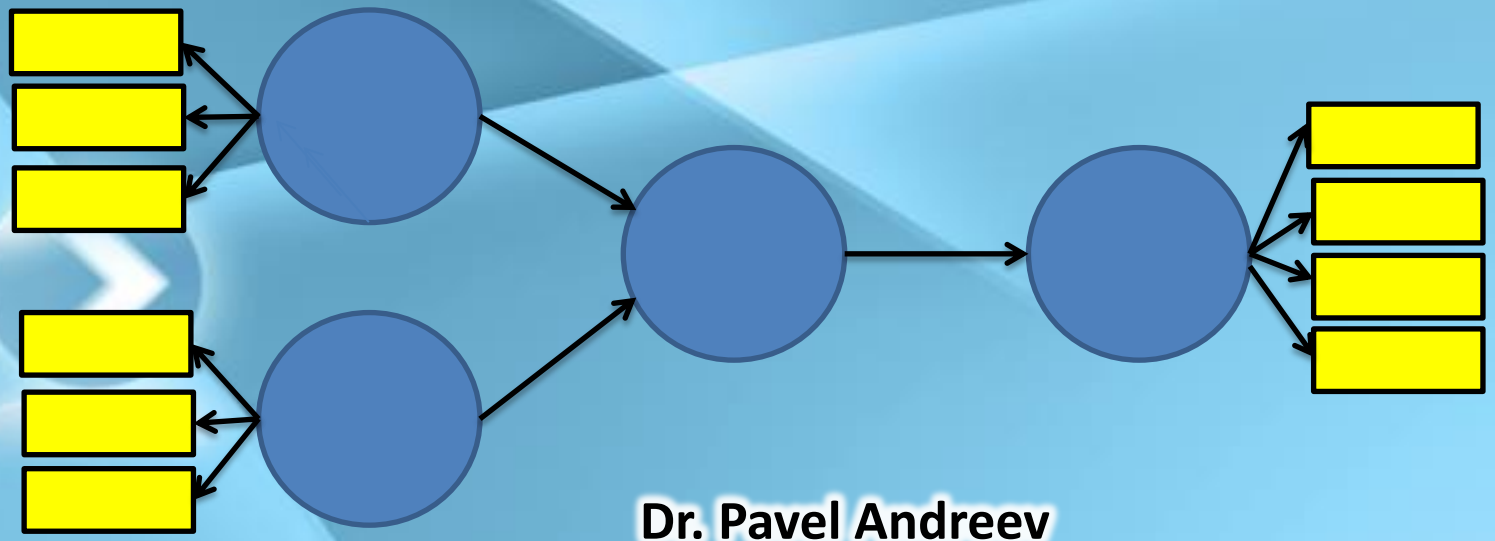
Implementation of Partial Least Squares (PLS) Modeling in Economics and Business Management Research



Dr. Pavel Andreev
University of Ottawa

uOttawa

INTRODUCING

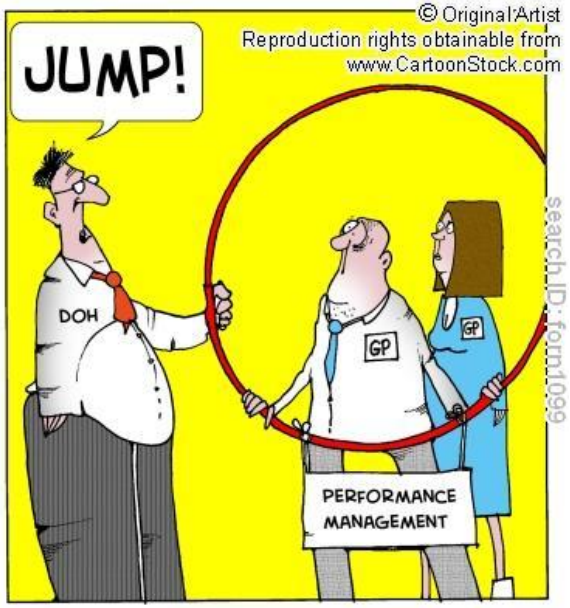
- Assistant Professor in Performance Management and Data Analytics

École de gestion TELFER School of Management

My research is focused on modeling and exploring impacts of information and communication technologies on the performance of commercial and non-commercial organizations at the individual, team, and organizational level.

- 2011 Postdoc, Visiting Professor at Telfer, uOttawa

Improving performance management of a chronic disease inter-professional healthcare team.



INTRODUCING

2010-2011 Research Fellow, Visiting Professor, Sagy Center for Internet Research, the Graduate School of Management, University of Haifa, Israel

- Mobile commerce opportunities that smart phones present to the organizations. M-Payment adoption

2009-2010 Postdoc at UCC, Visiting Professor Cork, Ireland

Open Code, Content and Commerce (O3C) Business Models

open production, innovation and value creation strategies, e.g. open source software, open content, open innovation, crowdsourcing, etc.

INTRODUCING

2009 - Ph.D. Ben-Gurion University, Israel

Impacts of Information and Communication Technologies (ICT) on Personal Activities

- *Teleactivities*
  - *teleworking, telemedicine, teleshopping, telelearning, telebanking, and teleleisure*

AGENDA

- Introduction to PLS modeling basics
- Examples of research with implementation of PLS as research methodology
  1. Modeling Open Innovation strategies of an organization
  2. Modeling Willingness to conduct m-payments
- Assessment of PLS model
  - Guideline for validation procedure
    - Examples of the validation procedure
- Practice (if we have time)

PLS –OVERVIEW

Exhibit 1.1 Organization of Multivariate Methods

	Primarily Exploratory	*Primarily Confirmatory*
First-generation techniques	• Cluster analysis • Exploratory factor analysis • Multidimensional scaling	• Analysis of variance • Logistic regression • Multiple regression
Second-generation techniques	• PLS-SEM	• CB-SEM, *including* • Confirmatory factor analysis

Hair et.al. (2013), “A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)”

SEM

- The desire to test research theories and concepts is one of the major reasons why authors conducting business research have embraced SEM.
- SEM is equivalent to carrying out covariance-based SEM (CB-SEM) analyses using software such as Amos, EQS, LISREL, Mplus, and others.

PLS-OVERVIEW

- However, there is also another SEM approach, called Partial Least Squares SEM (PLS-SEM).
- So, what is the difference between CB-SEM and PLS-SEM?

COV-SEM VS. PLS-SEM

- The philosophical distinction is pretty vivid:
- The research objective:
  - Theory testing and confirmation - CB-SEM.
  - Prediction and theory development - PLS-SEM.

SHOULD YOU USE SEM IN YOUR RESEARCH?

Journal reviewers rate SEM papers more favorably on key manuscript attributes . . .

	Mean Score		
Attributes	SEM	No SEM	p-value
Topic Relevance	4.2	3.8	.182
Research Methods	3.5	2.7	.006
Data Analysis	3.5	2.8	.025
Conceptualization	3.1	2.5	.018
Writing Quality	3.9	3.0	.006
Contribution	3.1	2.8	.328

Note: scores based on 5-point scale, with 5 = more favorable

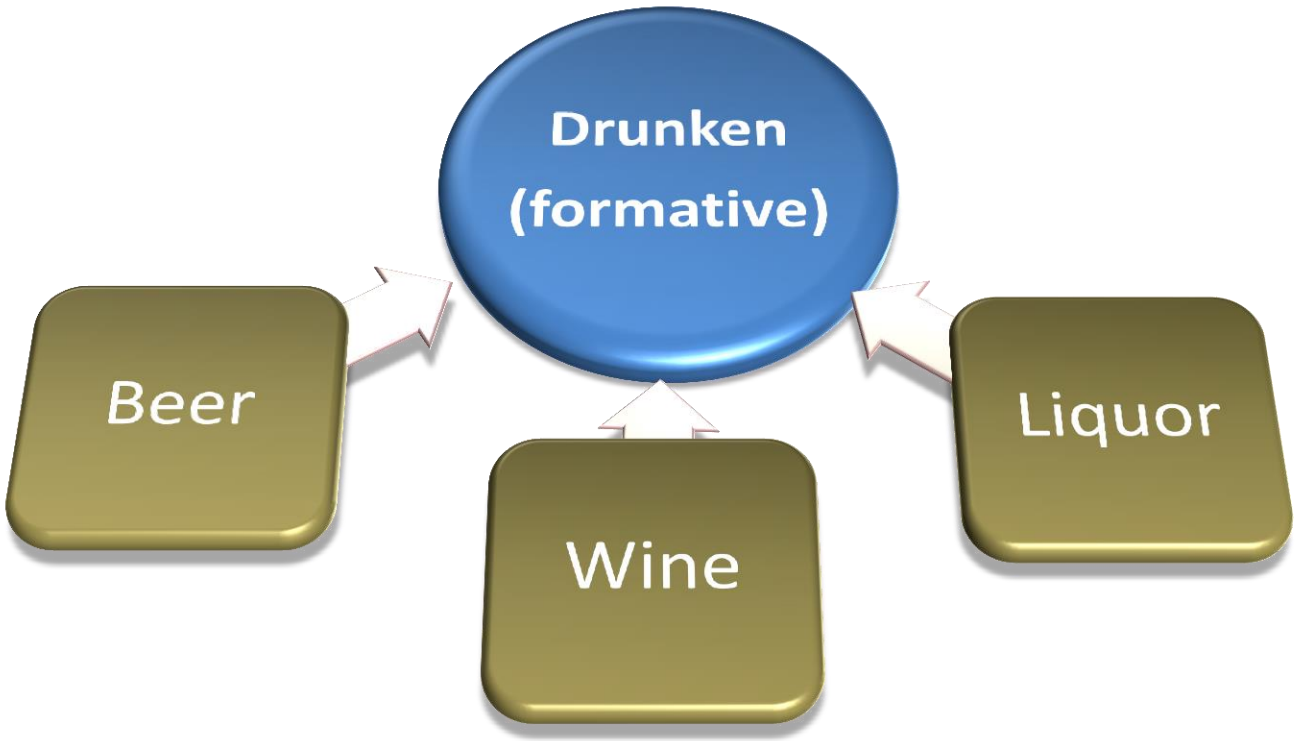
Source: Babin, Hair & Boles, Publishing Research in Marketing Journals Using Structural Equation Modeling, *Journal of Marketing Theory and Practice*, Vol. 16, No. 4, 2008, pp. 281-288.

SEM IN A NUTSHELL
PATH MODEL

- ***Path models*** - diagrams that visualize variables and the relationships between them.
- There are ***two types*** of variables: *Latent Variables* (LVs) and *Observed Variables* (OVs)
  - ***LVs or Constructs*** - variables that cannot be directly measured. In the path models they are represented as circles or ovals.
  - ***OVs or Indicators/Items/Manifest Variables*** – variables that are directly measured proxy variables that contain the raw data. In the path models they are represented as rectangles.
- ***Paths*** - relationships between constructs, and the associations of constructs with their items between constructs and their assigned indicators. In the path models they are shown as arrows.

FORMATIVE VS. REFLECTIVE

Formative



Source: Hubona G., SmartPLS Online Course 2009, c.f. Wynn Chin

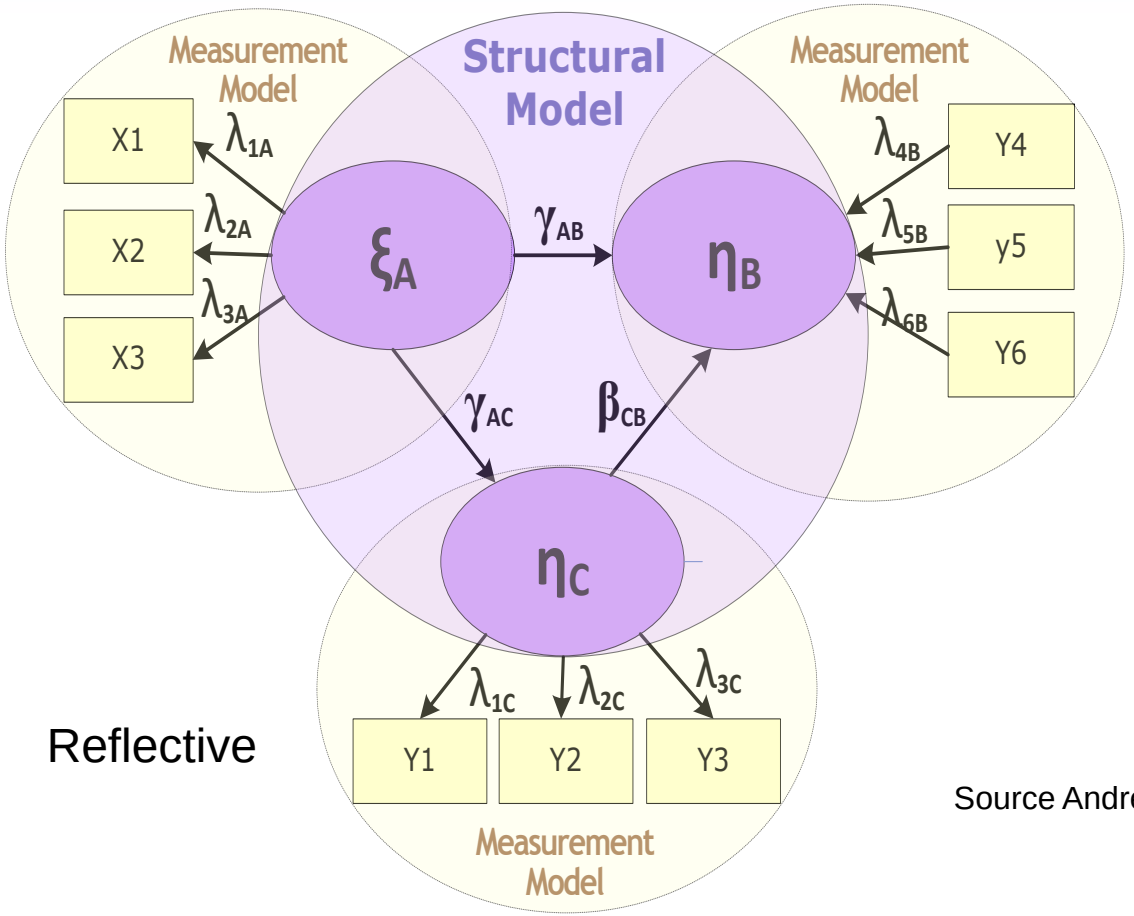
FORMATIVE VS. REFLECTIVE

Reflective

Source: Hubona G., SmartPLS Online Course 2009, c.f. Wynn Chin

SEM IN A NUTSHELL
PLS PATH MODEL

Reflective



Formative

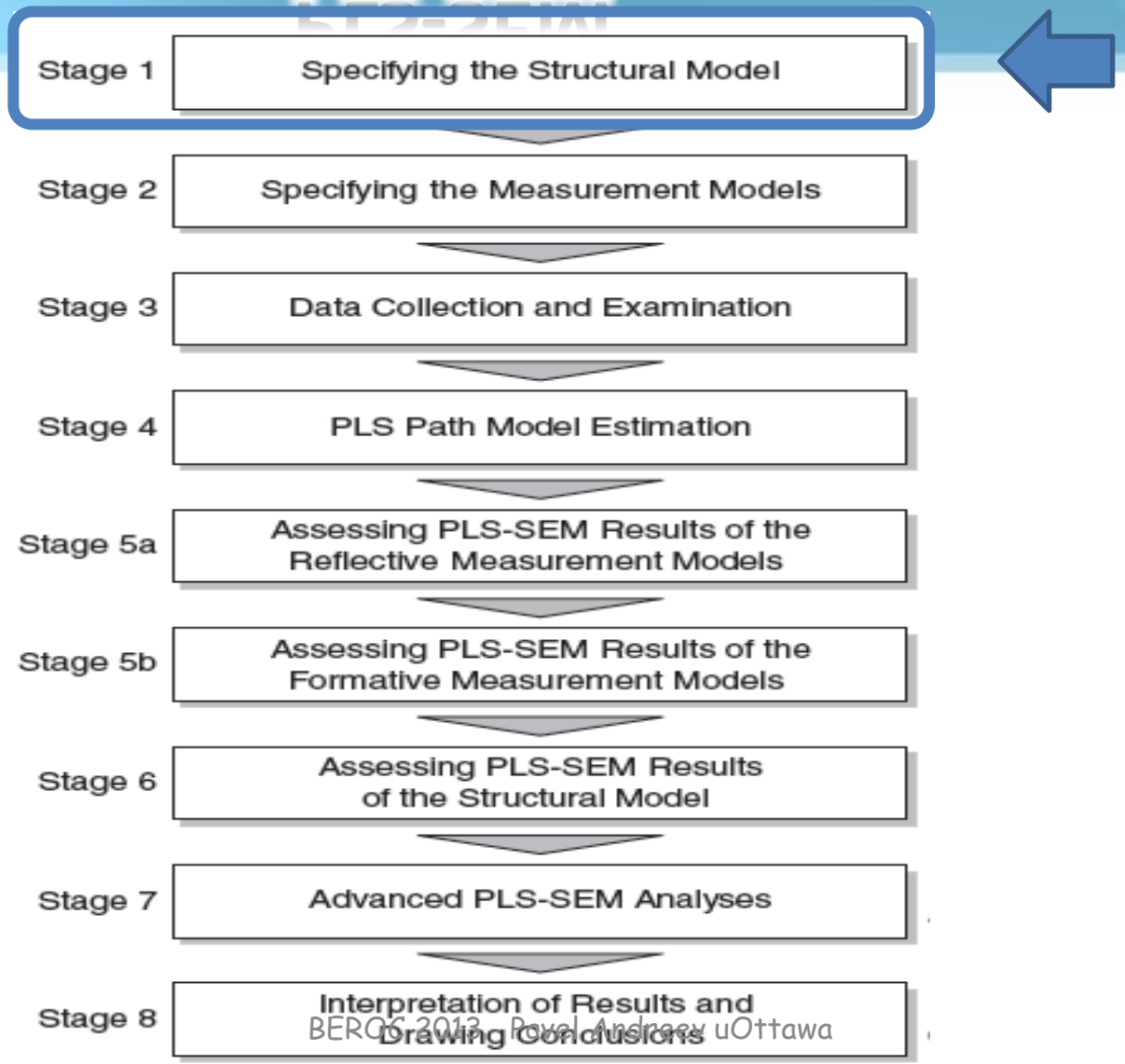
Reflective

Source Andreev et.al. (2009)

SEM IN A NUTSHELL
PATH MODEL

- A PLS path model consists of two elements:
  - Structural model (also referred to as the inner model) that represents the constructs (circles or ovals). The structural model also displays the relationships (paths) between the constructs.
  - Measurement models (also referred to as the outer models) of the constructs that display the relationships between the constructs and the indicator variables (rectangles).
- Two types of constructs in a SEM:
  - Exogenous latent variables (i.e., those constructs that explain other constructs in the model)
  - Endogenous latent variables (i.e., those constructs that are being explained in the model).

SYSTEMATIC PROCEDURE FOR APPLYING PLS-SEM



Source: Hair et.al. (2013), "A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)"

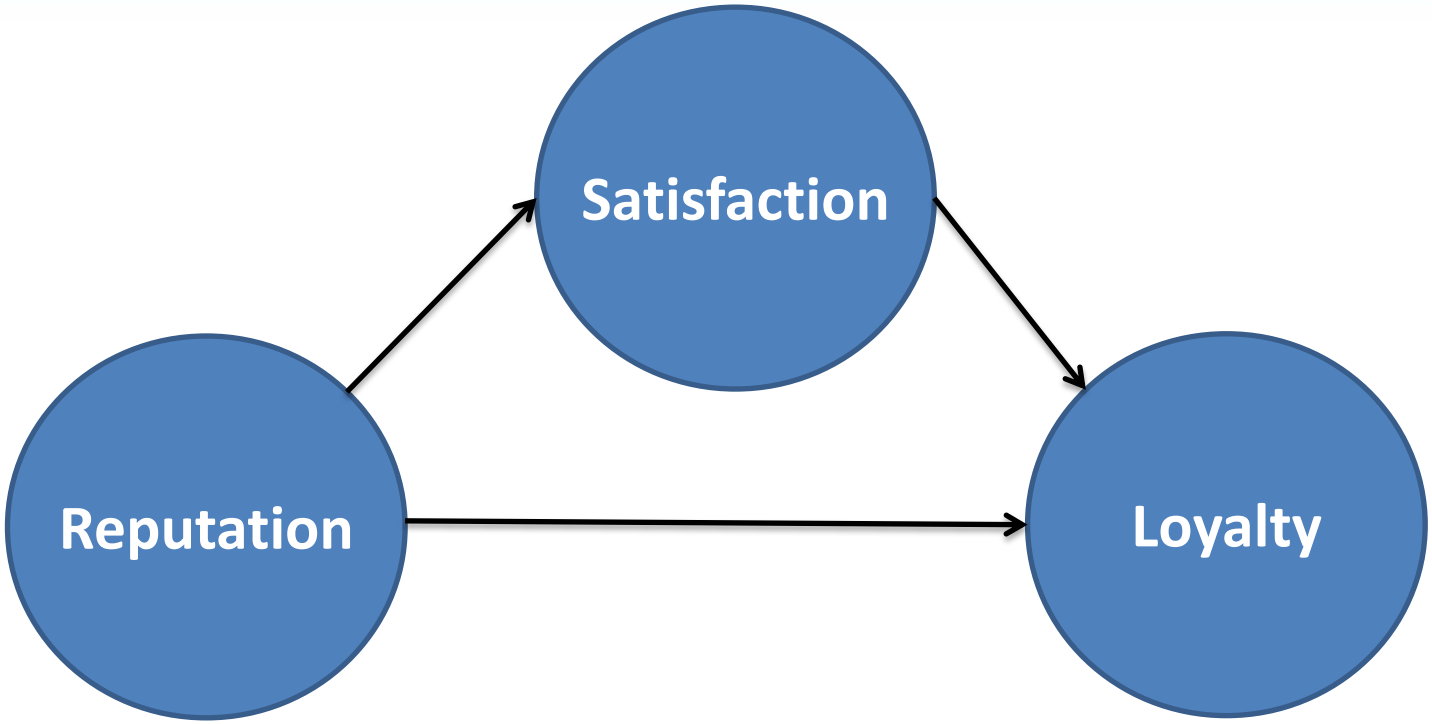
SPECIFYING THE STRUCTURAL MODEL

Independent Constructs in the structural model are generally referred to ***exogenous LVs***

Dependent Constructs in the structural model are referred to as ***endogenous LVs***.

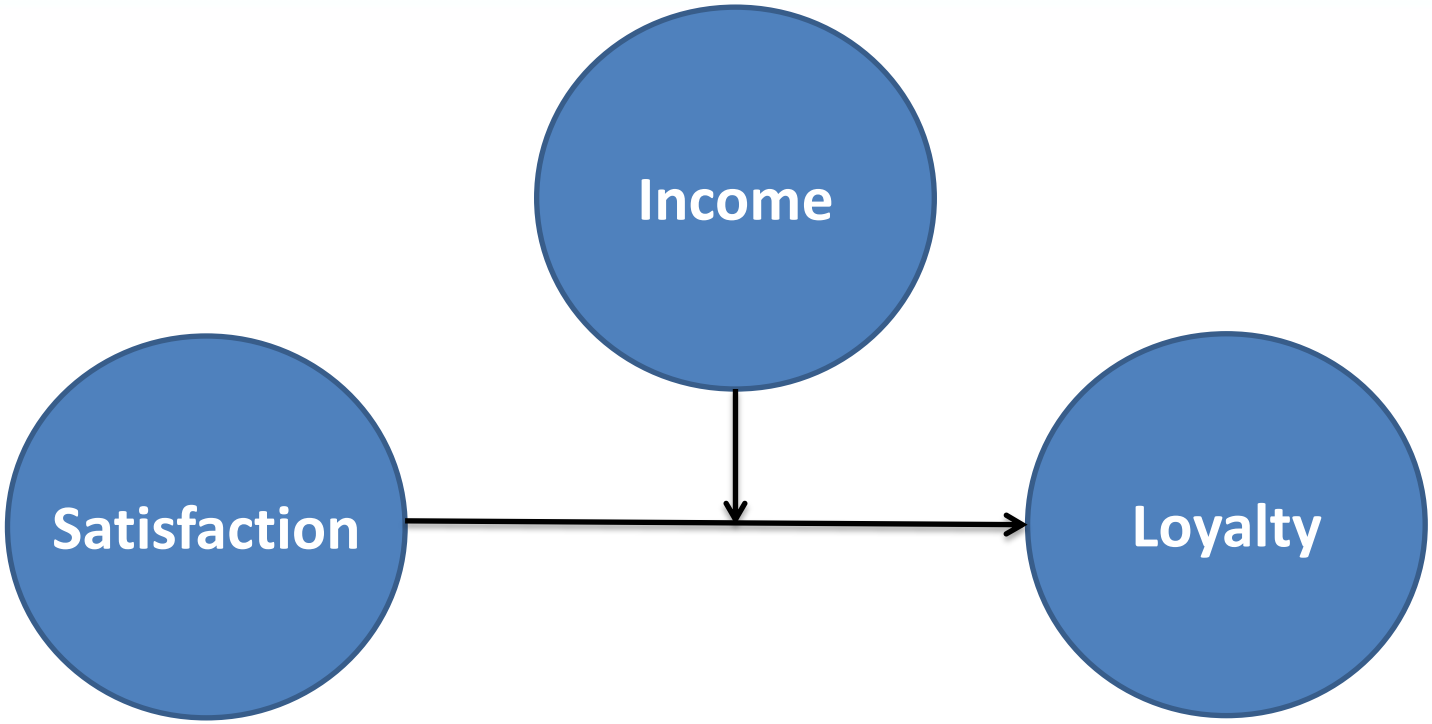
Theory and logic always determine the ***sequence*** of constructs in a structural model.

SPECIFYING THE STRUCTURAL MODEL



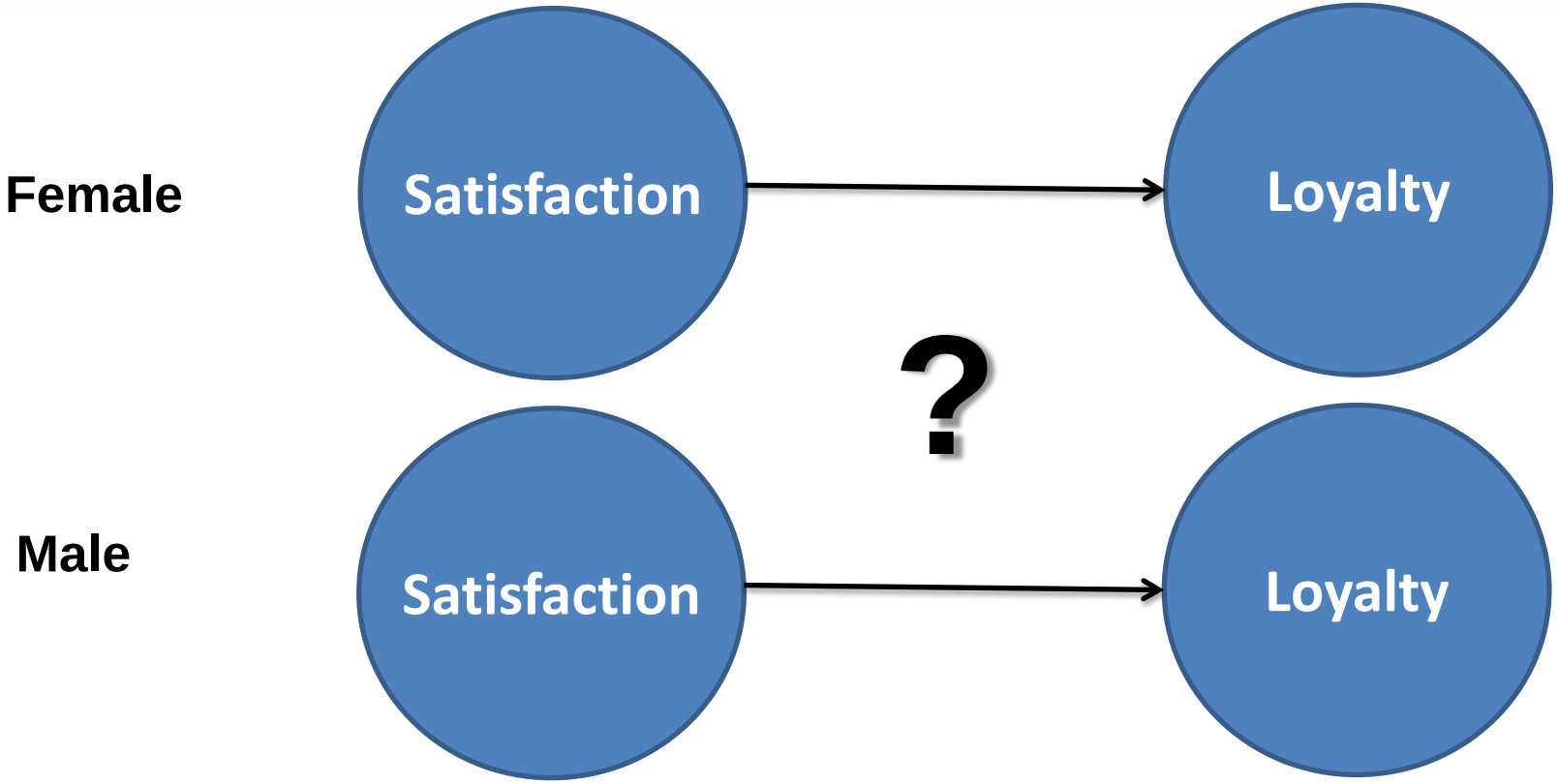
Mediation Effect

SPECIFYING THE STRUCTURAL MODEL



Continuous Moderating Effect

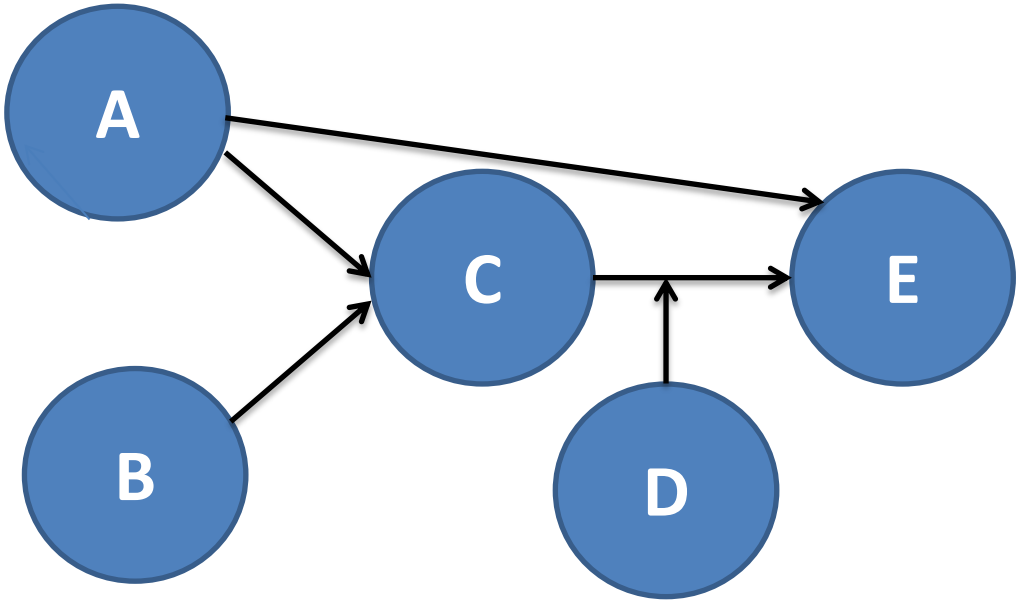
SPECIFYING THE STRUCTURAL MODEL



Categorical Moderating Effect

SPECIFYING THE STRUCTURAL MODEL

- Effects:
  - Direct effect
  - Indirect effect
  - Mediation effect
  - Moderator effect
    - continuous or categorical



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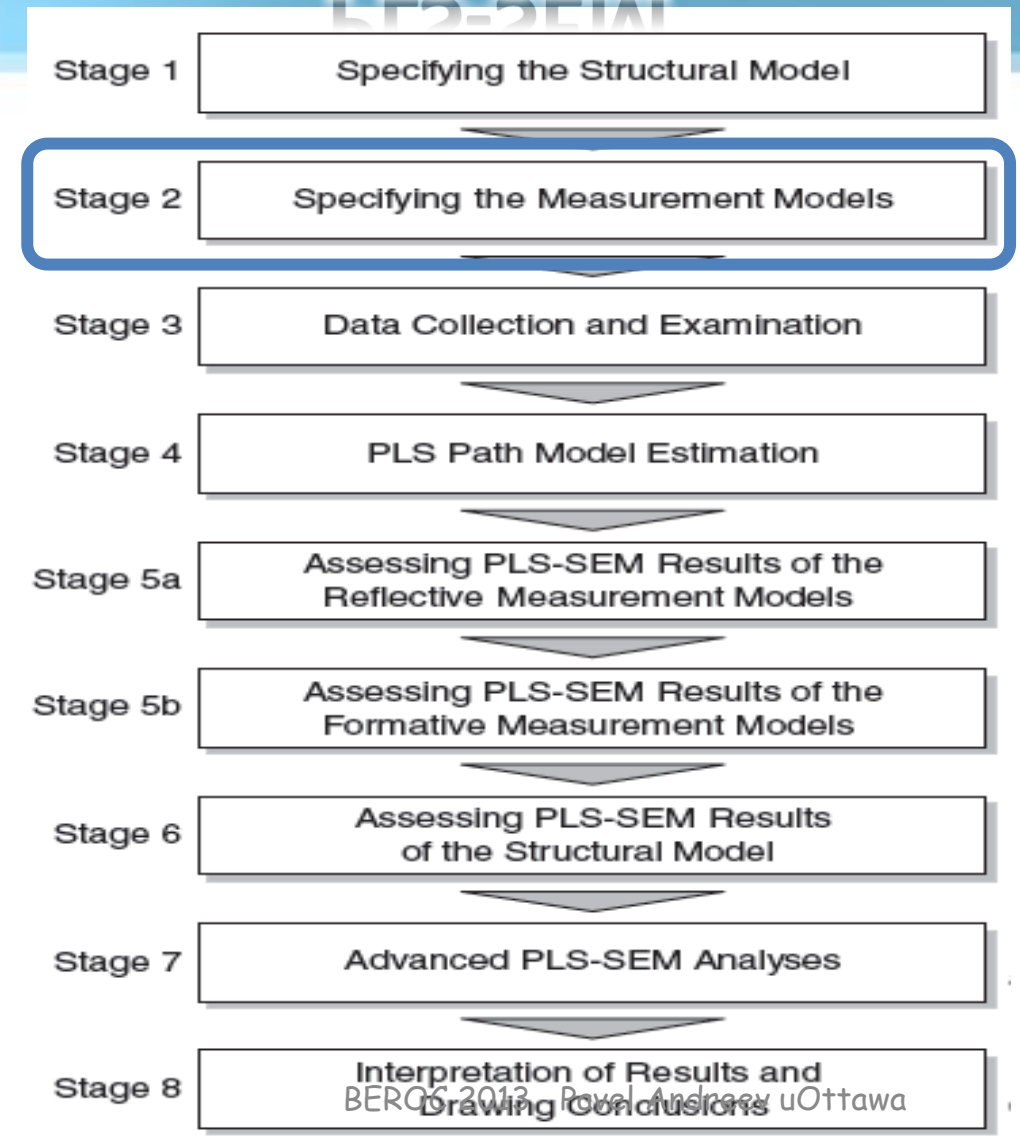
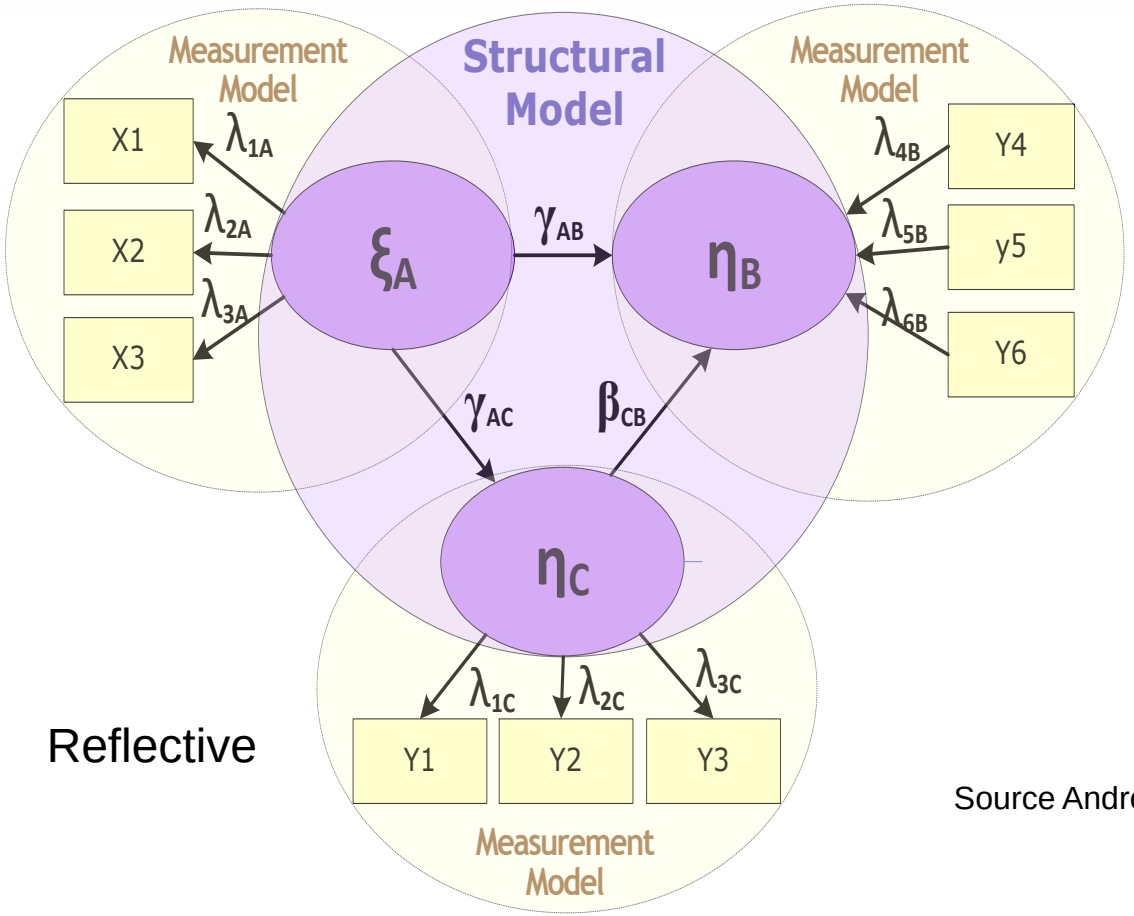
SYSTEMATIC PROCEDURE FOR APPLYING PLS-SEM



Source: Hair et.al. (2013), "A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)"

SEM IN A NUTSHELL
PATH MODEL

Reflective



Formative

Reflective

Source Andreev et.al. (2009)

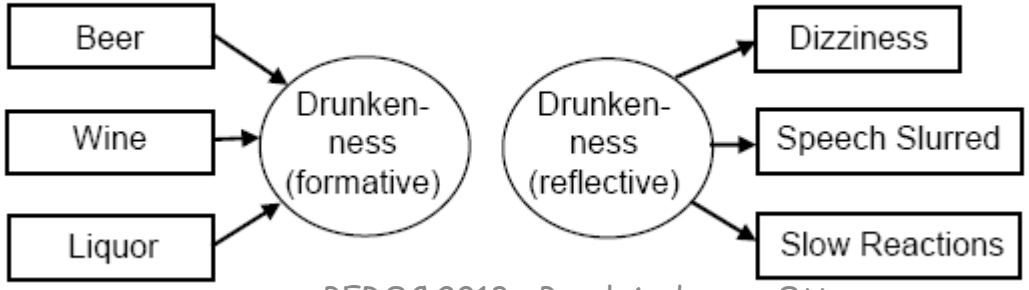
FORMATIVE VS. REFLECTIVE CONSTRUCTS

Formative

- Arrows point towards the latent construct
- Items do not need to co-vary
- Items create the construct rather than created by it
- Should capture the latent construct in its entirety
- Error at the construct level
- Weights are calculated via a multiple regression

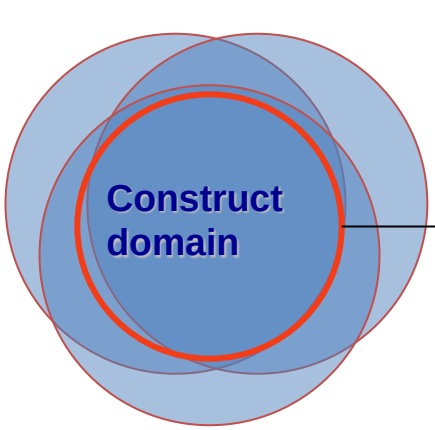
Reflective

- Arrows point away from the latent construct
- Items are expected to co-vary
- Items reflect the construct's concept
- Items are interchangeable, some can be dropped
- Error at the item level
- Loadings are calculated

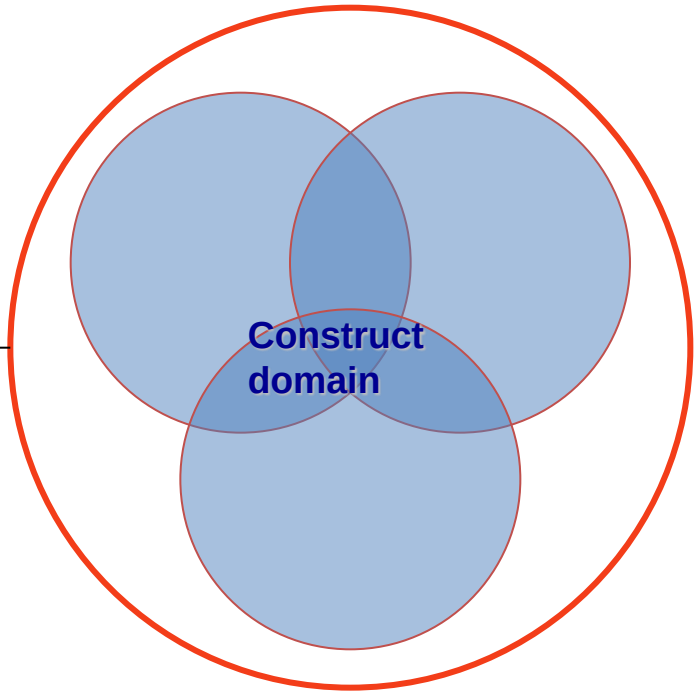


BASIC DIFFERENCE BETWEEN REFLECTIVE AND FORMATIVE MEASUREMENT APPROACHES

The **formative measurement** approach generally **minimizes** the **overlap** between complementary indicators



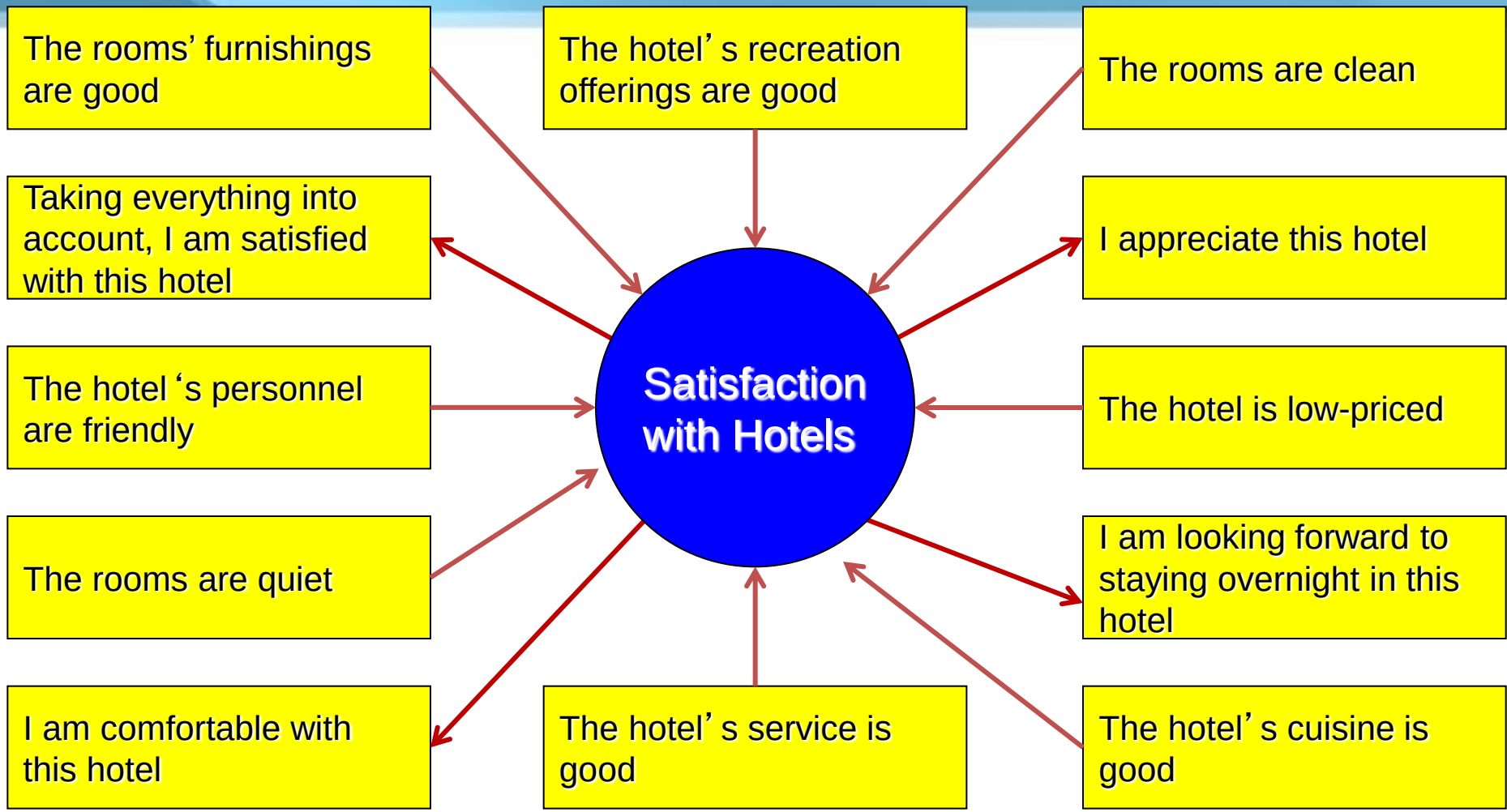
The **reflective measurement** approach focuses on **maximizing** the **overlap** between interchangeable indicators



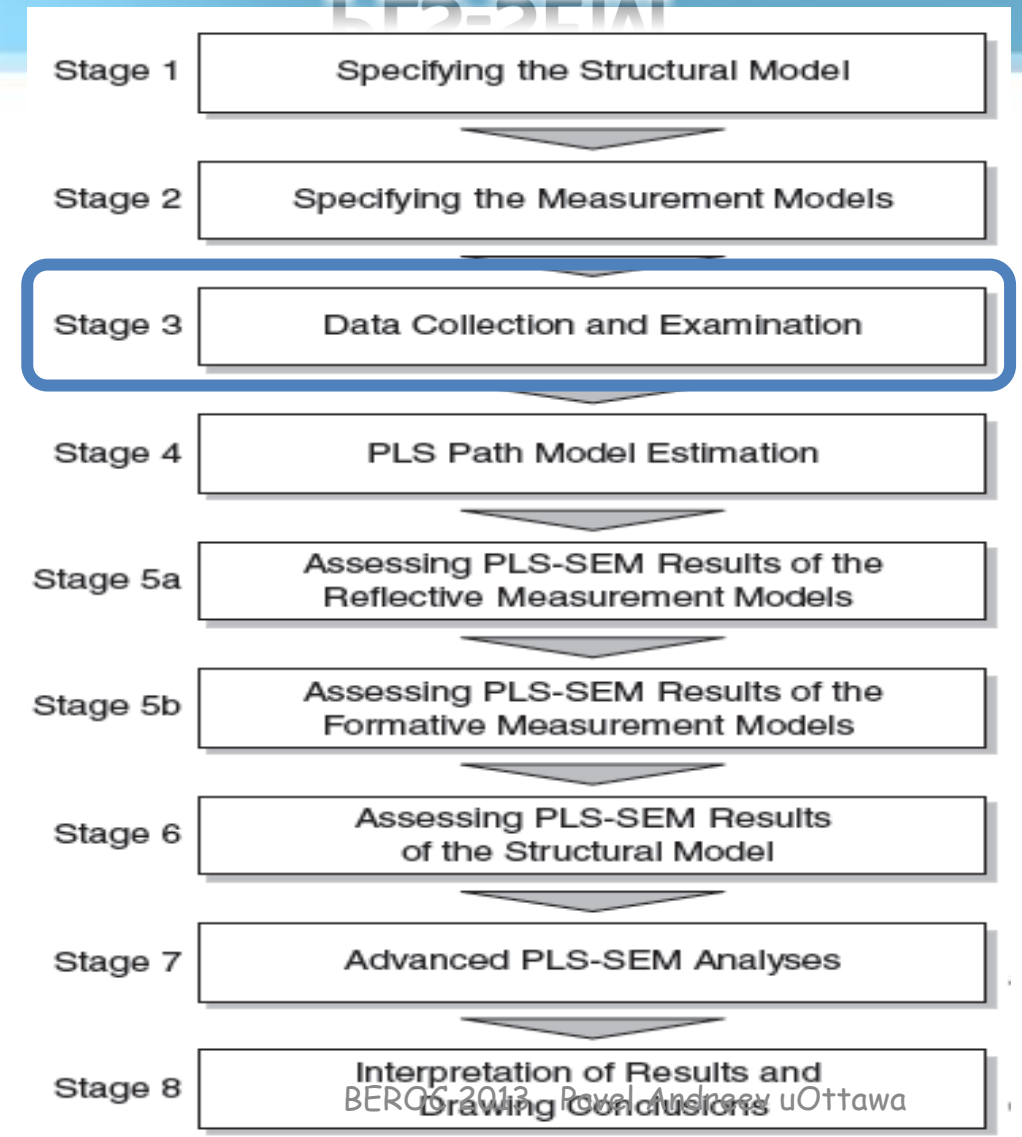
CONSTRUCT IDENTIFICATION DECISION CRITERIA

Rule	Description
Causality	Do items define or reflect the LV? If the indicators define the LV, the construct is *formative*. If the indicators are manifestations of the LV, the construct is *reflective*
The impact of change	*Formative*: Changes in formative measures influence the LV. Change in the LV does not necessarily impact all its observed items. *Reflective:* Changes in the LV impact all measurement items simultaneously.
Item interchangeability	*Formative*: Not interchangeable. *Reflective*: interchangeable
Item correlations	F*ormative* measures do not have to be correlated. *Reflective:* highly correlated
Antecedents and consequences	*Formative:* antecedents of the LV, may stem from various content domains. *Reflective:* consequences of the LV hence represent one content domain

EXERCISE: SATISFACTION IN HOTELS AS FORMATIVE AND REFLECTIVE OPERATIONALIZED CONSTRUCTS



SYSTEMATIC PROCEDURE FOR APPLYING PLS-SEM



Source: Hair et.al. (2013), "A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)"

DATA

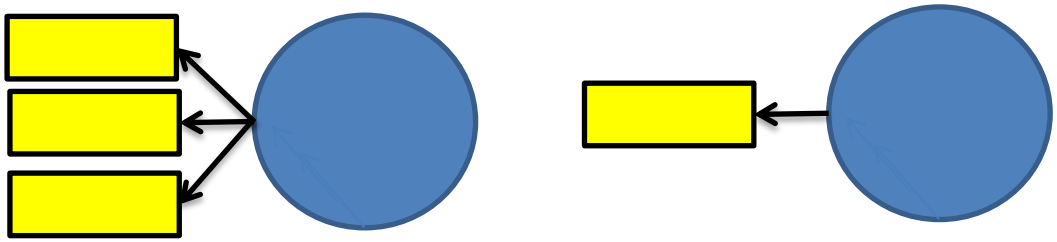
- Data Issues:
  - Data Type
  - Scale
  - Number of Indicators per Construct
  - Distribution
  - Sample size
  - Missing Data

DATA TYPES AND SCALES

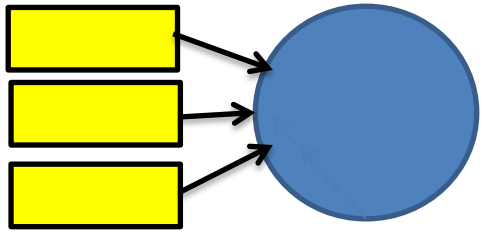
- **Nominal scale** assigns numbers to attribute to name the category. The numbers have no meaning by themselves, e.g. DRG code.
- **Ordinal scale** assigns numbers so that more of an attribute has higher values, e.g. Severity.
- In an **interval scale** the interval between the numbers has meaning, e.g. Fahrenheit scale
- **Ratio scale** is an interval scale where zero has true meaning, e.g. Age.

NUMBER OF INDICATORS PER CONSTRUCT

- Reflective



- Formative



DISTRIBUTION

- PLS-SEM's statistical properties provide very robust model estimations with data that have normal as well as extremely nonnormal (i.e., skewness and/or kurtosis) distributional properties. Collinearity, heteroscedasticity, and influential outliers, however, do influence the OLS regressions in PLS-SEM, and researchers should evaluate the data and results for these issues.

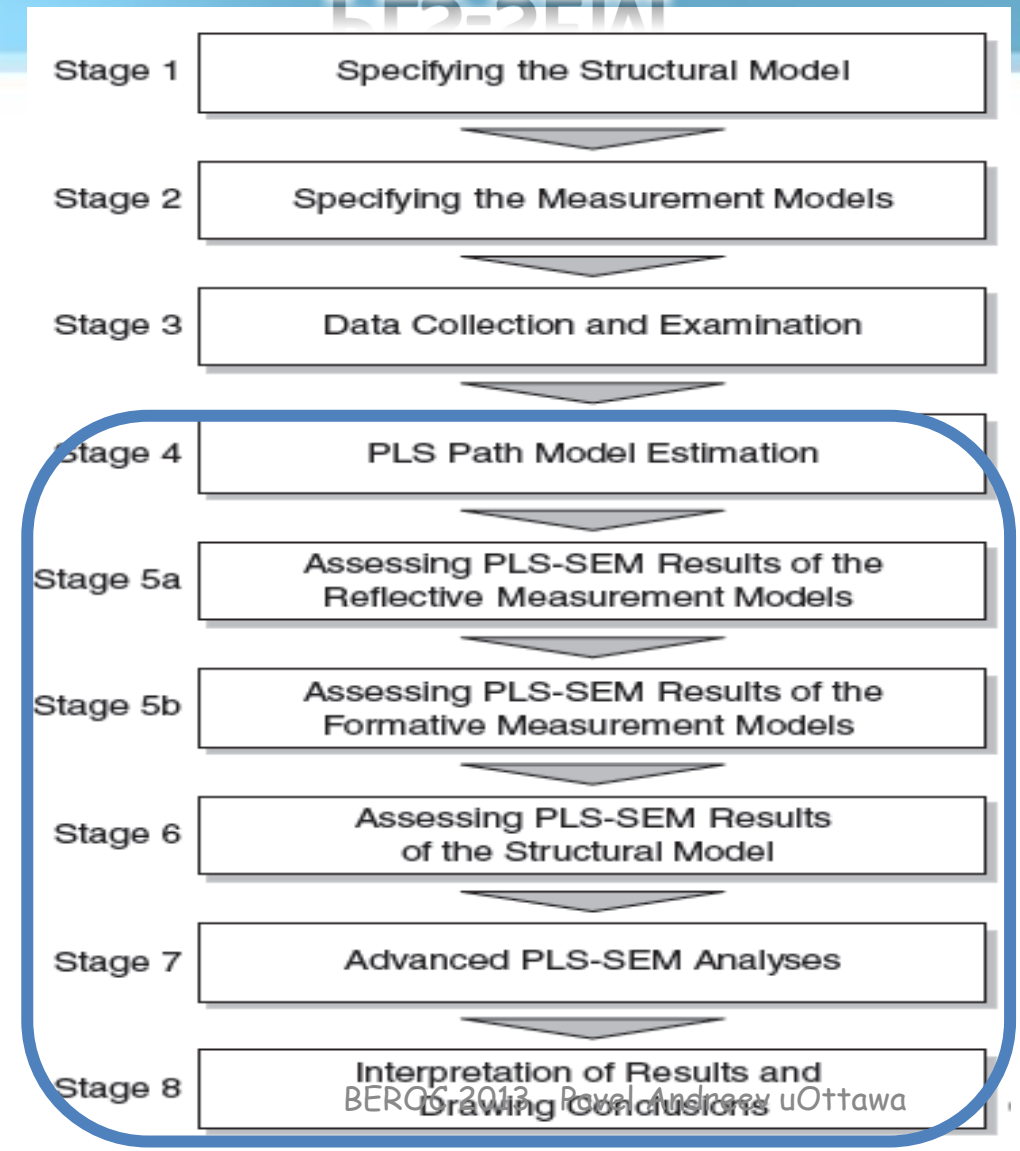
SAMPLE SIZE

- PLS-SEM is less restrictive than CV-SEM regardless of the level of the model complexity.
- The rule of thumb:
  - The 10 times rule indicates the sample size should be not less than:
    - (1) 10 times the largest number of formative indicators used to measure a single construct, or
    - (2) 10 times the largest number of structural paths directed at a particular latent construct in the structural model.

MISSING VALUES

- For reasonable limits (i.e., less than 5% values missing per indicator), missing value treatment options such as mean replacement, EM (expectation-maximization algorithm), and nearest neighbor generally result in only slightly different PLS-SEM estimations.

SYSTEMATIC PROCEDURE FOR APPLYING PLS-SEM



Source: Hair et.al. (2013), "A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)"

AGENDA

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- Examples of research with implementation of PLS as research methodology
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- Assessment of PLS model
  - Guideline for validation procedure
  - Examples of the validation procedure
- Practice (if we have time)

1. Leveraging a Network of Outsiders: Exploring the Sources for Open Innovation and Impacts on Innovation Effects

Pavel Andreev
Joseph Feller
Patrick Finnegan
Philip O'Reilly
Jeffrey Moretz

CHALLENGES

- Innovation expectations
- Information overload
- Penetration of technologies
- The need of dynamically changing BM
- Karim R. Lakhani (2007):
  - companies that perform best and especially in a tough economy are those that **innovate** and are **open** to outside ideas.

BACKGROUND

- Innovation challenge was addressed internally
  - NO innovation exchanges with external parties
  - Leverage the competencies of employees within the context of internal projects
  - exploiting these projects through the existing business models of the firm
- Innovation=Knowledge
  - *"No one company acting alone can hope to out-innovate every competitor, potential competitor, supplier or external knowledge source"* (Quinn 2000 p.13).

OPEN INNOVATION

- "***Open innovation***, "*a paradigm that assumes that firms can and should use external and internal ideas, and internal and external paths to market… The business model utilizes both external and internal ideas to create value*" (Chesbrough 2003 p. xxiv).

EXAMPLES

http://www.openinnovators.net/list-open-innovation-crowdsourcing-examples/

MOTIVATION

- *"The new leaders in innovation will be those who figure out the best way to leverage a network of outsiders"* (Pisano and Verganti 2008)
- Lack of empirical research on the success of the various open innovation strategies that organizations can pursue to be high performance organizations

RESEARCH OBJECTIVE

- To understand how organizations can leverage a network of outsiders to increase their innovation performance
  - explore the impacts of **various sources** of open innovation on an organization's **internal knowledge**, **process** innovation, and **product/service** innovation

BACKGROUND

- Innovation is all about knowledge.
  - An organization's internal knowledge base is widely identified as a key resource for individual firms (e.g. Drucker, 1993; Winter, 1987) and a key driver of competitive advantage (Dunford, 2000; Nonaka et al., 1995).

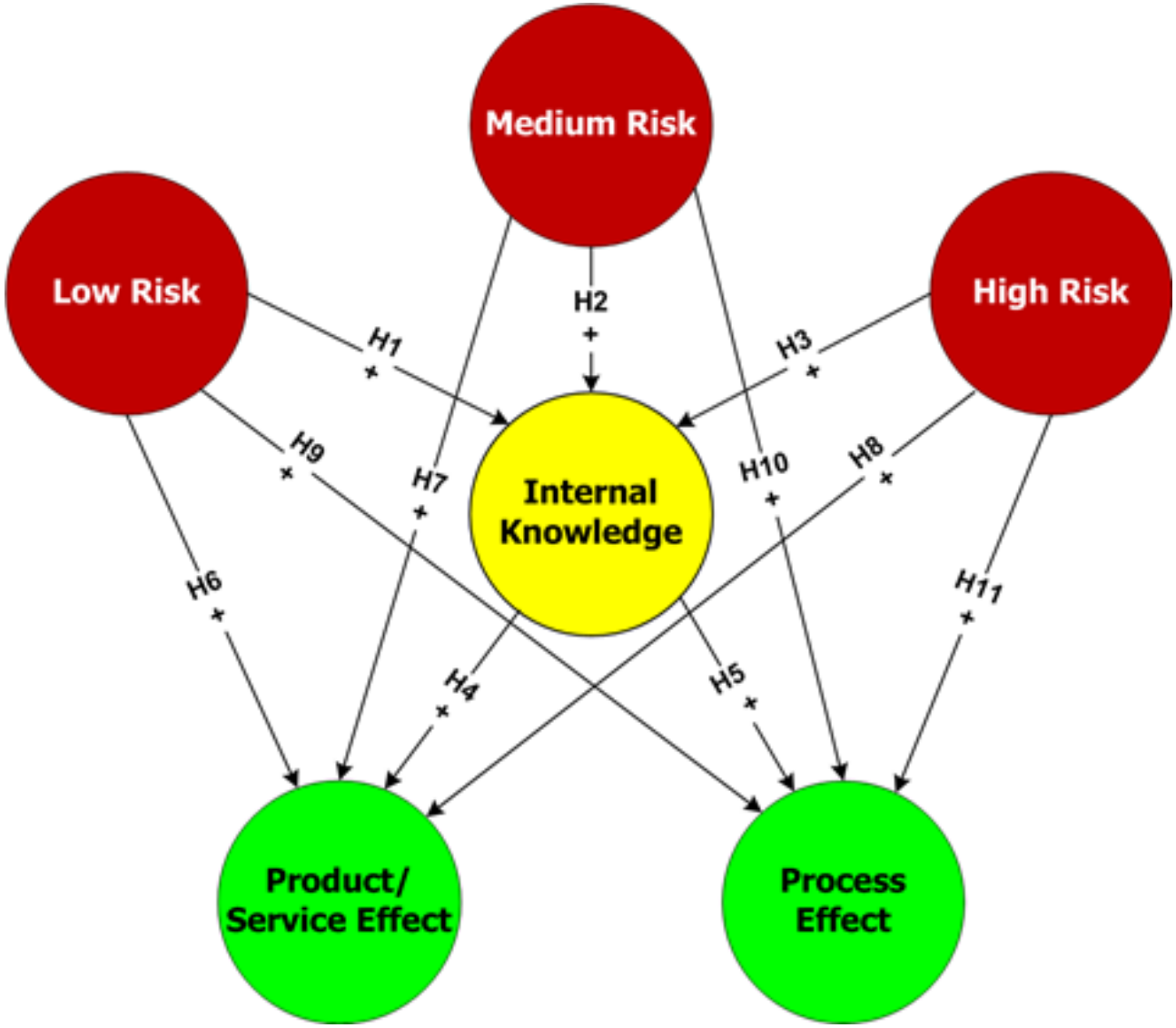
THEORETICAL DEVELOPMENT

- We have categorized the external parties that an organization can engage with when pursuing an open innovation strategy based on risk:
  - Low
  - Medium
  - High

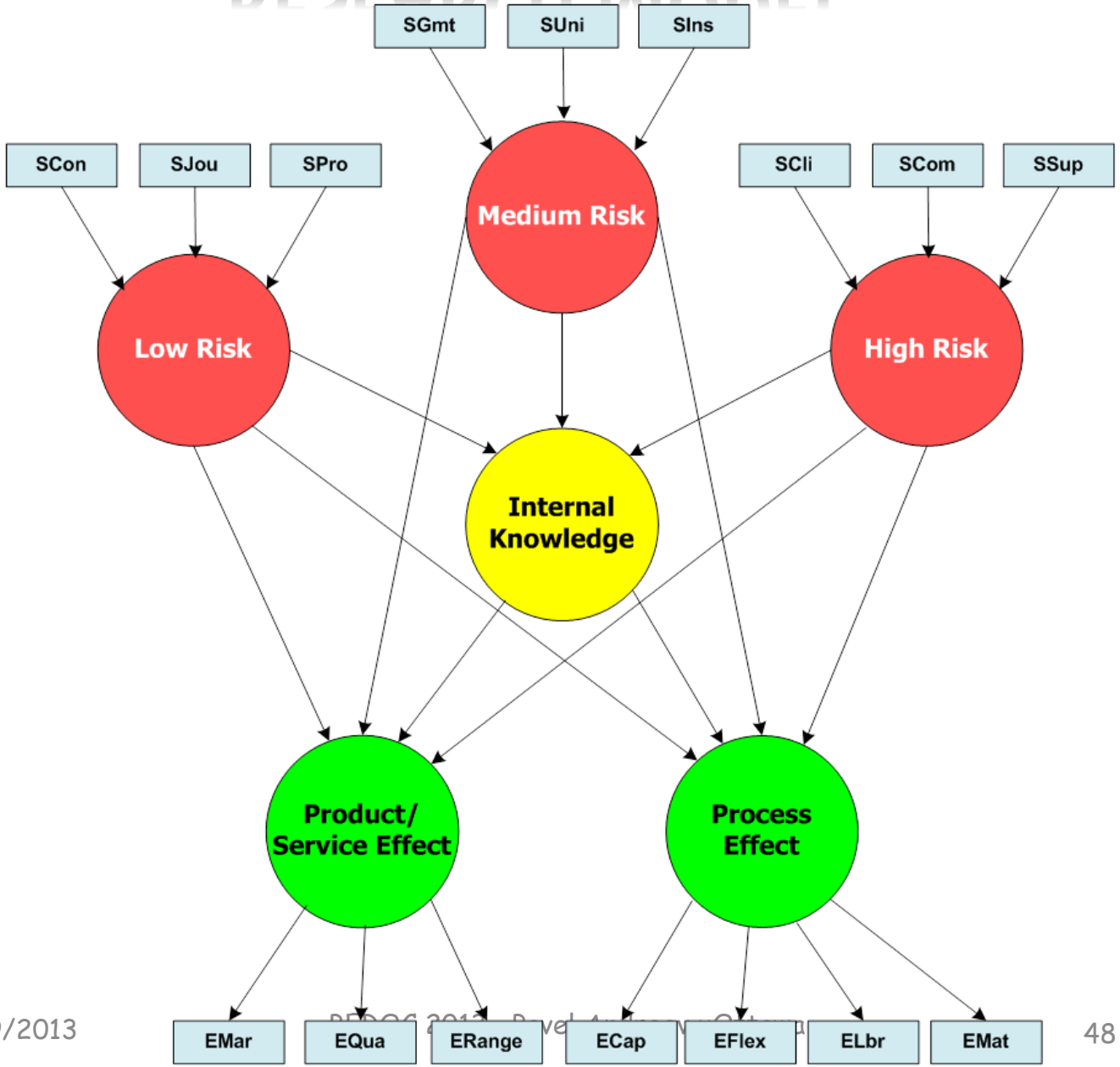
THEORETICAL DEVELOPMENT

Risk Level	Entities
Low	• Scientific journals and trade/technical publications; • Professional and industry associations; and • Conferences, trade fairs, exhibitions.
Medium	• Third party organizations such as universities or other higher education institutions; • Government or public research institutes; and • Consultants, commercial labs, or private R&D institutes.
High	• Clients or customers, • Competitors and • Suppliers

RESEARCH MODEL



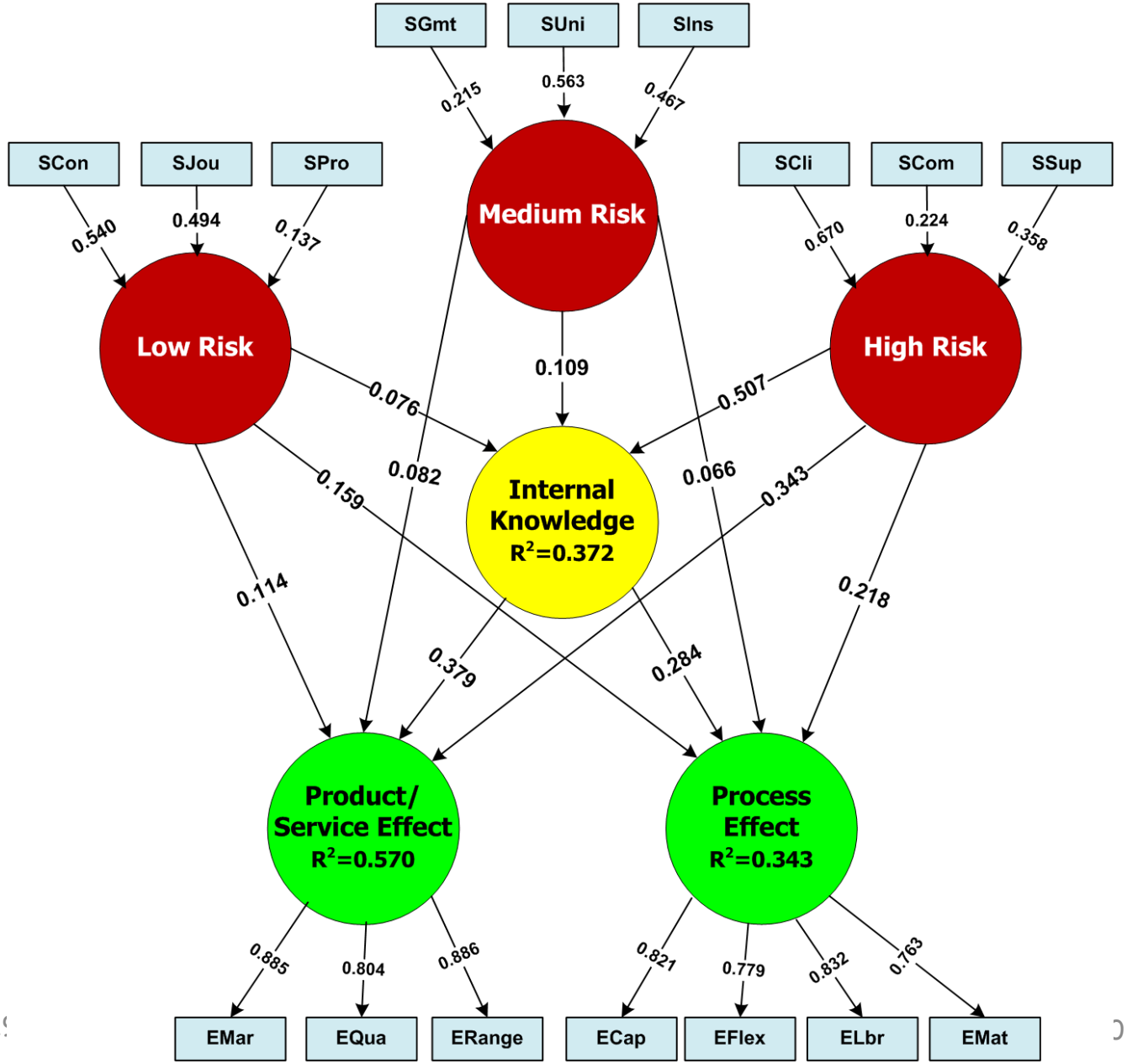
RESEARCH MODEL



DATA

- Data from the 4th Community Innovation Survey (CIS)
  - a series of surveys executed by national statistical offices throughout the EU
- Denmark
  - an 'innovation leader' in the 2008
  - data was obtained from 4,054 companies, representing a response rate of 62%
  - Our dataset reports on 3,236 (after data cleaning)

RESULTS


SGmt
SUni
SIns
0.215
0.563
0.467
SCon
SJou
SPro
0.540
0.494
0.137
Medium Risk
SCli
SCom
SSup
0.670
0.224
0.358
Low Risk
High Risk
0.109
0.076
0.507
0.082
0.159
Internal Knowledge
R²=0.372
0.066
0.343
0.114
0.218
0.379
0.284
Product/ Service Effect
R²=0.570
Process Effect
R²=0.343
0.885
0.804
0.886
0.821
0.779
0.832
0.763
EMar
EQua
ERange
ECap
EFlex
ELbr
EMat

CONTRIBUTION

- Understanding of how open innovation affects an organizational innovation performance
- First conceptualization
- Development & empirical innovation strategies model validation

CONCLUSION I – ABSORPTIVE CAPACITY

- There is a need to ensure meaningful engagement with external sources.
  - The relatively low impact of traditional external sources of innovation (considered low and medium risk) on internal knowledge
  - The imperative to engage with competitors, suppliers, and customers in order to enhance innovation knowledge within an organization.

CONCLUSION II

- The effect of high-risk innovation sources on process and product/service innovation is revealed **being as important** as the effect of internal innovation knowledge.
- The most dramatic improvements in innovation may be derived from working with competitors, customers, and suppliers.

2. To M-Pay or not to M-Pay – Realizing the Potential of Smart Phones: Conceptual Modeling and Empirical Validation

Pavel Andreev
Philip O'Reilly
Aidan Duane

THE PURPOSE OF THE STUDY

To conceptualize consumers' willingness to use *Smart Mobile Media Devices (SMMD)* for *M-Payments* for products/services, and to empirically validate the model.

DEFINITION – M-PAYMENT

"M-Payments are payments made or enabled through digital mobility technologies, via SMMD, with or without the use of mobile telecommunications networks. These payments are digital financial transactions, although not necessarily linked to financial institutions or banks"

Dinez et al. (2011)

DEFINITION - SMMD

- The **Smart Phone** is dead, long live the **SMMD**
- A **Smart Mobile Media Device (SMMD)** is an electronic mobile networked device that provides mobile network subscribers with integrated functions and *Smart Mobile Media Services* (SMMS) including:
  - phone, SMS and MMS; GPS and LBS; photo and video cameras; music players/recorders; email and mobile web access; and downloadable free/fee based applications; etc.

DEFINITION – SMMS

- **Smart Mobile Media Services (SMMS)** provide mobile network subscribers with:
  - permission and subscription based, dynamically profiled, location, context, and task specific, Mobile Web applications, content, products, services, and transactions for a *Smart Mobile Media Device*.

M-PAYMENT FACILITATES THE GROWTH OF SMMS

- A variety of technologies:
  - NFS-powered SMMD
  - Square (Richard Branson)
  - MNOs, banks, financial institutions…
- However, willingness to M-Pay is still low

THE RESEARCH ISSUE

- The commercial potential of SMMS via SMMD for M-Commerce organizations is enormous
- M-Payment completes M-Commerce transactional loop
- Willingness to M-Pay is the greatest impediment to Smart Mobile Media Services (SMMS) adoption.
- While growth forecasts for M-Payment have been very positive, the reality is quite different
  Schierz et al. (2010)

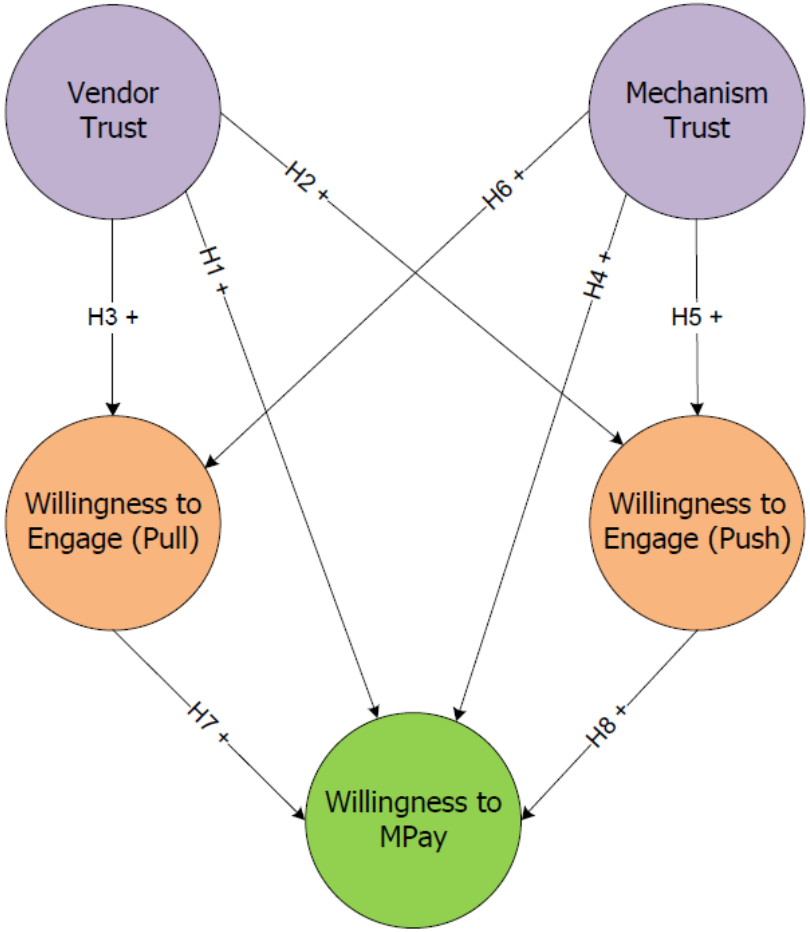
THE RESEARCH ISSUE

- Realizing consumers' willingness to use *Smart Mobile Media Devices (SMMD)* for *M-Payments* is highly critical to expend the performance horizon
- If Smart Mobile Media Services are to realise their full potential, the ability of consumers to Transact and M-Pay using their Smart Mobile Media Devices in an easy, secure, reliable, and consistent manner must be addressed.
- The lack of research is of concern

THEORETICAL BACKGROUND

- Technology Acceptance Model - **TAM** (Davis,1989)
- Diffusion of innovations - **DoI** (Rogers,1995, 2002)
- Perceived characteristics of innovations - **PCI** (Moore & Benbasat, 1991).

SMMS M-PAYMENT CONCEPTUAL MODEL



VENDOR AND MECHANISM TRUST INDICATOR DESCRIPTIONS

Table 2. Vendor and Mechanism Trust		
Constructs	Variable	Literature
Vendor Trust	*Perceived Security Control*: M-Commerce consumers perceptions of vendors' adequacy of security measures and their ability to secure personal private data	(Cheung and Lee 2003)
	Perceived Privacy Control: The M-Commerce consumers' perceptions of vendors' abilities and commitment to protect personal private data collected during registration, interaction, transaction and M-Payments from unauthorised use or disclosure	(Cheung and Lee 2003)
	Perceived Integrity: The M-Commerce consumers perceptions of vendors' honesty	(Cheung and Lee 2003; Gefen 2002)
	Perceived Ethical Commitment: The M-Commerce consumers' perceptions of vendors' commitment to being ethically responsible in the capturing, retaining, processing and management of personal data	(Dinev 2006; Garbarino and Lee 2003; Gefen 2002; Pavlou and Dimoka 2006; Treiblmaier and Chong 2007)
	Perceived Competence: The M-Commerce consumers' perceptions of the technical expertise, resources and knowledge of the vendors to provide the product/service required.	(Dinev 2006; Gefen 2002; Pavlou and Dimoka 2006; Sirdeshmukh et al. 2002; Treiblmaier and Chong 2007)
Mechanism Trust	*Legal Framework*: The legislation in place to protect a consumers data & privacy	(Cheung and Lee 2003)
	Regulatory Body: An independent party responsible for the enforcement of the legislation governing mobile consumers' data and ensuring vendor compliance with same.	(Cheung and Lee 2003)

WILLINGNESS TO ENGAGE INDICATOR DESCRIPTORS

Table 4. Willingness to Engage Constructs

Constructs	Variable	Literature
Willingness to Engage: Pull-Model SMMS	*GPS services*: Consumers' willingness to use GPS based services through their Smart Phone	Bruner and Kumar, 2007; Tsang et al., 2004;
	Information Services: Consumers' willingness to use Smart Phones to find information on goods/services	Chang et al., 2009
	Reservation Services: Consumers' willingness to use Smart Phones for booking/reservation tasks	Ngai and Gunasekaranb, 2007
	Ticketing: Consumers' willingness to use Smart Phones for ticketing tasks	Bruner and Kumar, 2007; Tsang et al., 2004
Willingness to Engage: Push-Model SMMS	*Unsolicited Ads*: Consumers' perceptions of unsolicited generic advertisements	Bruner and Kumar, 2007; Tsang et al., 2004
	Personalised Advertisements: Consumers' perceptions of receiving solicited advertisements customised to their specific interests/preferences	Leppaniemi and Karjaluoto, 2005
	Unsolicited Discounts: Consumers' perceptions of receiving unsolicited discounts on their Smart Phones	Leppaniemi and Heikki, 2005
	Unsolicited Location Based Messages: Consumers' perceptions of receiving unsolicited advertisements specific to business products/services of interest to them near their location	Bruner and Kumar, 2007; Tsang et al., 2004

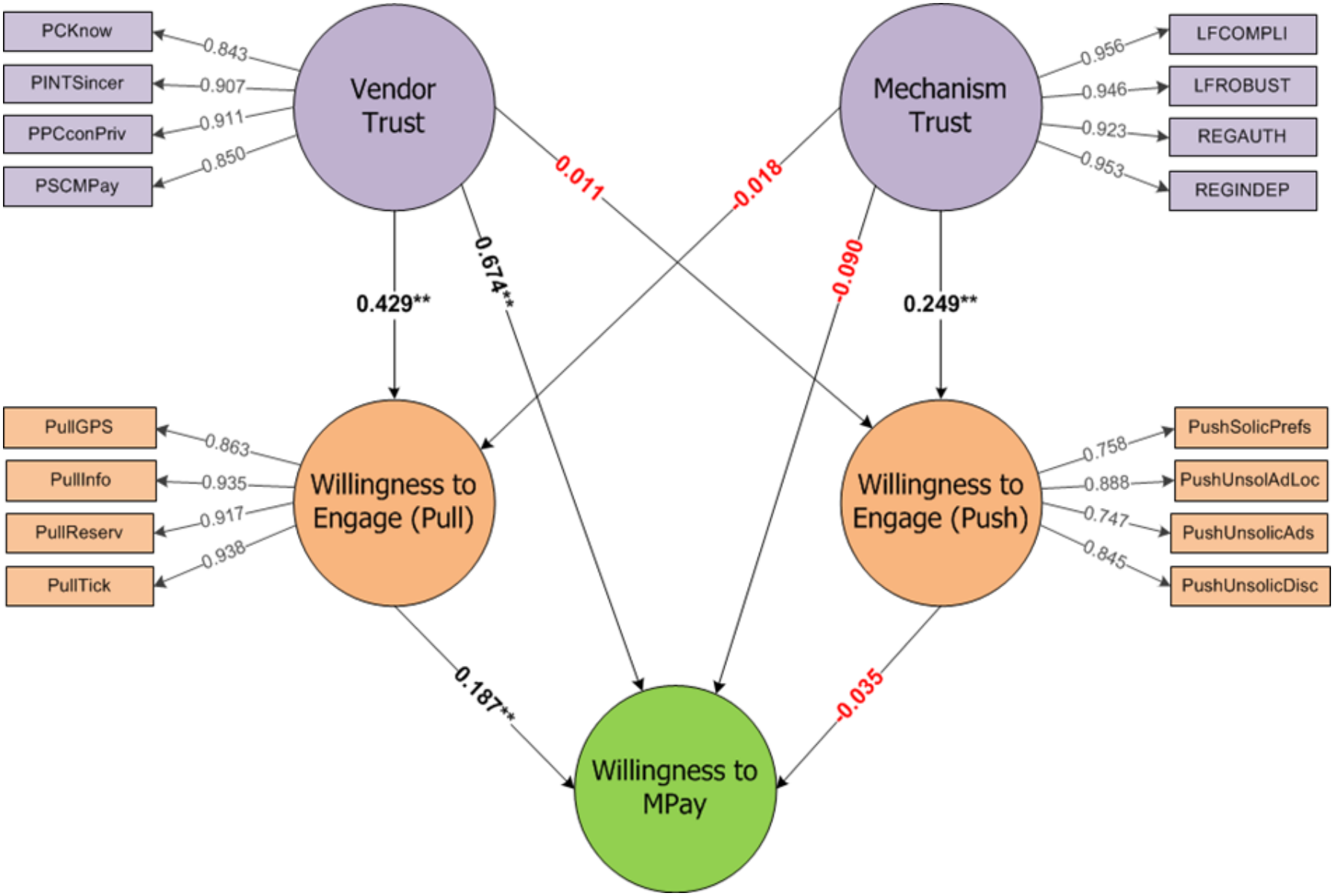
RESEARCH METHOD

- Data Collection
  - Survey pre-tested with SMMS “experts”.
  - Then hosted on Survey Monkey for 1 month in June 2010.
    - 82 valid responses from 12 of 26 Irish regions – 3 largest cities accounted for 68% of responses.

ANALYSIS

Descriptive Statistics

Prefer not to say	7.41%	18-21 yrs	3.70%	< €1.00	55.56%	Primary Level	0.00%
< €20,000	12.35%	22-25 yrs	9.88%	€1.00-2.00	11.11%	2nd Level	3.70%
€20,000-30,000	8.64%	26-30 yrs	13.58%	€2.01-5.00	16.05%	3rd Level Under-Graduate	28.40%
€30,001-40,000	7.41%	31-35 yrs	20.99%	€5.01-10.00	7.41%	3rd Level Post-Graduate	56.79%
€40,001-50,000	12.35%	36-40 yrs	32.10%	€10.01-20.00	3.70%	4th Level (PhD, Post-doc)	11.11%
€50,001-60,000	17.28%	41-50 yrs	17.28%	€20.01-30.00	2.47%		
€60,001-70,000	7.41%	51-60 yrs	1.23%	€30.01-50.00	1.23%		
€70,001-80,000	9.88%	>60 years	1.23%	> €50.00	2.47%		
> €80,000	17.28%						


PCKnow
PINTSincer
PPCconPriv
PSCMPay
0.843
0.907
0.911
0.850
Vendor Trust
Mechanism Trust
LFCOMPLI
LFROBUST
REGAUTH
REGINDEP
0.956
0.946
0.923
0.953
0.011
-0.018
0.674**
-0.090
0.429**
0.249**
PullGPS
PullInfo
PullReserv
PullTick
0.863
0.935
0.917
0.938
Willingness to Engage (Pull)
Willingness to Engage (Push)
PushSolicPrefs
PushUnsolAdLoc
PushUnsolicAds
PushUnsolicDisc
0.758
0.888
0.747
0.845
0.187**
-0.035
Willingness to MPay

KEY RESEARCH FINDING 1

- The study presents evidence of the association between Vendor Trust and consumers' Willingness to make an M-Payment using an SMMD.
  - Vendor Trust and consumer's Willingness to Engage in Pull SMMS positively impact on consumers' Willingness to Make an M-Payment.
  - The study shows that Vendor Trust does not statistically impact on Willingness to Engage in Push SMMS.

THIS MAY MEAN THAT CONSUMERS:

- are more willing to M-Pay for products/services proactively searched for and pulled to their SMMD from a trusted Vendor, while less likely to M-Pay for products/services pushed to their SMMD by Vendors without being asked to do so.
- perceive greater control over pull-based services as the decision to initiate contact with the Vendor is volitional and location based information may only be provided to complete the transaction.

KEY RESEARCH FINDING 2

- The study shows that Willingness to Engage in Push is positively impacted by Mechanism Trust.
  - Two measurement variables of Mechanism Trust (LFCOMPLI and LFROBUST) that represent compliance and robustness of the legal framework also have a high loading on Vendor Trust.
- The study shows that Mechanism Trust does not statistically impact consumer's Willingness to M-Pay.

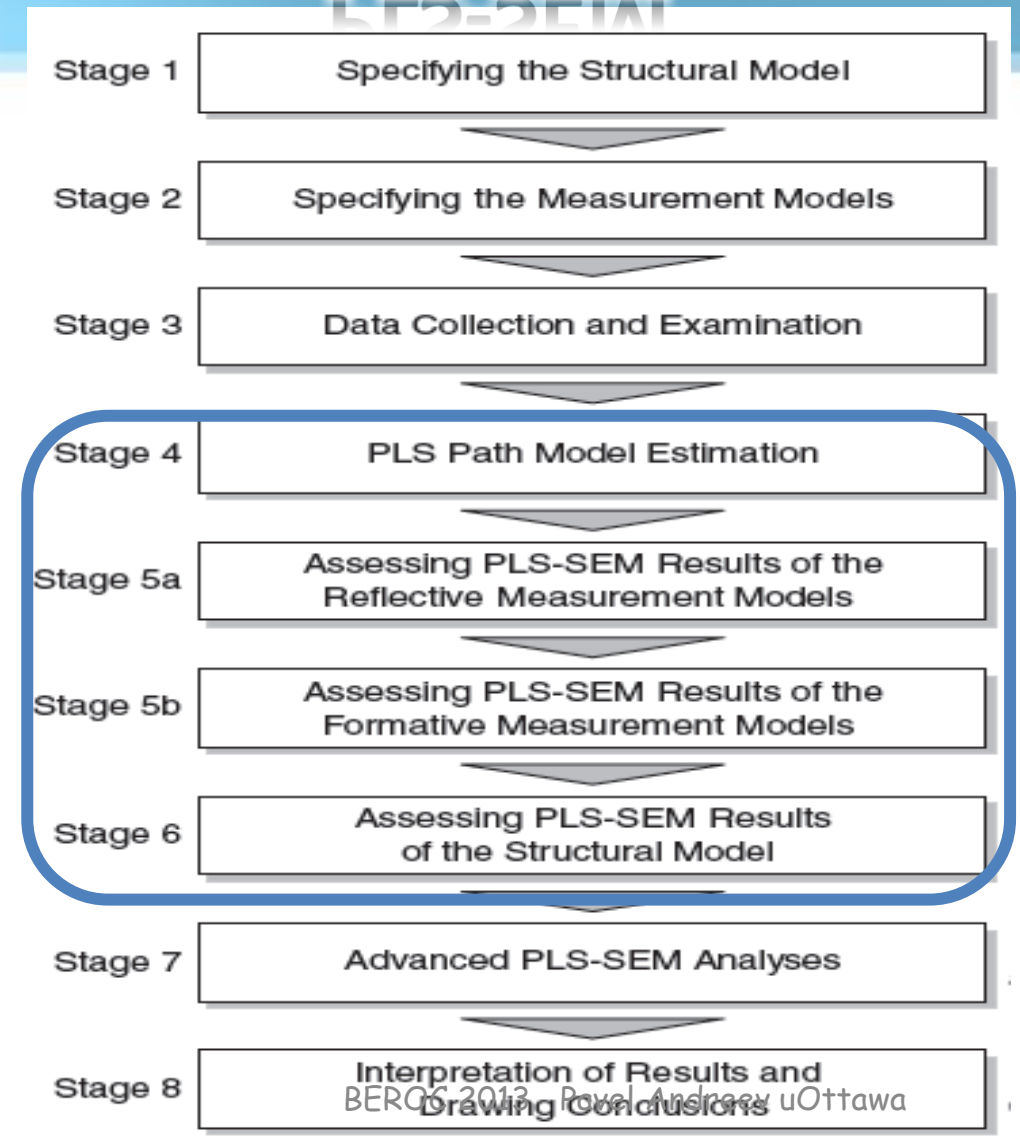
THIS MAY MEAN THAT CONSUMERS:

- are more concerned with legislation and regulation as it pertains to Push Model SMMS and Vendor Trust.
- may be more Willing to Engage in Push SMMS with Vendors in the future, once there is adequate legislation to protect data and privacy, and an independent party responsible for the enforcement of the legislation.

AGENDA

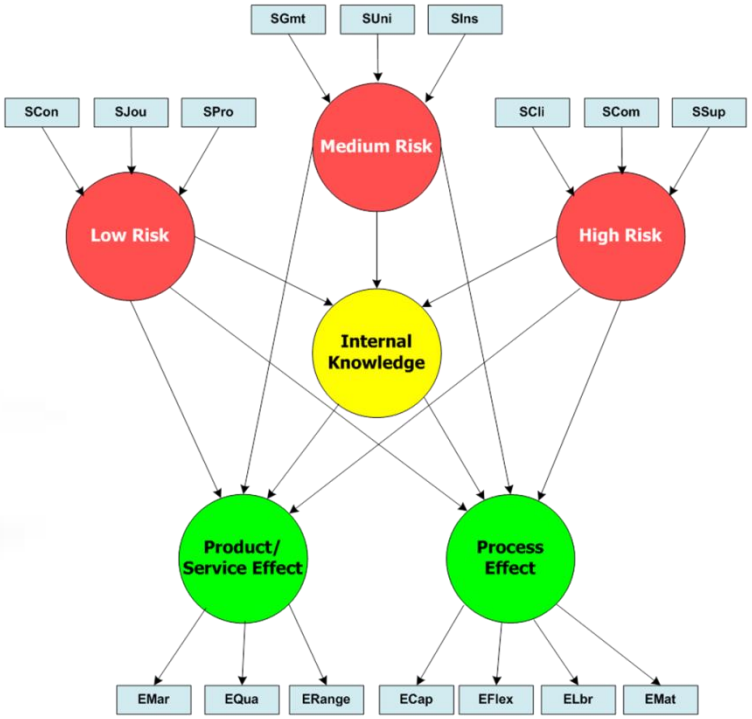
- Introduction to PLS modeling basics
- Examples of research with implementation of PLS as research methodology
  1. Modeling Open Innovation strategies of an organization
  2. Modeling Willingness to conduct m-payments
- Assessment of PLS model
  - Guideline for validation procedure
  - Examples of the validation procedure
- Practice (if we have time)

SYSTEMATIC PROCEDURE FOR APPLYING PLS-SEM



Source: Hair et.al. (2013), "A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)"

ASSESSMENT OF PLS MODEL



PLS MODEL EVALUATION

- Model Evaluation
  - Testing the quality of the measurement models (outer)
    - Reliability
    - Validity
  - Assessment of the structural model (inner)
    - Assessment of effects
    - Prediction quality
  - SmartPLS 2.0 M3 was used for the PLS model assessment.

ASSESSMENT OF PLS MODEL

- Stage 5: Measurement Models

Reflective	Formative
Reliability	
Internal Consistency reliability • Cronbach's Alpha or/and • Composite reliability	NA
Indicator Reliability	*Significance and relevance of weights*
Validity	
Convergent validity (AVE)	*Convergent validity*
Discriminant Validity	*Collinearity among indicators*

MEASUREMENT MODELS ASSESSMENT

Reliability*:*

- *Internal consistency reliability might be tested either by Cronbach's, which indicates an estimation for the reliability assuming that all items are equally reliable, or by composite reliability*
  - Composite Reliability & Cronbach's Alpha values are above 0.811, while the requirement value is only above 0.7 (early stage research) (Chin, 1998)

Construct	Composite Reliability	Cronbach's Alpha
Process Effect	0.876	0.811
Product/Service Effect	0.894	0.821

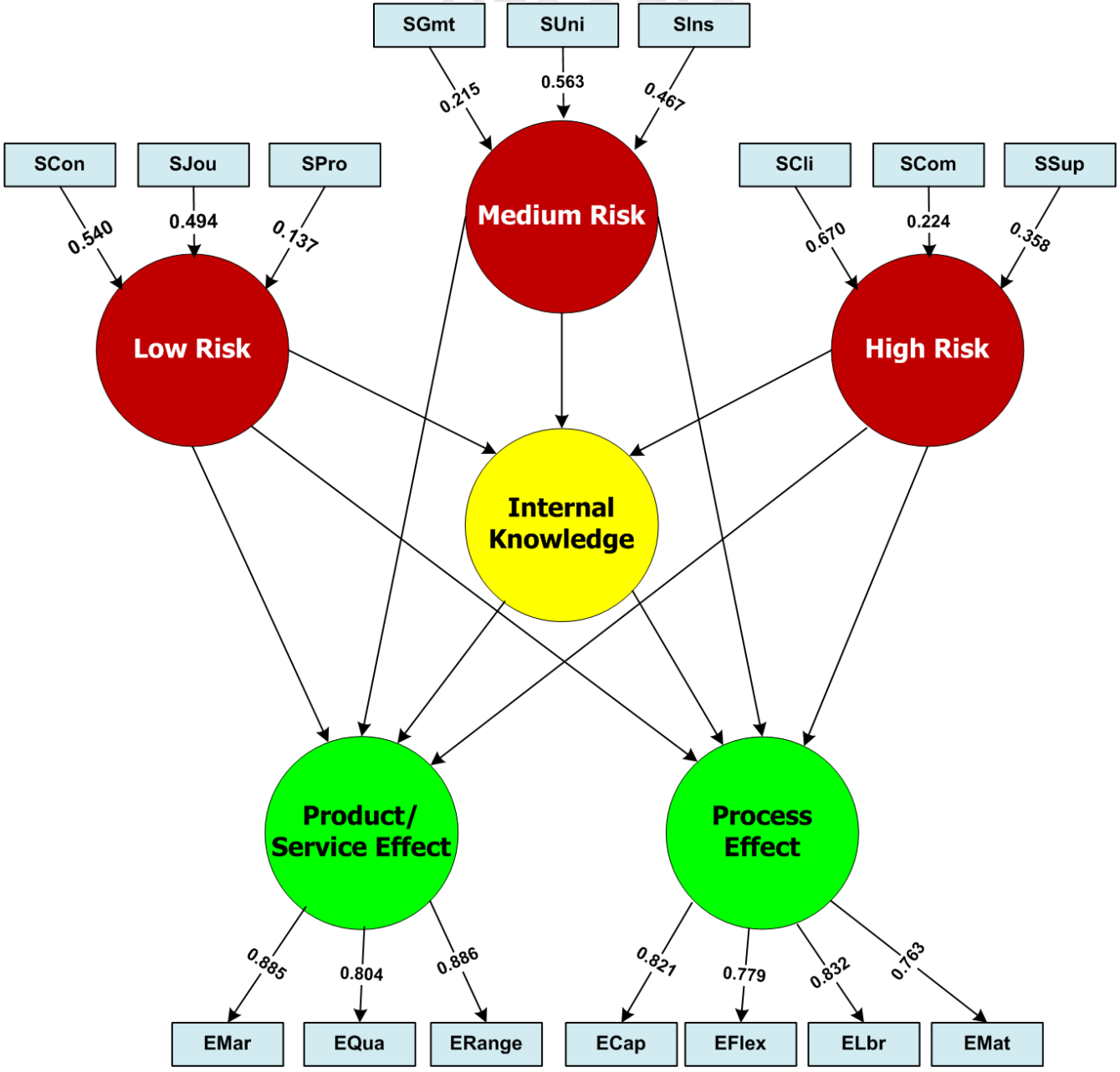
MEASUREMENT MODELS ASSESSMENT

Reliability*:*

- *Individual Indicator Reliability:*
  - Relies on the expectation that latent variable variance should explain at least 50% of the indicator. In other words, loadings of manifest variables should not be less than 0.707 (Chin, 1998).

Construct/Measures	Loading	SD	t-stat.	p-value
Innovation Process Effect				
Increased Capacity	0.822***	0.007	116.14	0.000
Improved Flexibility	0.779***	0.008	93.18	0.000
Reduced Labor Costs	0.832***	0.006	142.12	0.000
Reduced Materials	0.763***	0.009	88.28	0.000
Innovation Product/Service Effect				
New/Increased Market	0.885***	0.004	203.75	0.000
Improved Quality	0.804***	0.008	102.93	0.000
Increased Range	0.886***	0.004	199.97	0.000

RESULTS


SGmt
SUni
SIns
0.215
0.563
0.467
SCon
SJou
SPro
SCli
SCom
SSup
0.540
0.494
0.137
0.670
0.224
0.358
Medium Risk
Low Risk
High Risk
Internal Knowledge
Product/ Service Effect
Process Effect
0.885
0.804
0.886
0.821
0.779
0.832
0.763
EMar
EQua
ERange
ECap
EFlex
ELbr
EMat

MM ASSESSMENT– CONVERGENT AND DISCRIMINANT VALIDITY

- Convergent Validity
  - Average variance extracted (AVE – Column 1) for all constructs is higher than 0.5, and means that each latent variable explains more than 50% of their indicator.
- Discriminant Validity
  - Constructs have sufficient discriminant validity as the square root of each latent construct's AVE (values on the diagonal) is larger than the correlation of the specific construct with any other reflective constructs in the model.

AVE	Construct	Inter Knowledge	Process Effect	Prod/Service Effect
1.000	Inter Knowledge	1		
0.639	Process Effect	0.503	0.799	
0.738	Product/Service Effect	0.660	0.623	0.859

DISCRIMINANT VALIDITY USING A CROSS LOADINGS TEST

- *Discriminant Validity*
  - Also tested with a cross-loading test (next slide) which demonstrates that any indicator of any specific reflective construct has a higher loading on its own construct than on any other constructs' (horizontal loading).
- These results show that the manifest variables (indicators) presented in the model are reliable and valid.

DISCRIMINANT VALIDITY USING A CROSS LOADINGS TEST

Reflect Construct	Items	Prod/Service Effect	Process Effect	Internal Knowledge	Low Risk	Med Risk	High Risk
Product/ Service Effect	EMar	0.8851	0.5283	0.5574	0.4321	0.4051	0.5815
	EQua	0.8037	0.5983	0.5612	0.444	0.3207	0.5622
	ERange	0.8862	0.4804	0.5802	0.4072	0.3503	0.5734
Process Effect	ECap	0.4757	0.8215	0.4015	0.3275	0.2545	0.375
	EFlex	0.5538	0.7786	0.4597	0.3671	0.2357	0.4366
	ELbr	0.5012	0.8319	0.3835	0.3286	0.2653	0.4144
	EMat	0.4512	0.7627	0.3526	0.3372	0.3236	0.3759
Internal Knowledge	SEntg	0.6595	0.5029	1	0.4085	0.3595	0.5952

MM – FORMATIVE CONSTRUCTS

- Multicolliniarity

Construct/Measures	Weight	Collinearity Statistics	
		Tolerance	VIF
Low Risk			
Conferences	0.540***	.591	1.691
Journals	0.494***	.554	1.805
Professional Assoc.	0.137***	.811	1.233
Medium Risk			
Government	0.215***	.568	1.762
Universities	0.563***	.542	1.844
Consultants	0.467***	.851	1.176
High Risk			
Clients	0.670***	.725	1.379
Competitors	0.224***	.701	1.427
Suppliers	0.358***	.826	1.210

MM – FORMATIVE CONSTRUCTS

- *Discriminant Validity*

Table 7: Inter-Construct Correlations						
Construct	High Risk	Inter Knowledge	Low Risk	Med Risk	Process Effect	P&S Effect
High Risk	1					
Inter Knowledge	0.599	1				
Low Risk	0.562	0.403	1			
Med Risk	0.409	0.333	0.472	1		
Process Effect	0.512	0.480	0.425	0.320	1	
P&S Effect	0.657	0.643	0.482	0.387	0.631	1

ASSESSMENT OF PLS MODEL

- Stage 6: Structural Model

Explanatory Power

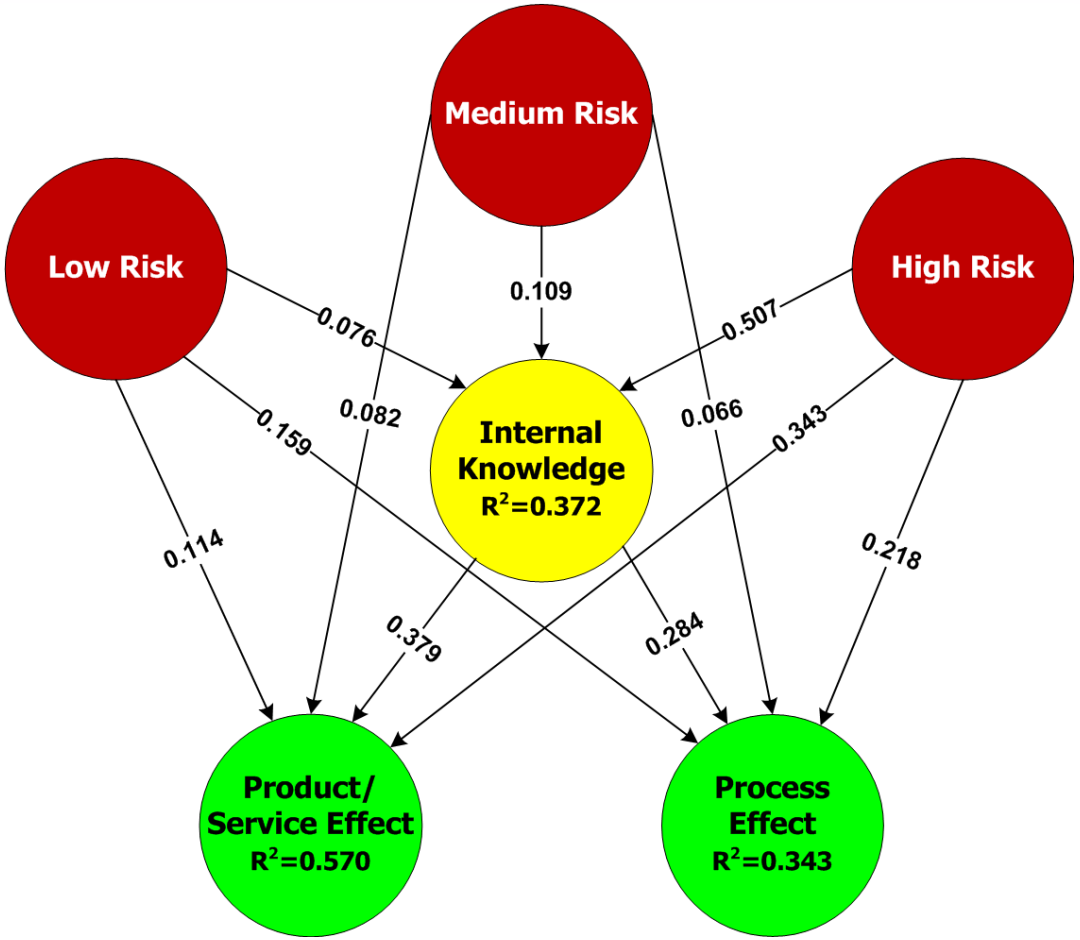
- R-square
- The effect size test

Predictive Power

- Significance of Path Coefficients
- Contribution Power
- Predictive relevance

STRUCTURAL MODEL ASSESSMENT – EXPLANATORY POWER (R^2)

- The central criterion for evaluating the structural model is the level of explained variance of the dependent constructs
- *Statistical significance of path coefficients*



STRUCTURAL MODEL ASSESSMENT – EFFECT SIZE TECHNIQUE – F^2 OF PLS CONSTRUCTS

- Investigates the substantive impact of each independent construct on the dependent constructs.
- Table represents a summary of the quantitative results of the effect size test. (Chin (1998) - Small (f^2=0.02), Medium (f^2=0.15), and Large (f^2=0.35).

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

Predicted Constructs	Predictor Constructs	f^2	effect
Process Effect	Low Risk	0.02	small
	Medium Risk	0.00	small
	High Risk	0.04	small
	Internal Knowledge	0.07	small
P&S Effect	Low Risk	0.02	small
	Medium Risk	0.01	small
	High Risk	0.15	medium
	Internal Knowledge	0.22	medium
Internal Knowledge	Low Risk	0.01	small
	Medium Risk	0.01	small
	High Risk	0.27	medium

ASSESSMENT OF THE STRUCTURAL MODEL PREDICTIVE POWER BOOTSTRAPPING RE-SAMPLING TECHNIQUE

Paths	(H)	Path	SD	t-stat
LowRisk -> InterKnowl	H1	0.159	0.02	8.44
LowRisk -> ProcEffect	H9	0.066	0.02	3.66
LowRisk -> P&S Effect	H6	0.218	0.02	10.42
MedRisk -> InterKnowl	H2	0.285	0.02	15.59
MedRisk -> ProcEffect	H10	0.114	0.02	7.13
MedRisk -> P&S Effect	H7	0.082	0.01	5.73
HighRisk -> InterKnowl	H3	0.343	0.02	20.71
HighRisk -> ProcEffect	H11	0.379	0.02	24.86
HighRisk -> P&S Effect	H8	0.076	0.02	4.05
InterKnowl-> ProcEffect	H5	0.109	0.02	6.62
InterKnowl-> P&S Effect	H4	0.507	0.02	28.79

ASSESSMENT OF THE STRUCTURAL MODEL

BLINDFOLDING TEST FOR PREDICTIVE RELEVANCE – STONE AND GEISSER Q^2 TEST

- *Enables the evaluation of the predictive relevance of the structural model.*
  - Q^2 reflects an index of the strength of reconstruction by model and parameter estimations.
  - A positive Q^2 >0 provides evidence that the omitted observations were well-reconstructed and that predictive relevance is achieved,
  - A negative Q^2 reflects absence of predictive relevance.
  - All values of Q^2 were greater than zero, indicating predictive relevance for the endogenous constructs of the model.

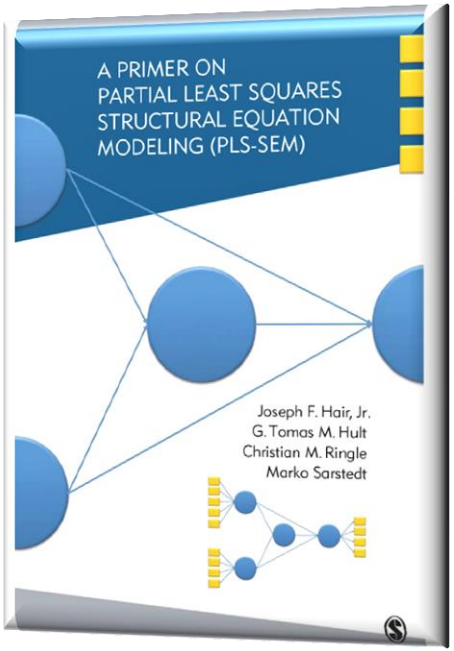
$$Q^2{}_j = 1 - \frac{\sum_G SE_{jG}}{\sum_G SO_{jG}}$$

–

Construct	$\sum$ SO	$\sum$ SE	Q^2
Inter Knowledge	236	2041.1	0.37
Process Effect	2944	10308.7	0.20
Product/Service Effect	708	5675.8	0.42

MORE INFORMATION

- I'd glad to send a list of papers regarding PLS methodology
- Book



Source: Hair et.al. (2013), "A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)"

Thank you