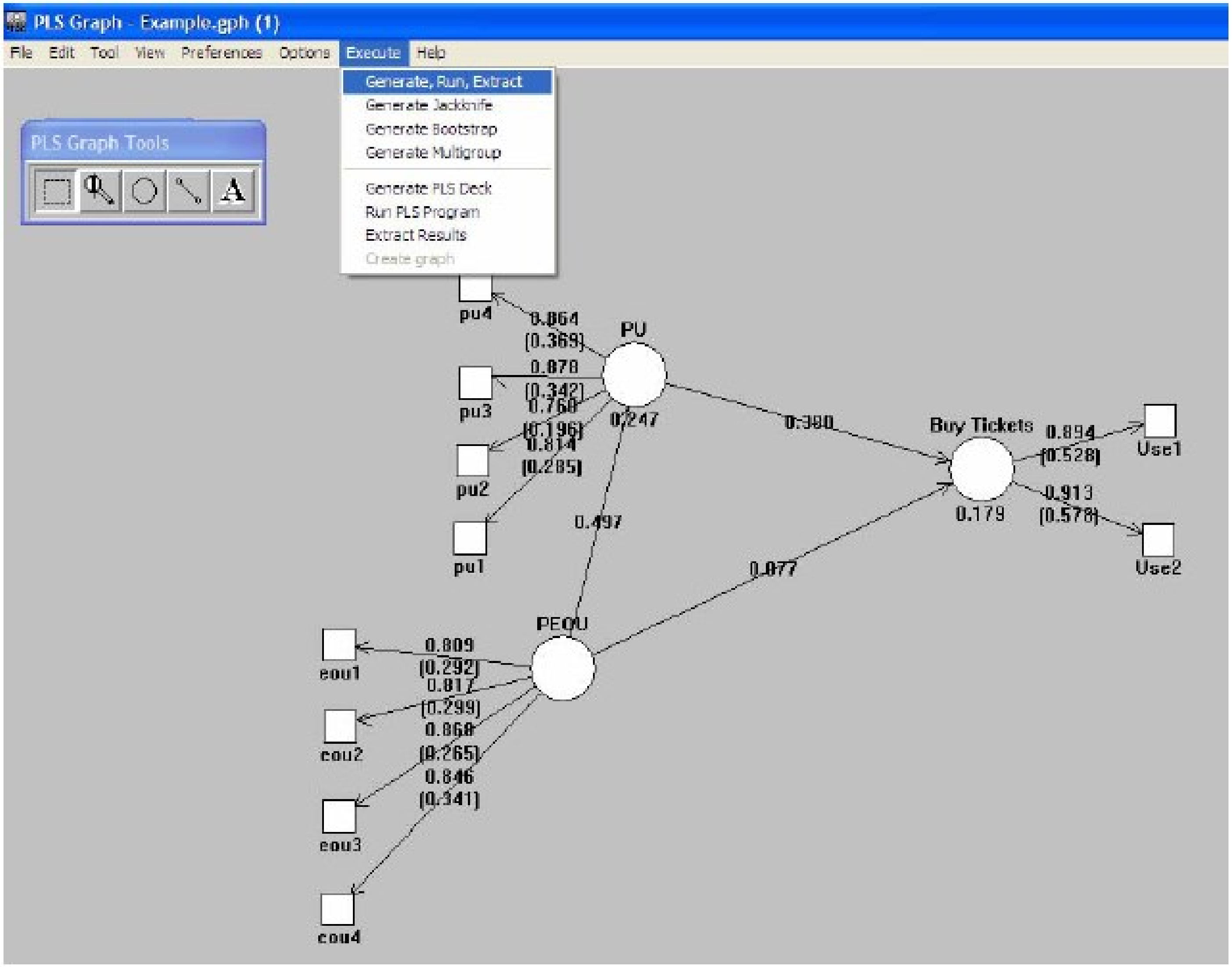
Source: Gefen, David and Straub, Detmar (2005)

Extracting PLS-Graph Model



Source: Gefen, David and Straub, Detmar (2005)

Displaying the PLS-Graph Model



Source: Gefen, David and Straub, Detmar (2005)

PCA with a Varimax Rotation of the Same Data

	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.

Source: Gefen, David and Straub, Detmar (2005)

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

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

Source: Gefen, David and Straub, Detmar (2005)

Explaining Information Technology Usage: A Test of Competing Models

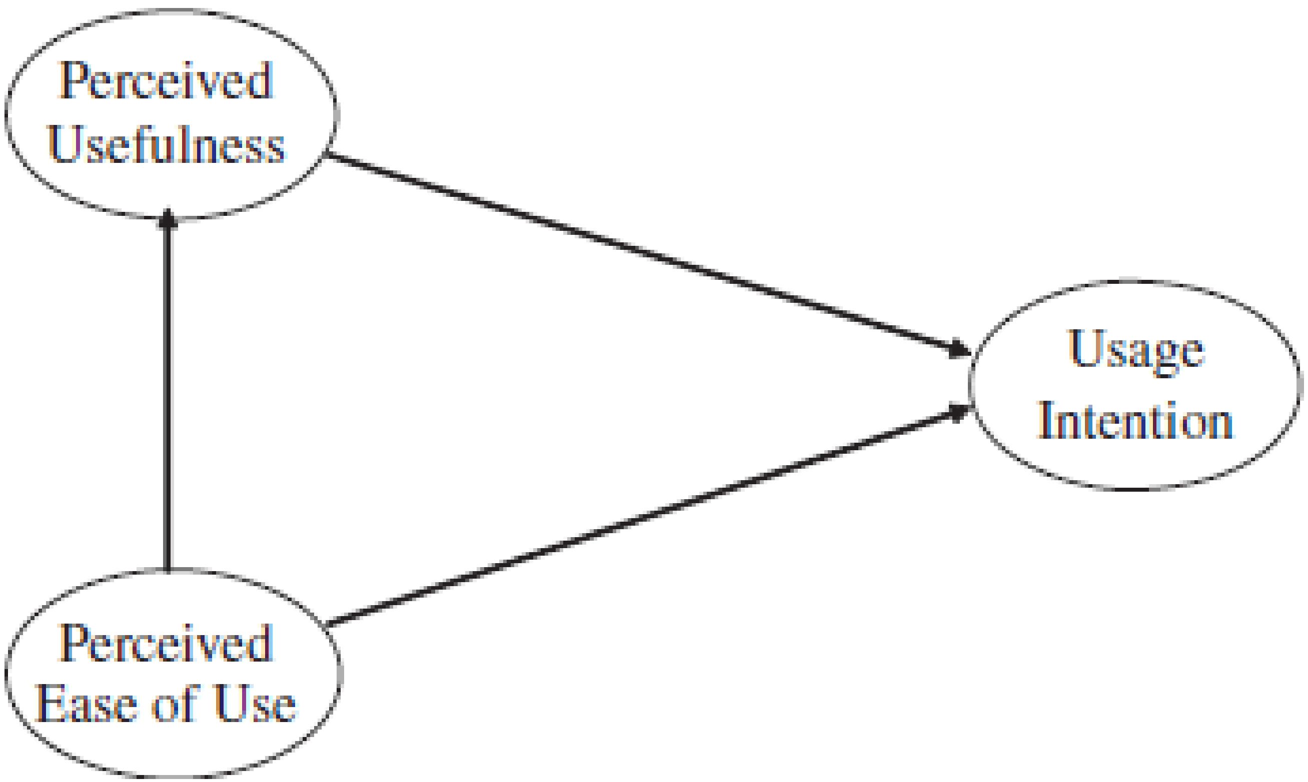


Fig. 1. Simplified technology acceptance model.

Source: Premkumar, G., and Anol Bhattacherjee (2008), "Explaining information technology usage: A test of competing models," Omega 36(1), 64-75.

Explaining Information Technology Usage: A Test of Competing Models

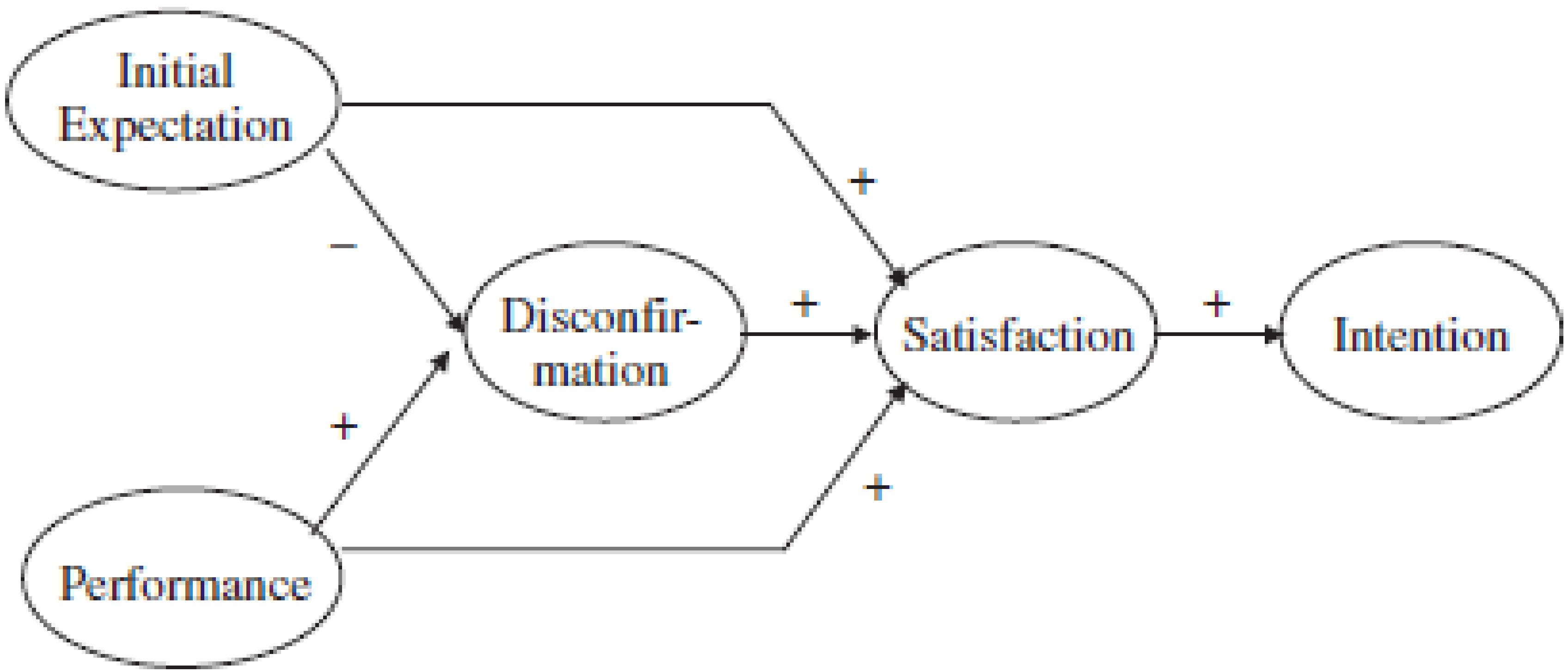


Fig. 2. Expectation–disconfirmation model.

Source: Premkumar, G., and Anol Bhattacherjee (2008), "Explaining information technology usage: A test of competing models," Omega 36(1), 64-75.

Explaining Information Technology Usage: A Test of Competing Models

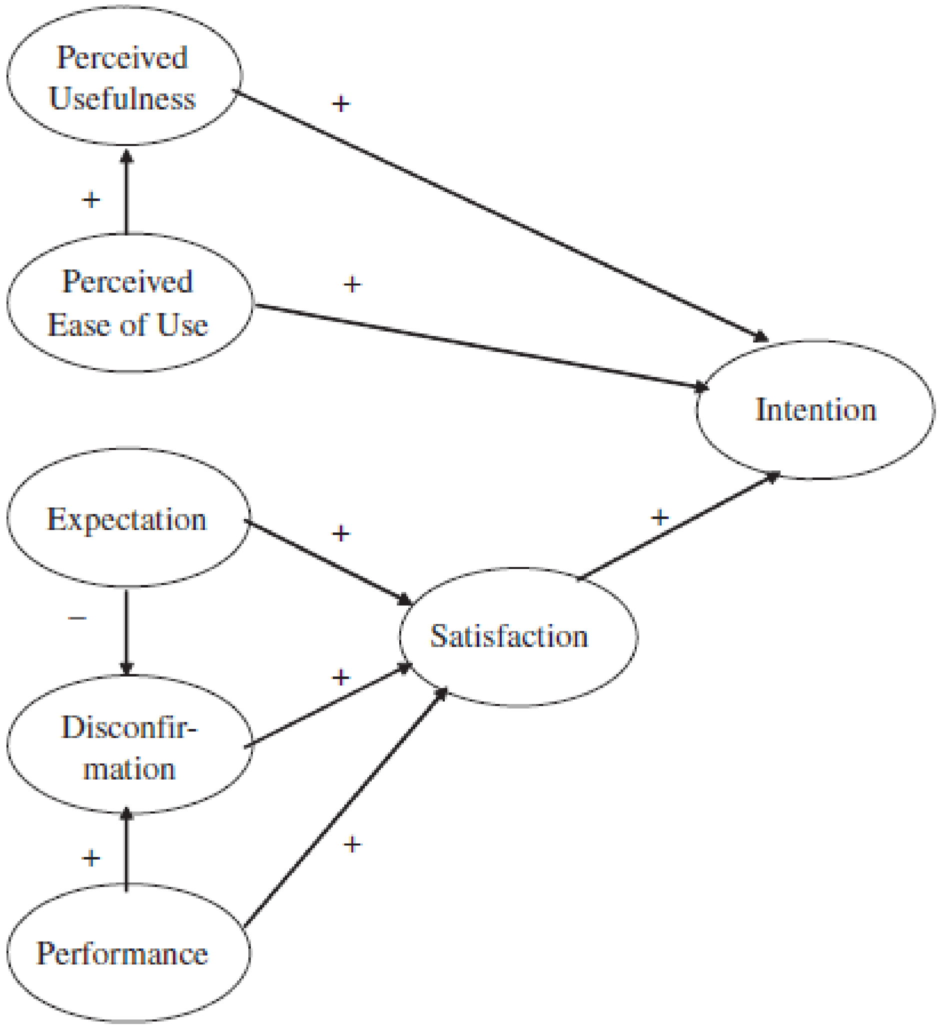


Fig. 3. Integrated model.

Source: Premkumar, G., and Anol Bhattacherjee (2008), "Explaining information technology usage: A test of competing models," Omega 36(1), 64-75.

Explaining Information Technology Usage: A Test of Competing Models

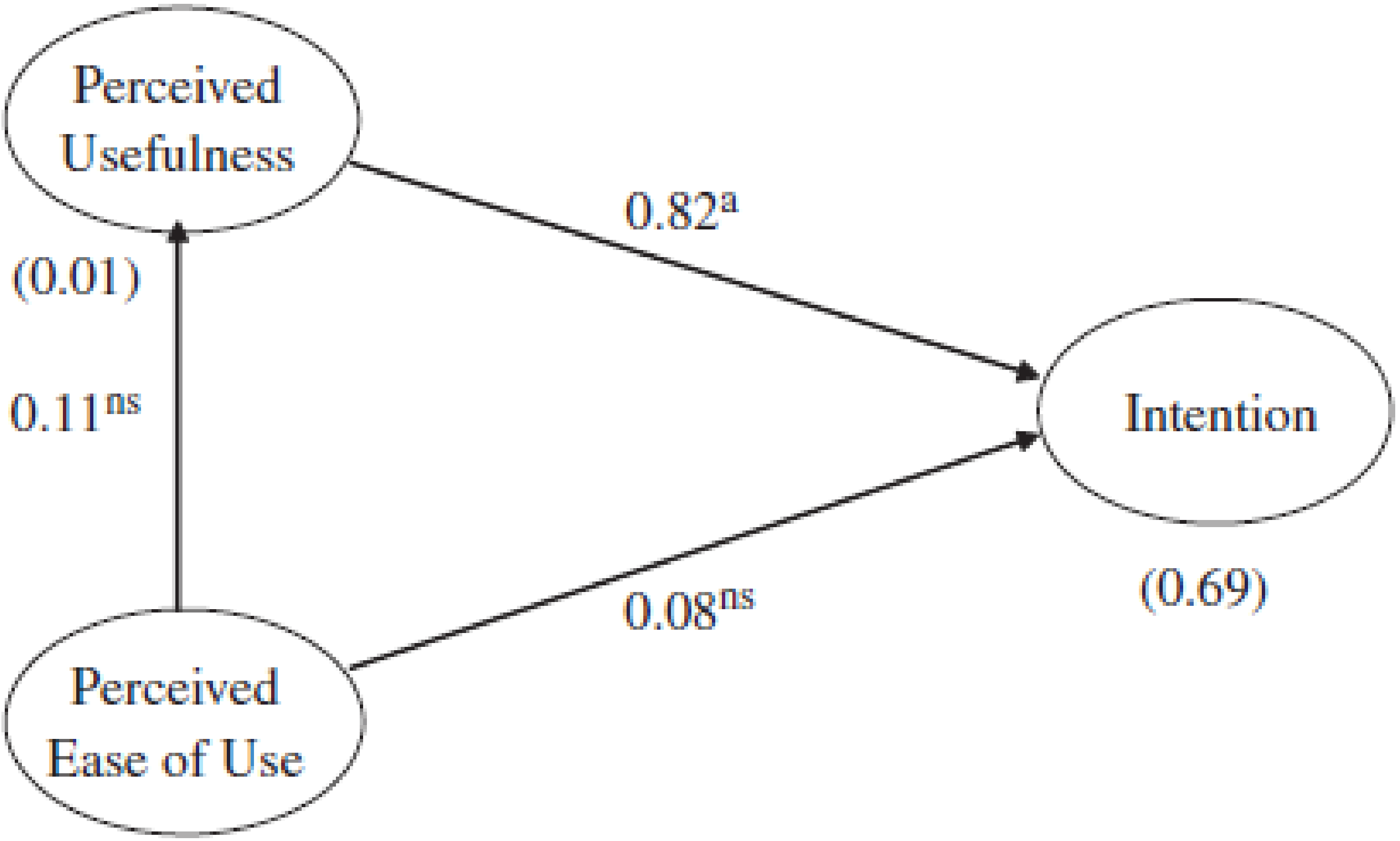


Fig. 4. PLS analysis of TAM. Path significance: [a] $p < 0.001$; [b] $p < 0.01$; [c] $p < 0.05$; [ns] $p > 0.05$. Parentheses indicate R^2 values.

Source: Premkumar, G., and Anol Bhattacherjee (2008), "Explaining information technology usage: A test of competing models," Omega 36(1), 64-75.

Explaining Information Technology Usage: A Test of Competing Models

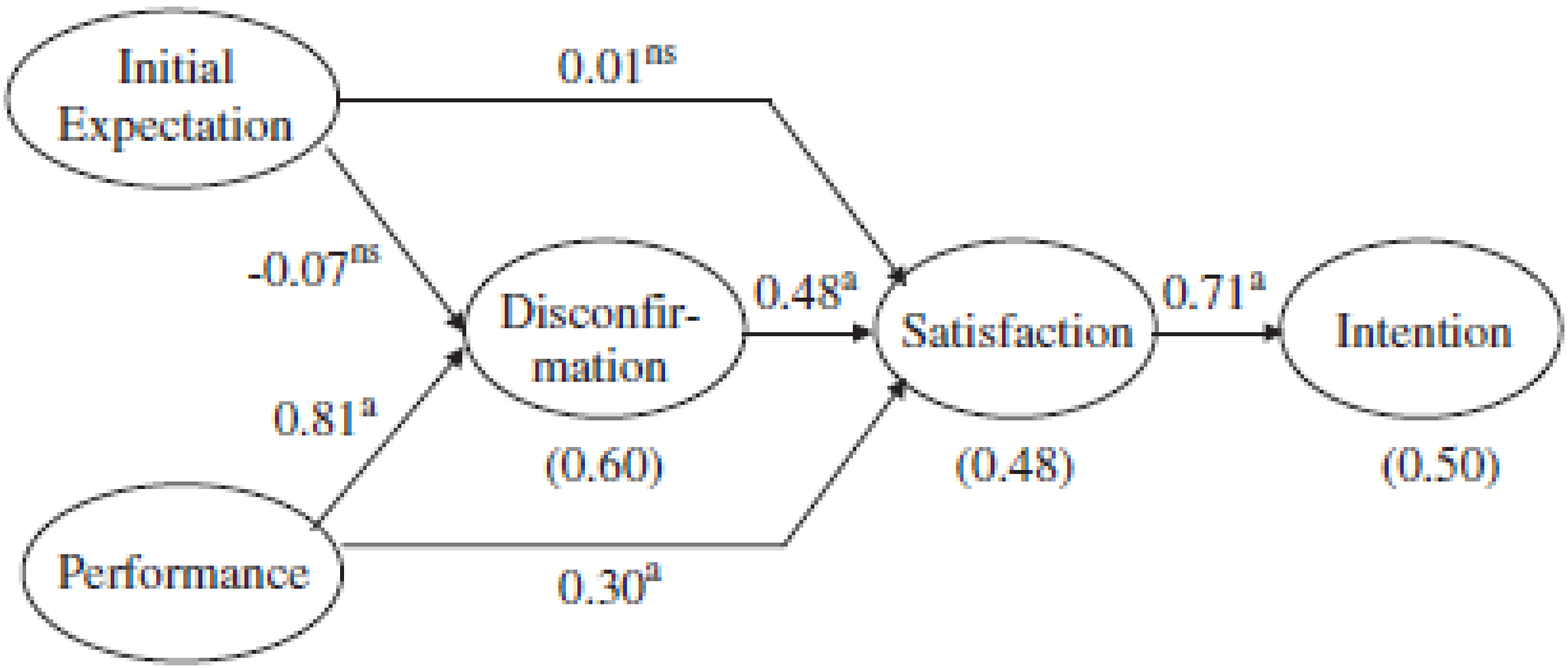


Fig. 5. PLS analysis of EDT. Path significance: [a] $p < 0.001$; [ns] $p > 0.10$. Parentheses indicate R^2 values.

Source: Premkumar, G., and Anol Bhattacherjee (2008), "Explaining information technology usage: A test of competing models," Omega 36(1), 64-75.

Explaining Information Technology Usage: A Test of Competing Models

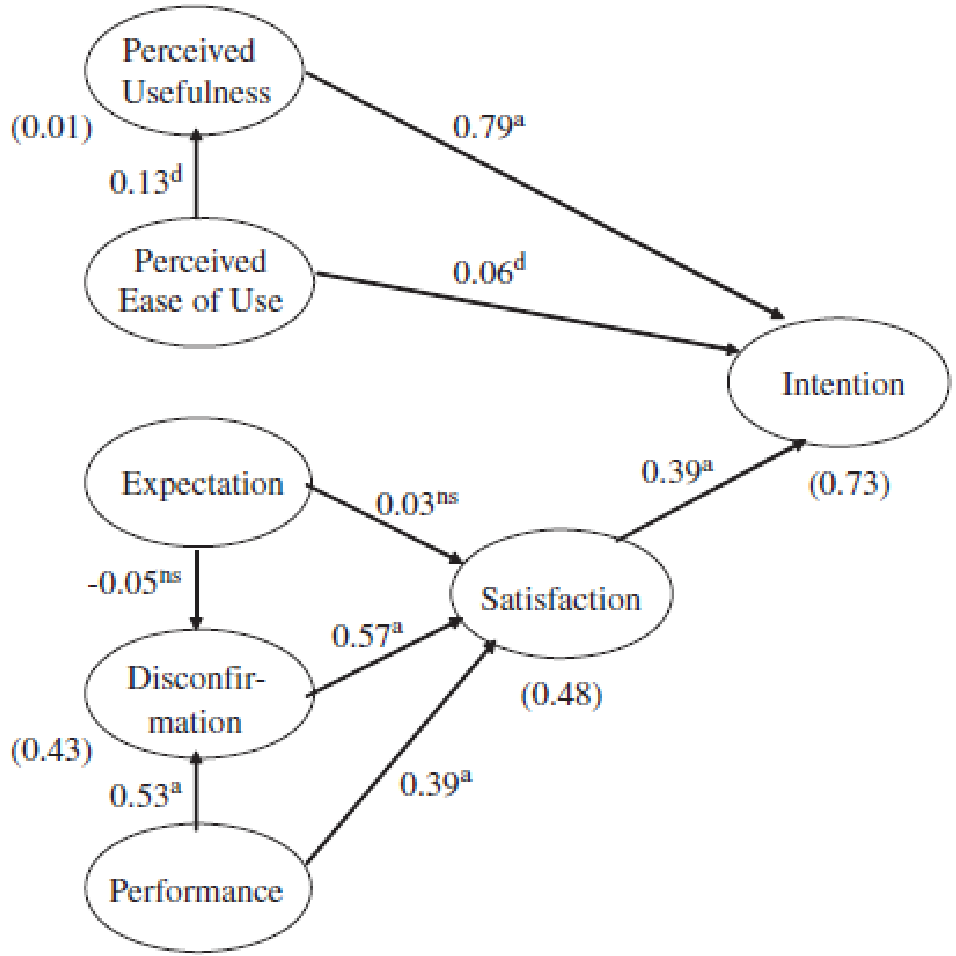


Fig. 6. PLS analysis of the integrated model. Path significance: [a] $p < 0.001$; [b] $p < 0.01$; [c] $p < 0.05$; [d] $p < 0.10$; [ns] $p > 0.10$. Parentheses indicate R^2 values.

Source: Premkumar, G., and Anol Bhattacherjee (2008), "Explaining information technology usage: A test of competing models," Omega 36(1), 64-75.

Summary

- Confirmatory Factor Analysis (CFA)
- Structured Equation Modeling (SEM)
- Partial-least-squares (PLS) based SEM (PLS-SEM)
  - PLS
- Covariance based SEM (CB-SEM)
  - LISREL

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