BAYESIALAB PARIS

5TH ANNUAL BAYESIALAB CONFERENCE 2017

From Marketing Science to Artificial Intelligence with Bayesian Networks

Benoit Hubert

Géraldine Michel

Agenda

- Inspiration
- Global Process
- Example n°1 - Loyalty and Brand Personality
- Example n°2 - Satisfaction and Loyalty
- Next Steps

Inspiration

Bayesian networks can bring Artificial Intelligence to problems for which we possess little or no data.

Stefan Conrady, Bayesia US

http://www.bayesia.com/2017-07-bn-ai-toronto-on


Microsoft
RSLN
3
Les chercheurs doivent
déterminer comment
coordonner différentes
compétences
(à l'image des humains)

We are constellation of competences, constellation of abilities, components coordinated in a beautiful way so well that it feels like a unitary intelligence

Eric Horvitz, Microsoft

I think that there is a rich symphony
of many intelligences working together

Eric Horvitz, Microsoft

Human behavior provides information about human values

Stuart Russel, Berkeley

https://www.ted.com/talks/stuart_russell_how_ai_might_make_us_better_people/reading-list?goback=.gde_1830899_member_277410621&language=fr#t-575854

Learn to predict which life each human will prefer

Stuart Russel, Berkeley

https://www.ted.com/talks/stuart_russell_how_ai_might_make_us_better_people/reading-list?goback=.gde_1830899_member_277410621&language=fr#t-575854

For a hundred years, marketers have collected data on what, how and why consumers buy what they buy. **The data is there**.

Philip Kotler

Marketing science is a field that approaches marketing – the understanding of customer needs, and the development of approaches by which they might be fulfilled – predominantly through scientific methods

https://en.wikipedia.org/wiki/Marketing_science

The field of marketing Science has a rich history of modeling marketing phenomena using disciplines of economics, statistics, operation research and other related fields

The history of marketing science – Winer Neslin

Marketing science and Big Data [edit]

The marketing profession has long relied on data. But as the data flood gets bigger, progressive marketers are turning to big data analysis methods as well as systematic observation, testing and measurement to study broad behavioral patterns, drill down from the aggregate to the individual and produce new insights that improve business outcomes.

https://en.wikipedia.org/wiki/Marketing_science

Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods

Joseph F. Hair[1] · G. Tomas M. Hult[2] · Christian M. Ringle[3,4] · Marko Sarstedt[4,5] · Kai Oliver Thiele[3]

Received: 7 July 2016 / Accepted: 12 January 2017

Abstract Composite-based structural equation modeling (SEM), and especially partial least squares path modeling (PLS), has gained increasing dissemination in marketing. To fully exploit the potential of these methods, researchers must know about their relative performance and the settings that favor each method's use. While numerous simulation studies have aimed to evaluate the performance of composite-based SEM methods, practically all of them defined populations using common factor models, thereby assessing the methods on erroneous grounds. This study is the first to offer a comprehensive assessment of composite-based SEM techniques on the basis of composite model data, considering a broad range of model constellations. Results of a large-scale simulation study substantiate that PLS and generalized structured component analysis are consistent estimators when the underlying population is composite model-based. While both methods outperform sum scores regression in terms of parameter recovery, PLS achieves slightly greater statistical power.

Keywords Composite · Generalized structured component analysis · GSCA · Partial least squares · PLS · SEM · Simulation · Structural equation modeling · Sum scores regression

John Hulland served as Area Editor for this article.

Electronic supplementary material The online version of this article (doi:10.1007/s11747-017-0517-x) contains supplementary material, which is available to authorized users.

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Introduction

Structural equation modeling (SEM) has become a quasi-standard with respect to analyzing cause–effect relationships between latent variables. Its ability to model latent variables while simultaneously taking into account various forms of measurement error makes SEM useful for a plethora of research questions (e.g., Babin et al. 2008; Steenkamp and Baumgartner 2000), particularly in the marketing field, which typically focuses on examining unobservable phenomena such as consumer attitudes, perceptions, and intentions.

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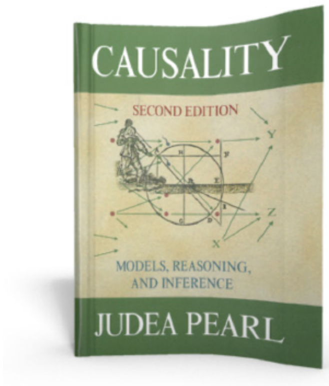
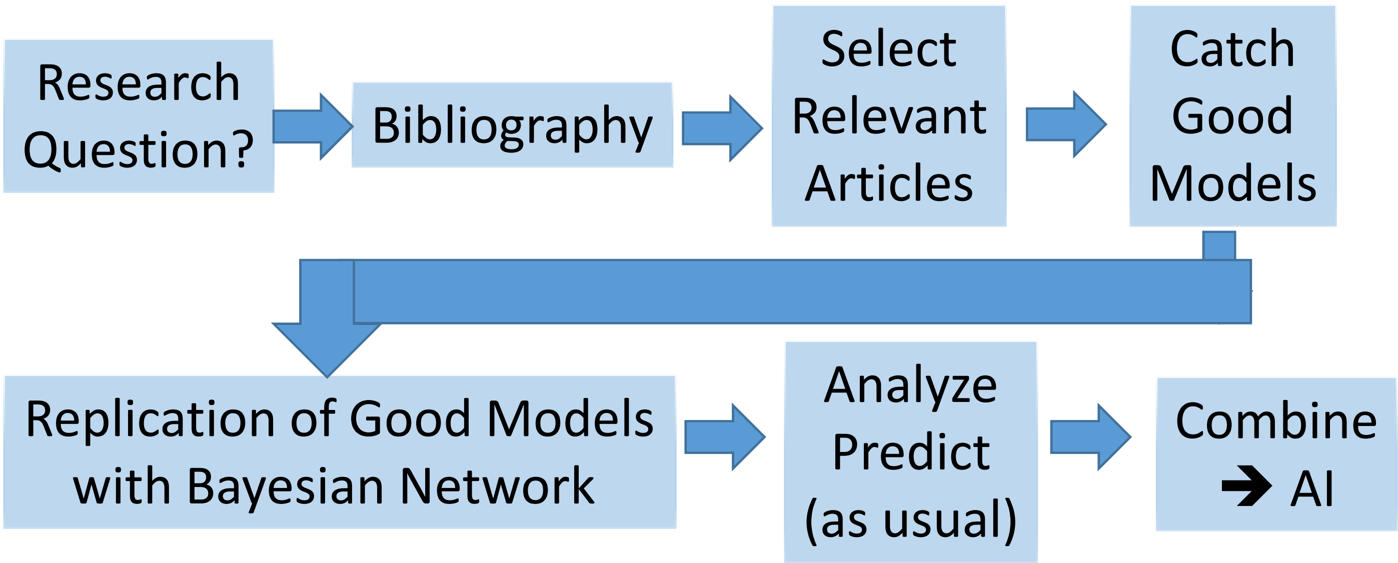
Causal Analysis with Structural Equation Models and Bayesian Networks

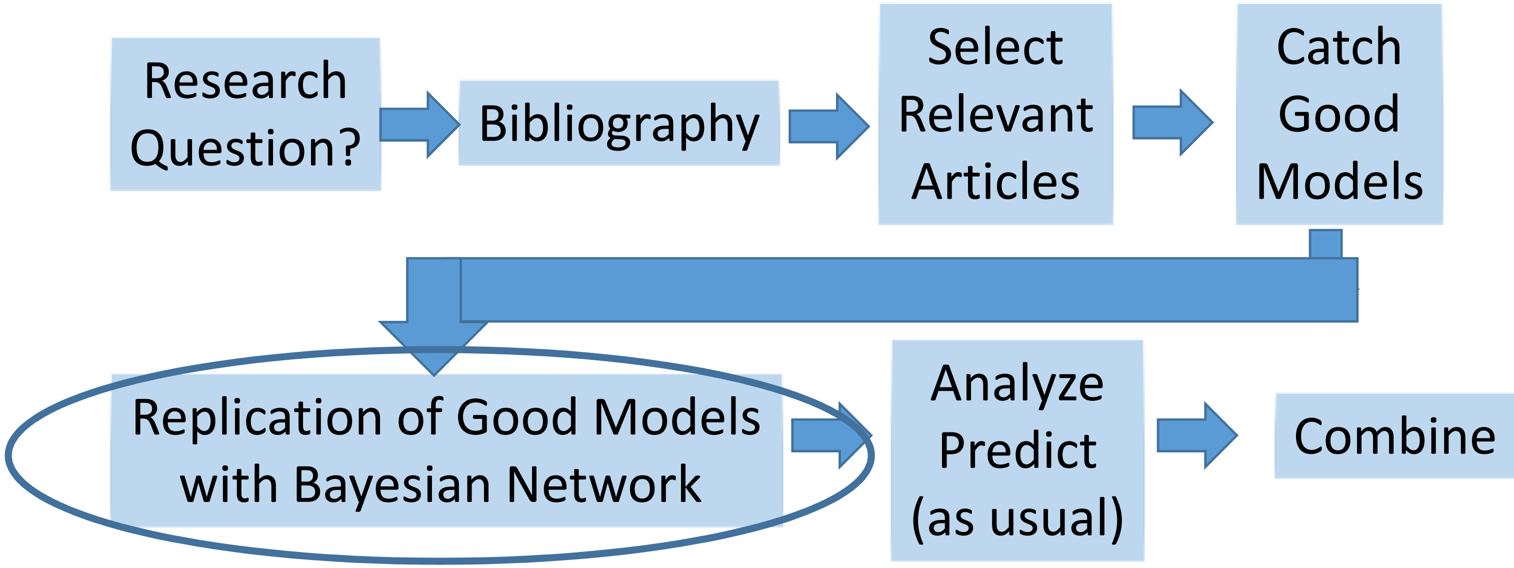


From theory to practical research

Dr. Lionel Jouffe
CEO, Bayesia S.A.S.
BayesiaLab User Conference
Los Angeles, September 24, 2014

General Process


Research Question?
Bibliography
Select Relevant Articles
Catch Good Models
Replication of Good Models with Bayesian Network
Analyze Predict (as usual)
Combine ➔ AI



Research Question?
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Research Question?

Example n°1

Loyalty and Brand Personality

Select Relevant Articles

Implementing an intended brand personality: a dyadic perspective

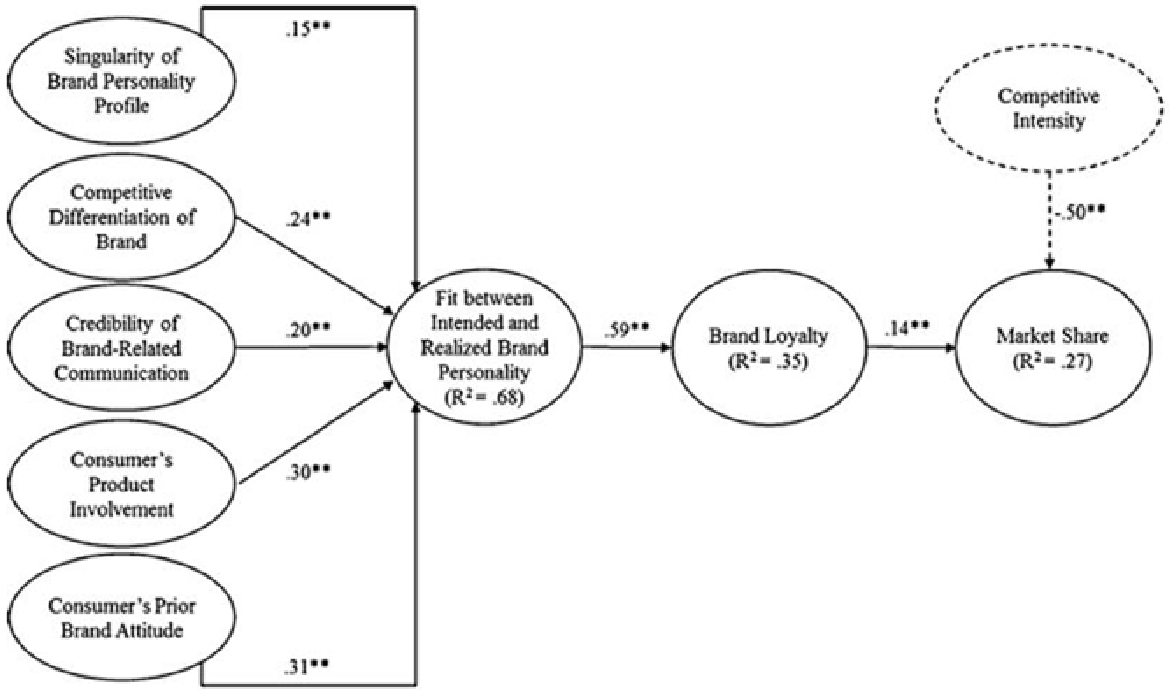
Lucia Malär · Bettina Nyffenegger · Harley Krohmer · Wayne D. Hoyer

Received: 29 March 2010 / Accepted: 8 February 2011 / Published online: 25 February 2011

Abstract The authors examine the transformation of an intended brand personality (i.e., the way brand management would like consumers to perceive the brand's personality) into a realized brand personality (i.e., the consumer's actual perception of the brand's personality). Drawing on the results of a dyadic empirical cross-industry study of 137 brand managers and 3,048 consumers, the authors show that the singularity of the brand personality profile, the competitive differentiation of the brand, the credibility of brand communication, consumers' depth of product involvement, and consumers' prior brand attitude all affect the degree to which the realized brand personality resembles the intended brand personality.

Keywords Perceived brand personality · Intended brand personality · Brand strategy implementation
Brand performance

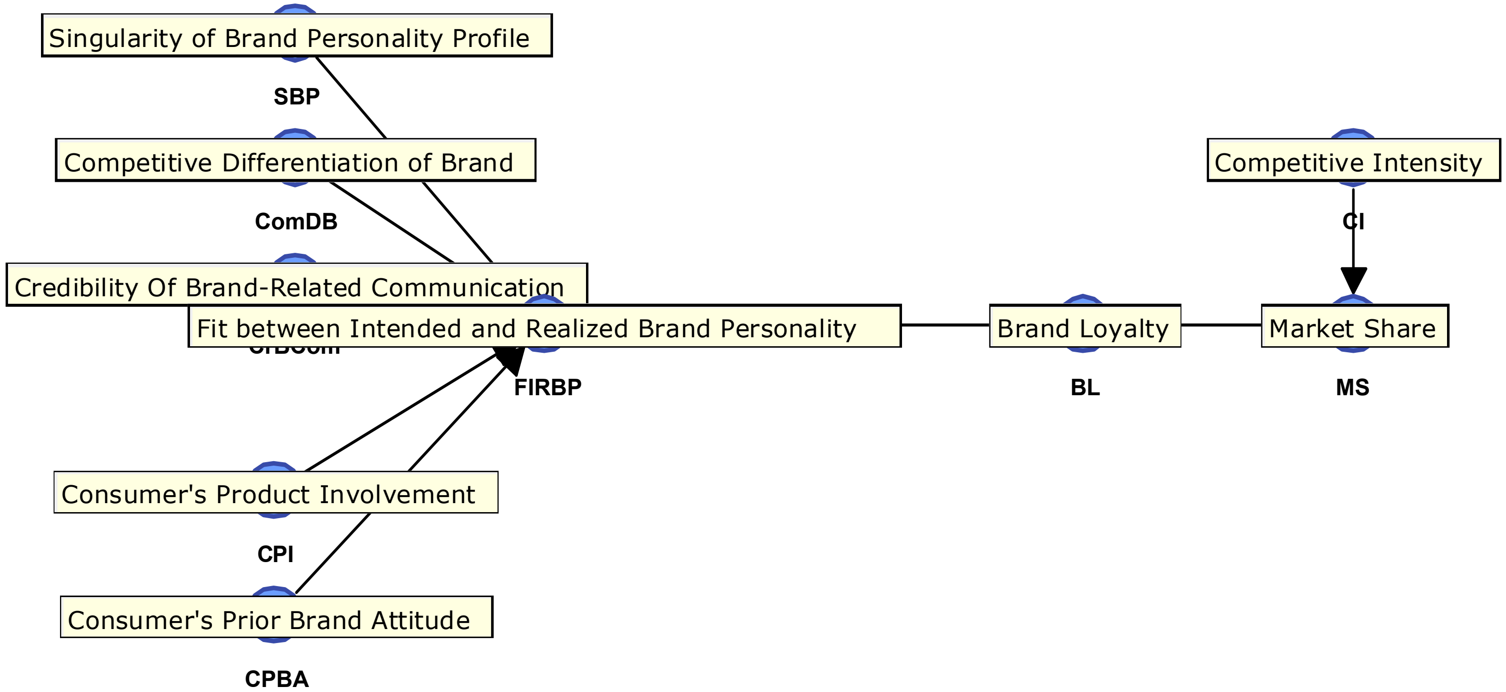
Catch
Good
Models



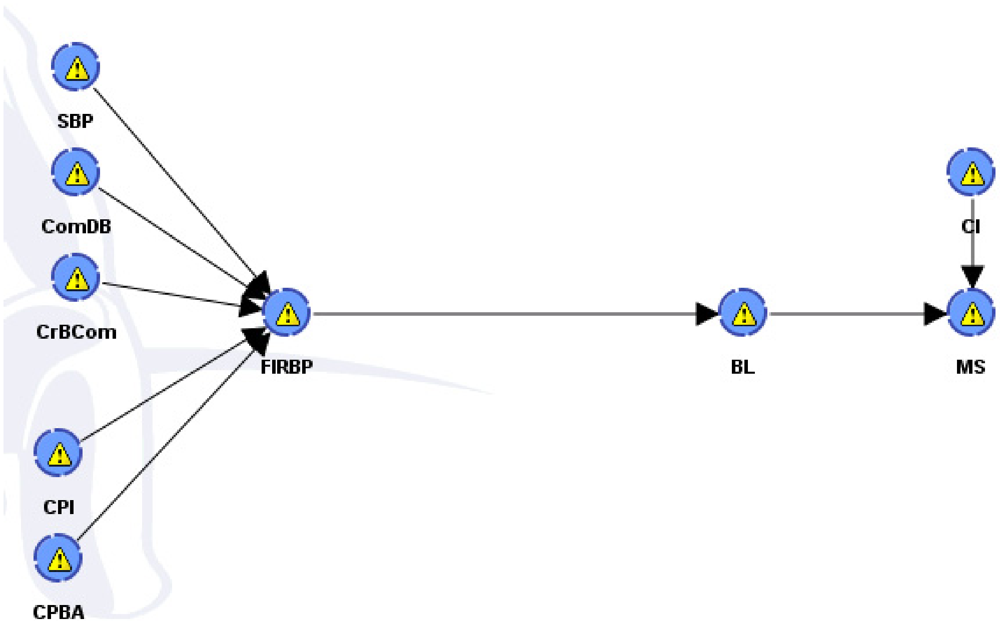
Implementing an intended brand personality: a dyadic perspective

Lucia Malär · Bettina Nyffenegger · Harley Krohmer ·
Wayne D. Hoyer

Replication of Good Models with Bayesian Network



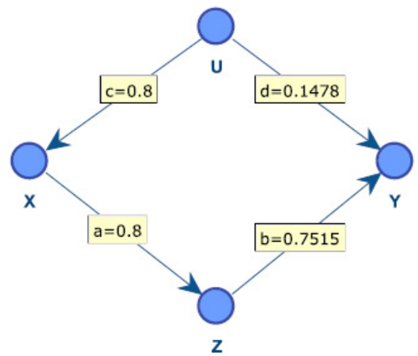
Replication of Good Models with Bayesian Network



Replication of Good Models with Bayesian Network

Causal Analysis with SEM and BBN

Here is a path diagram representing the SEM linear equations. The coefficients are called ***path coefficients*** or ***structural parameters*** and they carry causal information (below, *a* stands for the change in Z induced by raising X by 1 unit, while keeping all other (Z non descendant) variables constant.



These coefficients correspond to the ***BayesiaLab's Standardized Direct Effects*** (SDE) on each child

Replication of Good Models with Bayesian Network

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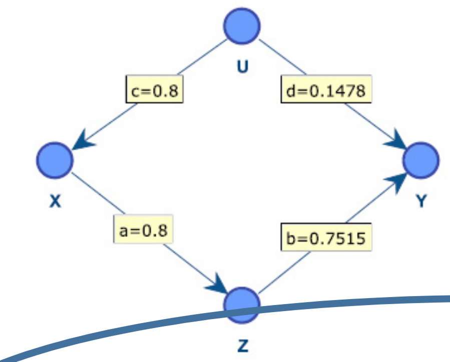

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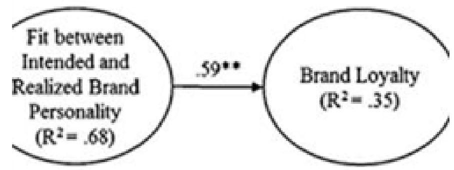
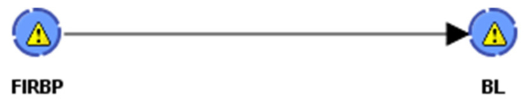
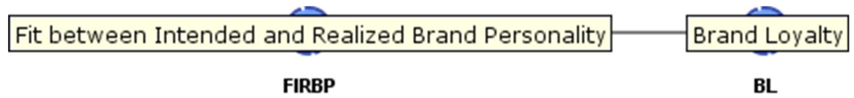
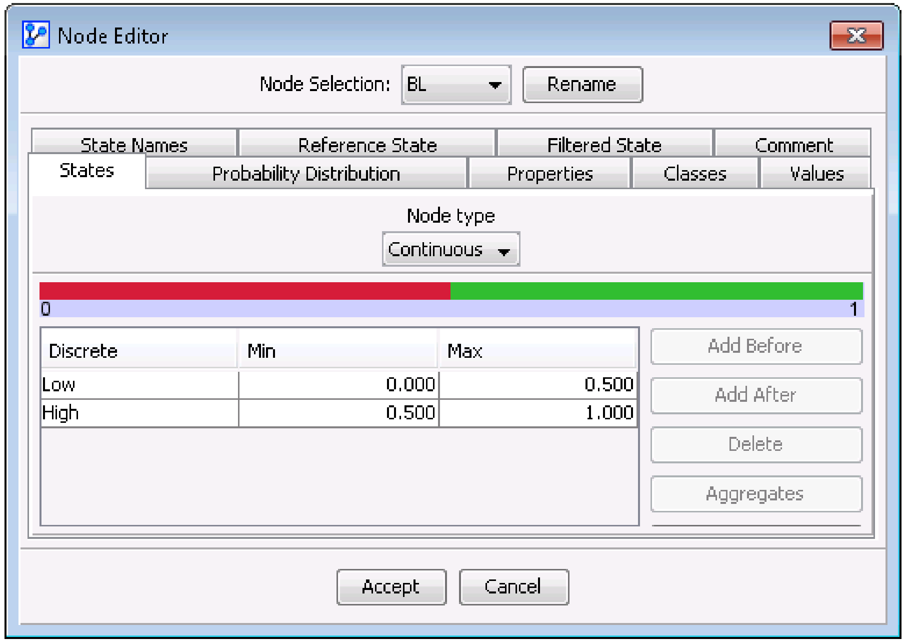
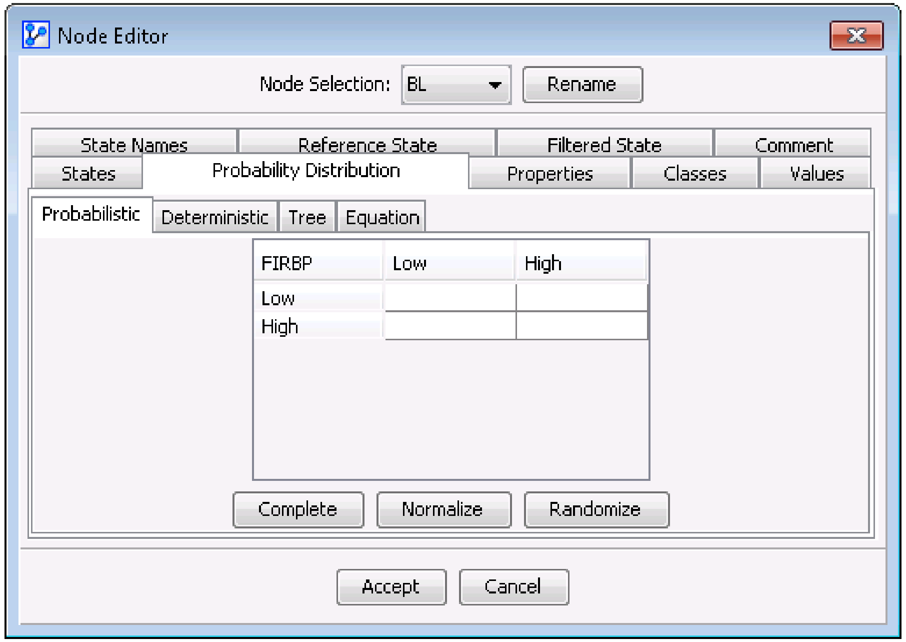
Replication of Good Models with Bayesian Network



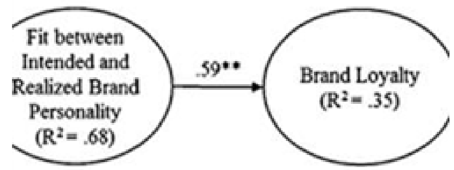


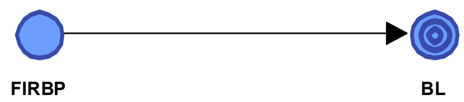


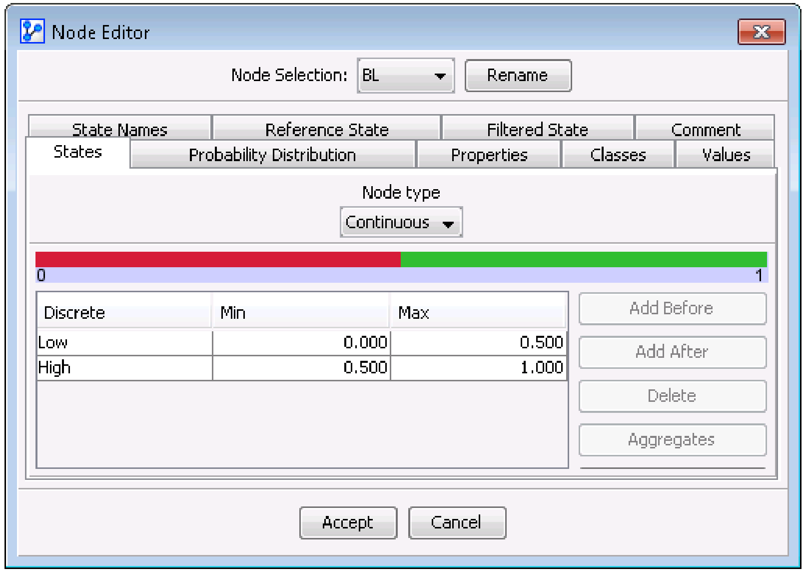


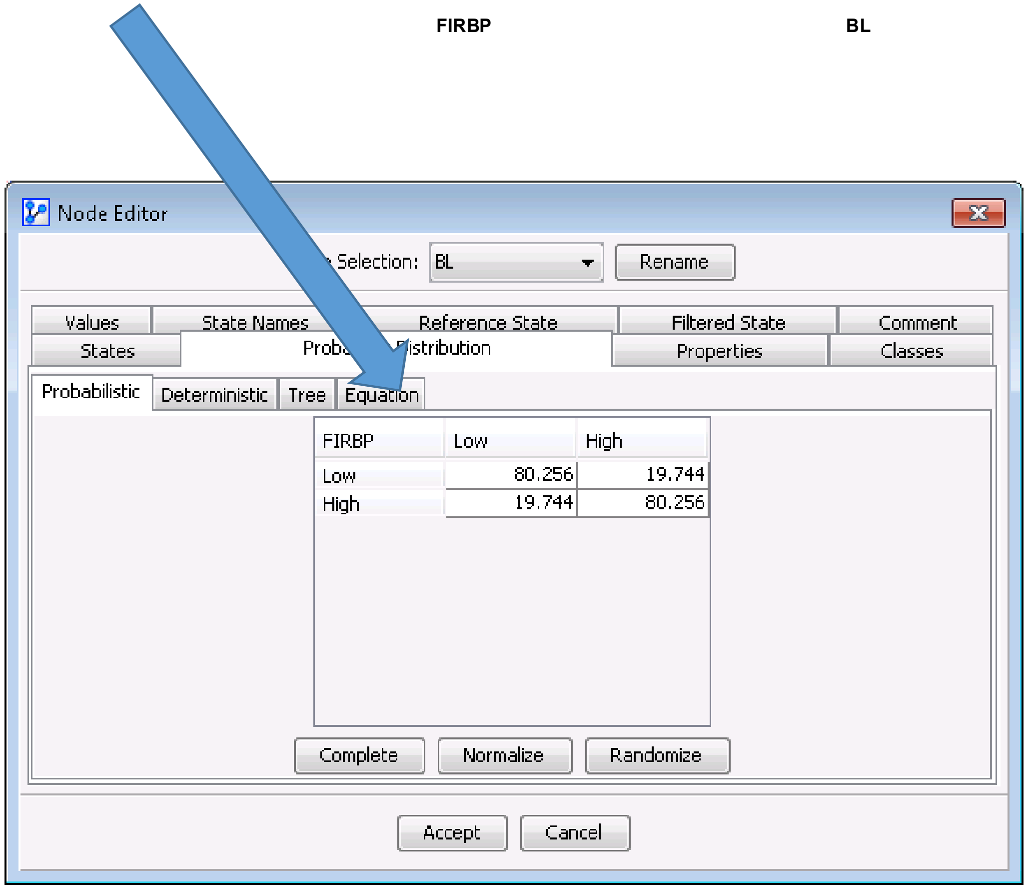


Replication of Good Models with Bayesian Network

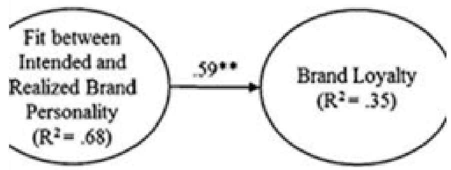






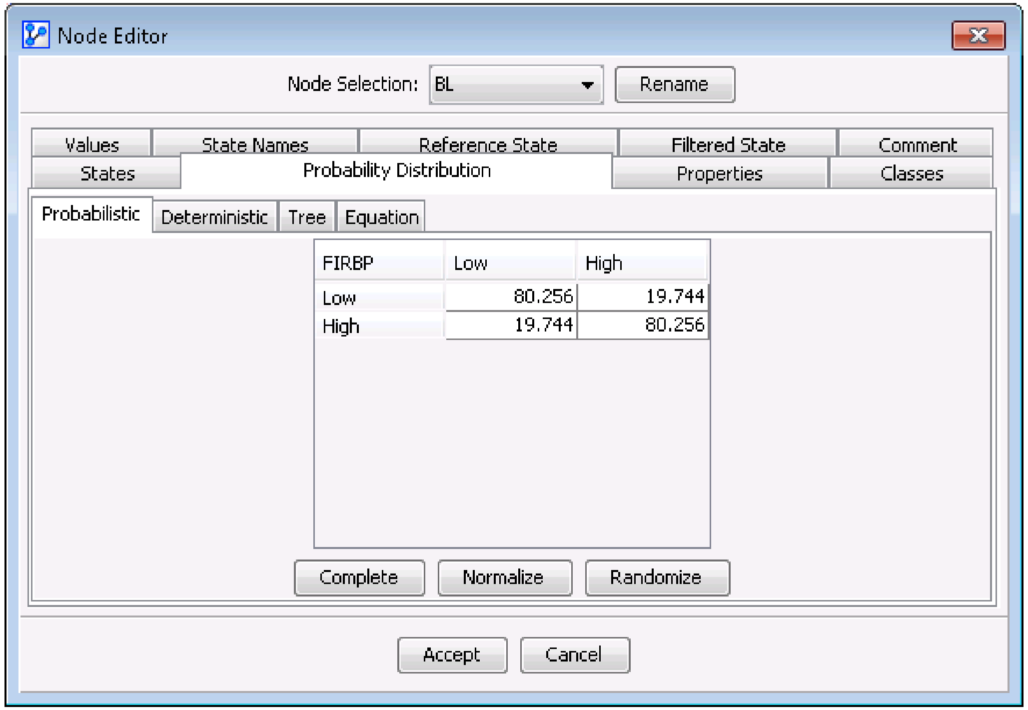


Replication of Good Models with Bayesian Network



Direct Effects on Target BL

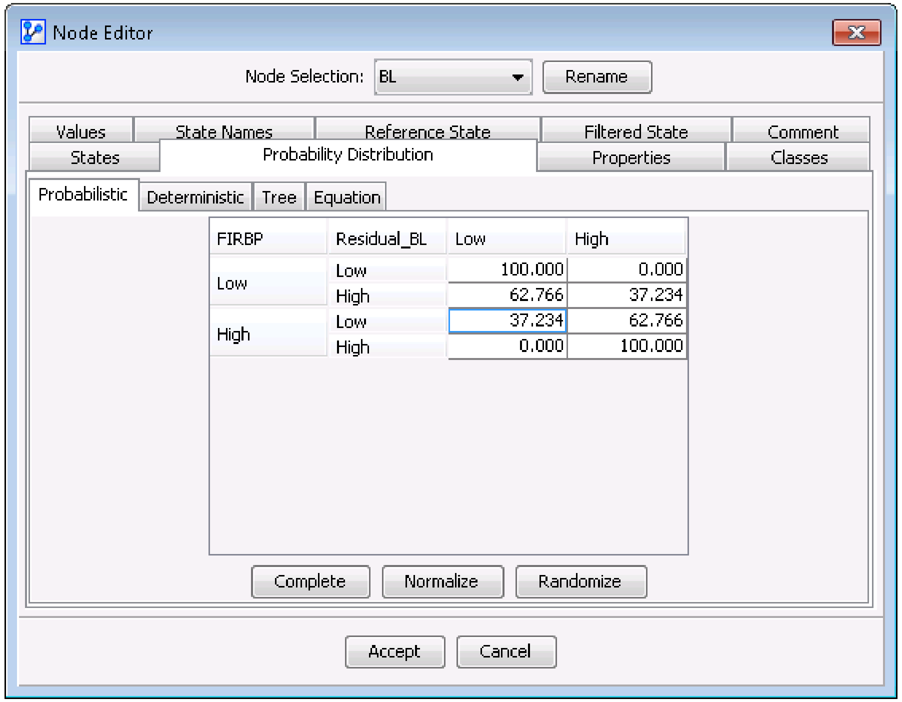
Node	Comment	Value/Mean	Final Value/Mean	Standardized Direct Effect	Direct Effect	Contribution	Elasticity
FIRBP	Fit between Intended and Realized Brand Personality	0.5000	0.5050	0.5900	0.5900	100.0000%	58.9968%



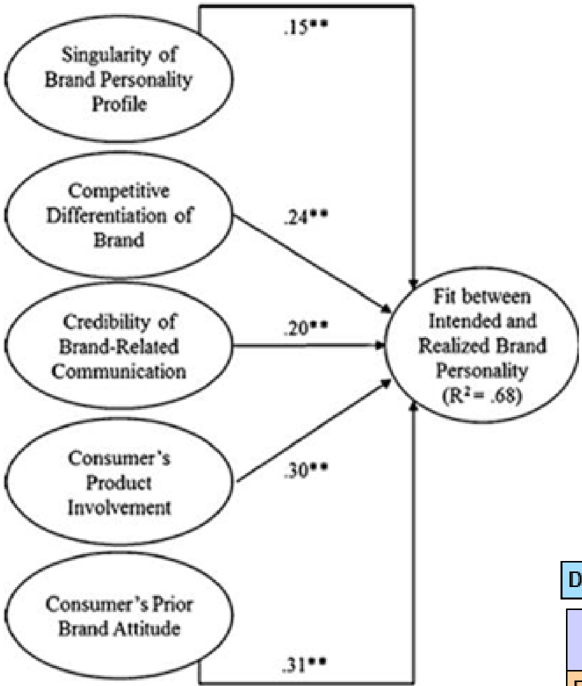
Replication of Good Models with Bayesian Network

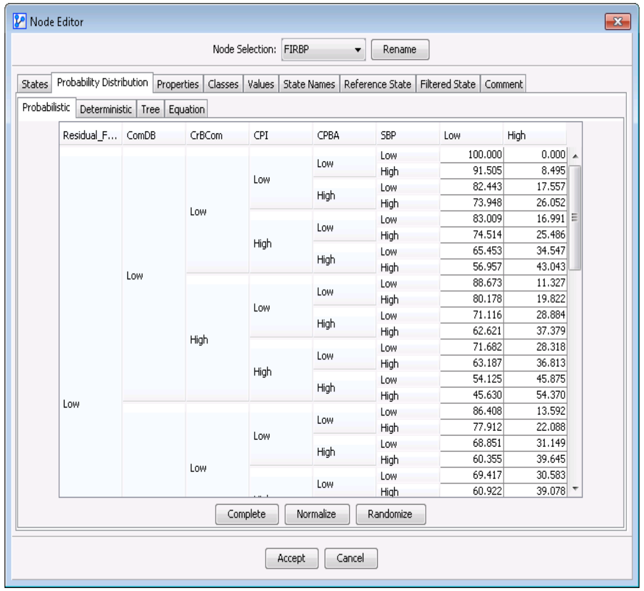
Direct Effects on Target BL

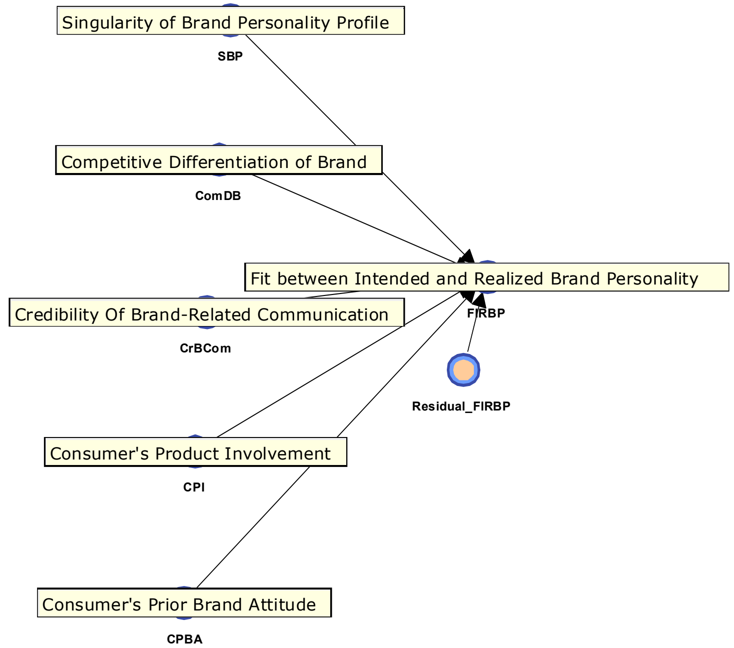
Node	Comment	Value/Mean	Final Value/Mean	Standardized Direct Effect	Direct Effect	Contribution	Elasticity
Residual_BL		0.5000	0.5050	0.5662	0.5662	57.7626%	56.6184%
FIRBP	Fit between Intended and Realized Brand Personality	0.5000	0.5050	0.4140	0.4140	42.2374%	41.4008%
CPBA	Consumer's Prior Brand Attitude	0.5000	0.5000	0.0000	0.0000	0.0000%	0.0000%
SBP	Singularity of Brand Personality Profile	0.5000	0.5000	0.0000	0.0000	0.0000%	0.0000%



Replication of Good Models with Bayesian Network



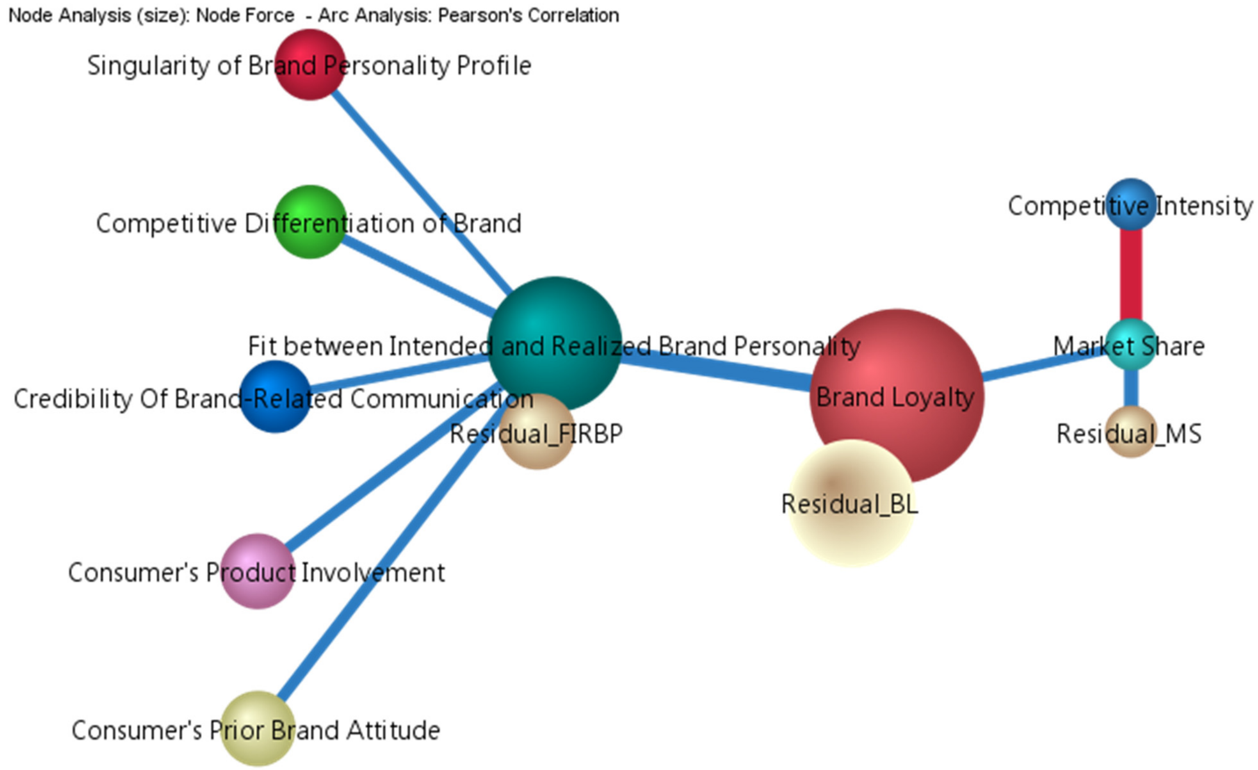




Direct Effects on Target FIRBP

Node	Comment	Value/Mean	Final Value/Mean	Standardized Direct Effect	Direct Effect	Contribution	Elasticity
Residual_FIRBP		0.0000	0.0050	0.3204	0.3204	32.0377%	32.0377%
CPBA	Consumer's Prior Brand Attitude	0.5000	0.5050	0.1756	0.1756	17.5569%	17.5569%
CPI	Consumer's Product Involvement	0.5000	0.5050	0.1699	0.1699	16.9906%	16.9906%
ComDB	Competitive Differentiation of Brand	0.5000	0.5050	0.1359	0.1359	13.5925%	13.5925%
CrBCom	Credibility Of Brand-Related Communication	0.5000	0.5050	0.1133	0.1133	11.3270%	11.3270%
SBP	Singularity of Brand Personality Profile	0.5000	0.5050	0.0850	0.0850	8.4953%	8.4953%

Replication of Good Models with Bayesian Network



Research Question?

Example n°2

Satisfaction and Loyalty

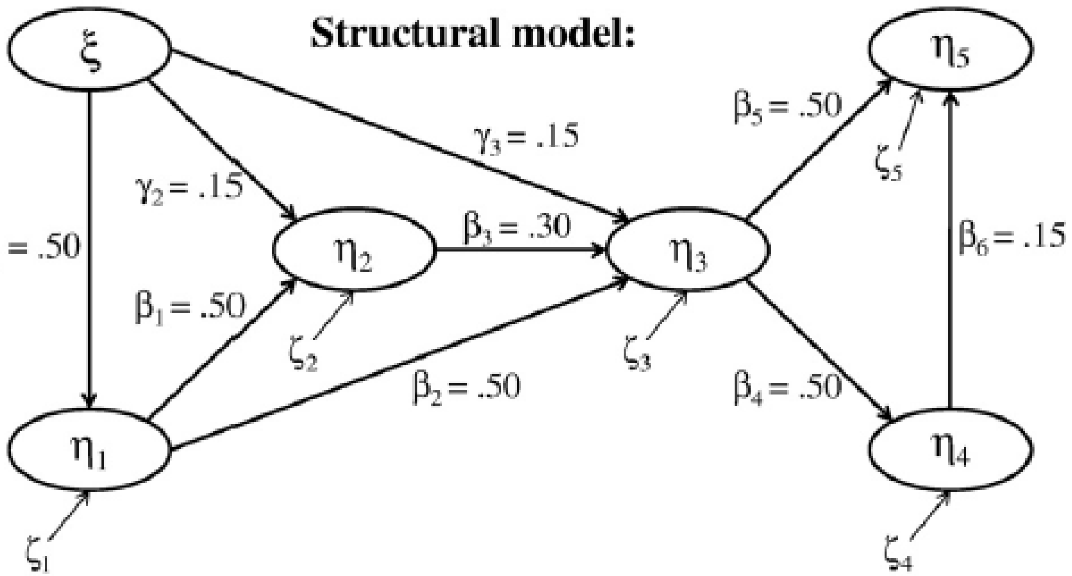
Catch Good Models

http://www.theacsi.org/about-acsi/the-science-of-customer-satisfaction

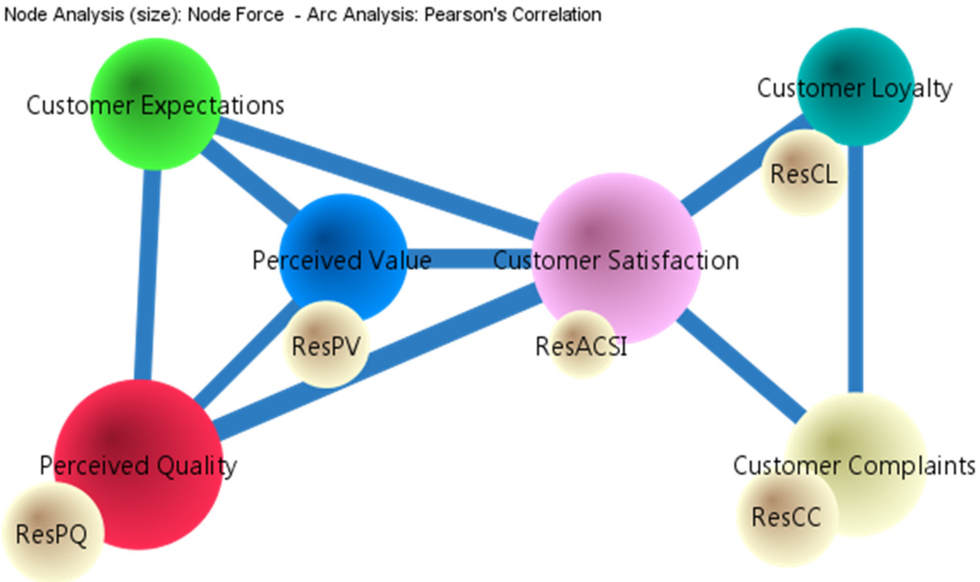
ACSI

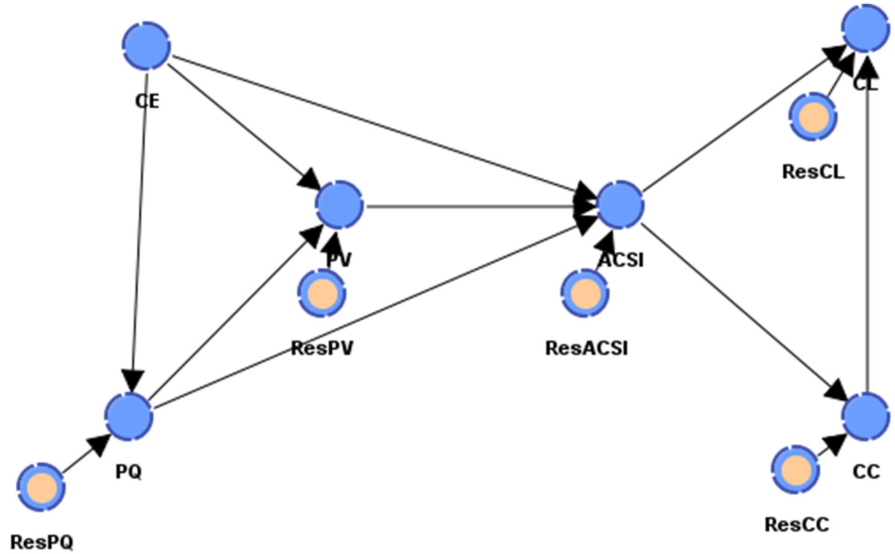
Catch Good Models

W. Reinartz et al. / Intern. J. of Research in Marketing 26 (2009) 332–344 337



Analyze
Predict
(as usual)

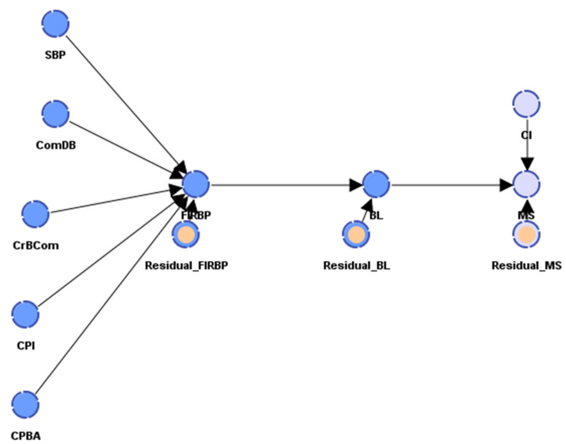




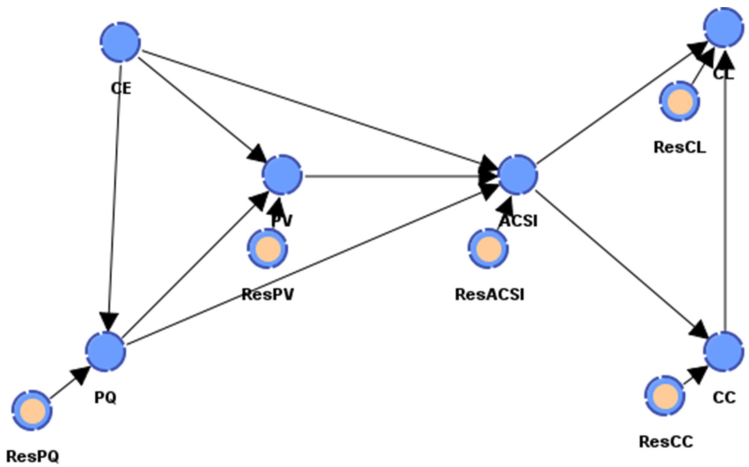
Example n°3 – Combining 1 & 2

Combine Brand Personality Loyalty research and ASCI

Combine



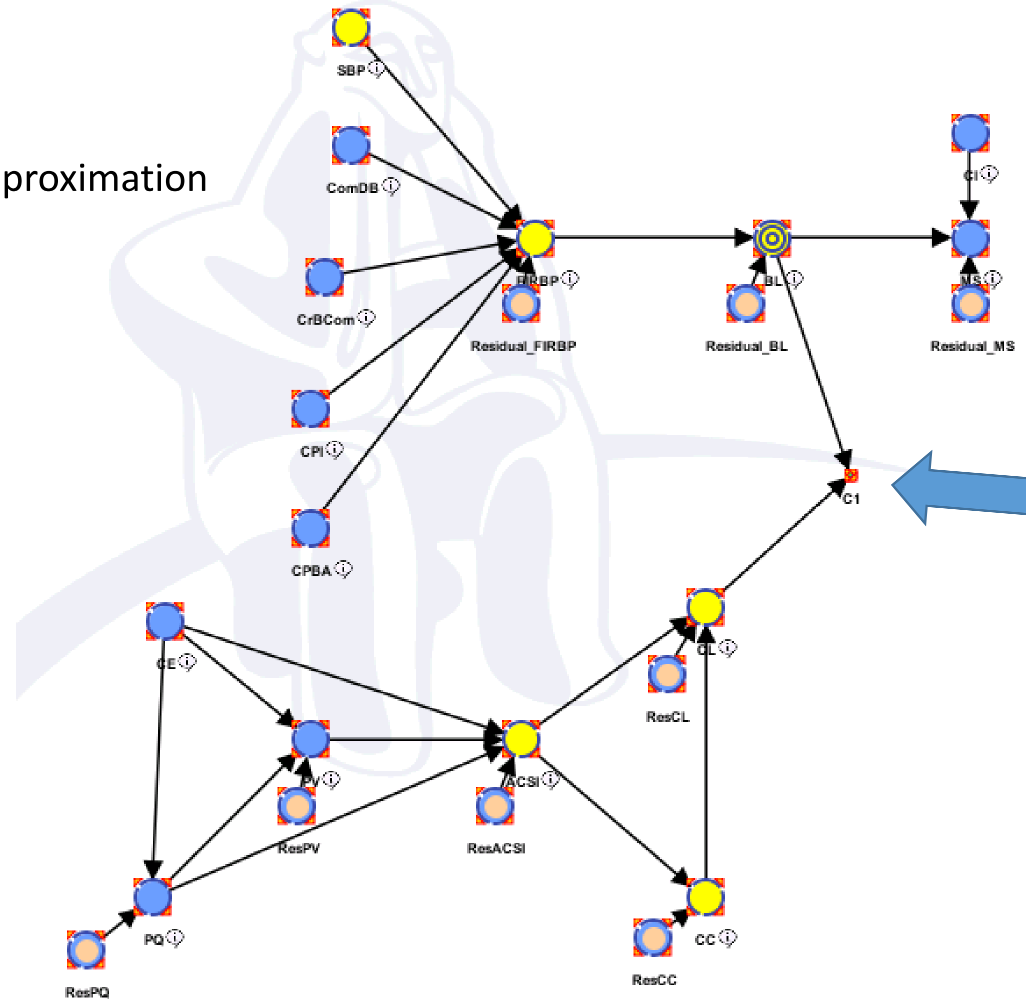
Model n°1

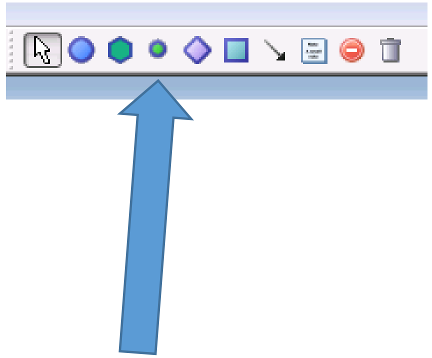


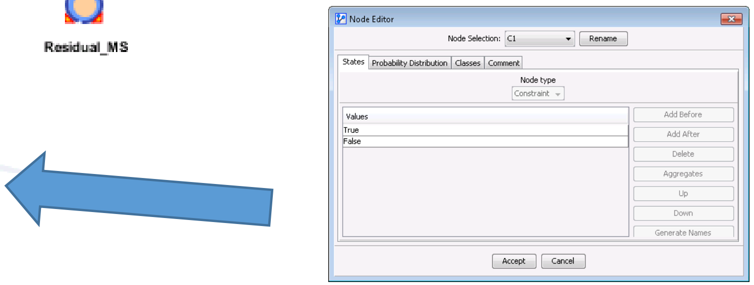
Model n°2

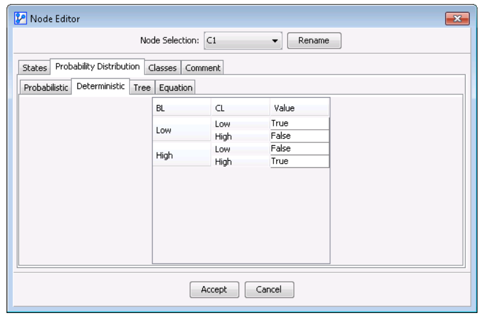
Combine

Approximation



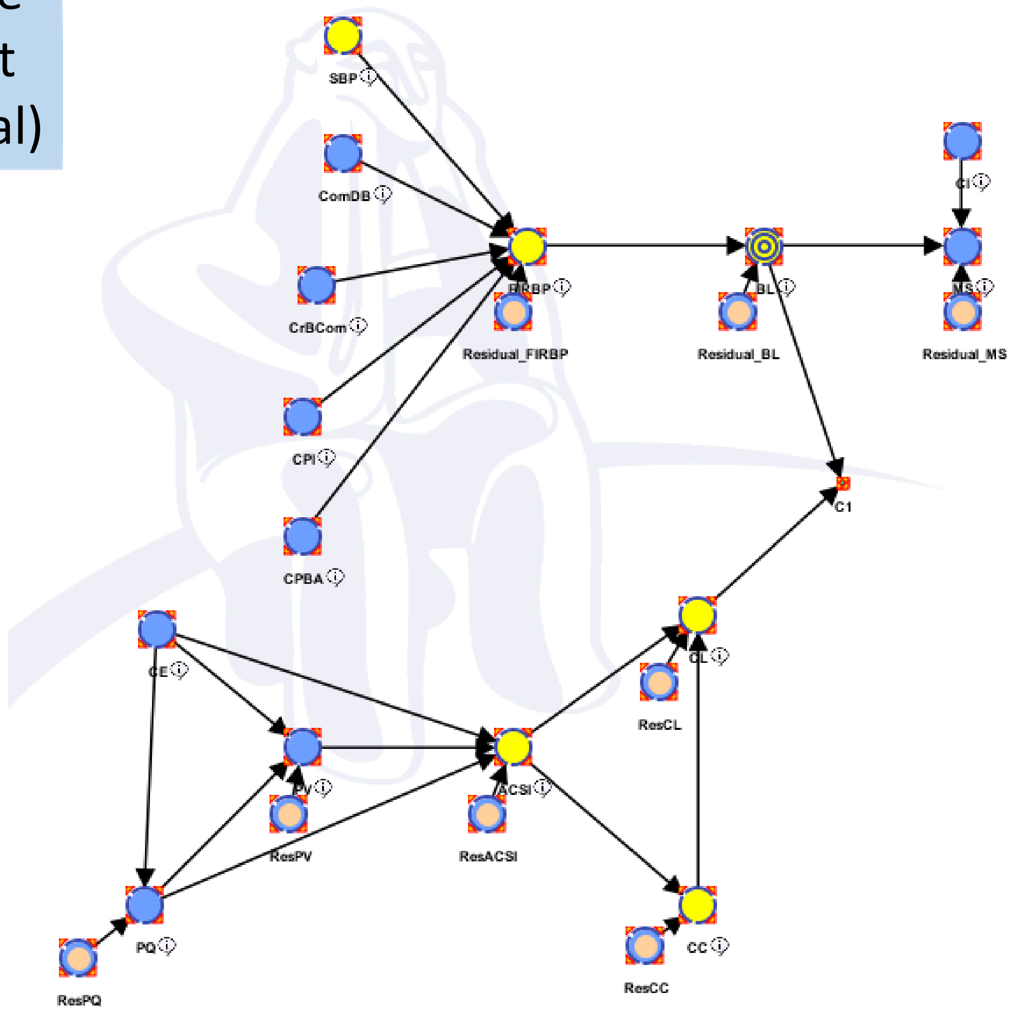






Combine

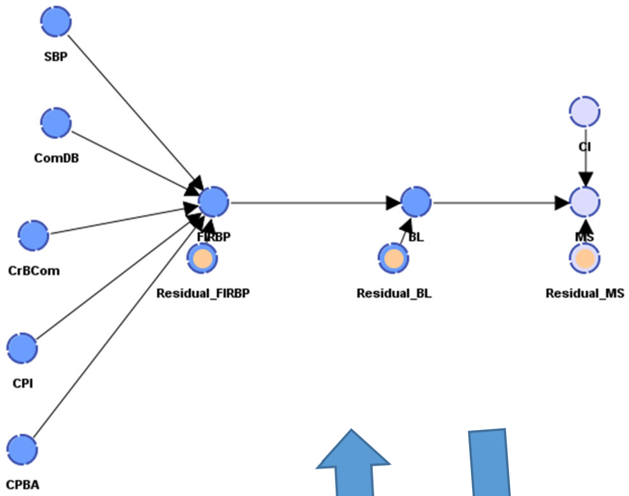
Analyze
Predict
(as usual)

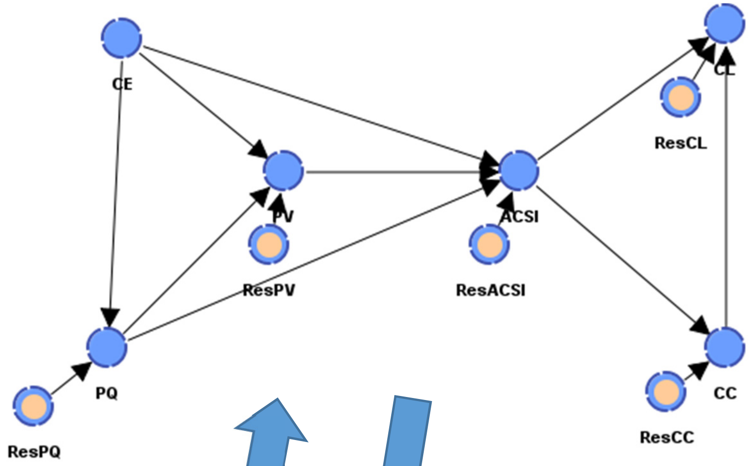


Node significance with respect to the information gain brought by the node to the knowledge of BL					
Node	**Comment**	**Mutual information**	**Normalized Mutual Information (%)**	**Relative significance**	**Mean Value**
CL	Customer Loyalty	0.5000	50.0000%	1.0000	0.5000
FIRBP	Fit between Intended and Realized Brand Personality	0.1533	15.3305%	0.3066	0.5000
ACSI	Customer Satisfaction	0.1269	12.6883%	0.2538	0.5000
CC	Customer Complaints	0.0594	5.9355%	0.1187	0.5000
PQ	Perceived Quality	0.0592	5.9240%	0.1185	0.5000
Residual_BL		0.0512	5.1228%	0.1025	0.5000
ResCL		0.0451	4.5132%	0.0903	0.5000
PV	Perceived Value	0.0418	4.1798%	0.0836	0.5000
CE	Customer Expectations	0.0398	3.9823%	0.0796	0.5000
ResPQ		0.0089	0.8891%	0.0178	0.5000
MS	Market Share	0.0086	0.8571%	0.0171	0.5000
Residual_FIRBP		0.0063	0.6316%	0.0126	0.5000
CPBA	Consumer's Prior Brand Attitude	0.0055	0.5549%	0.0111	0.5000
CPI	Consumer's Product Involvement	0.0055	0.5549%	0.0111	0.5000
ComDB	Competitive Differentiation of Brand	0.0039	0.3851%	0.0077	0.5000

Close Save As... Print Quadrants

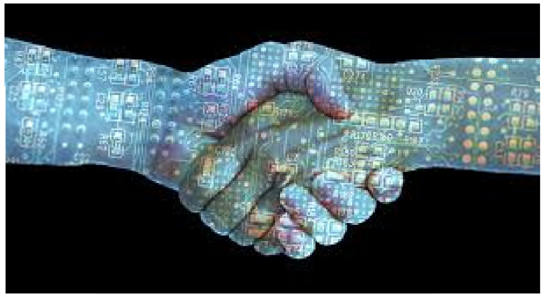
Combine





API

API



External Algorithme

Any AI Algorithme

Géraldine Michel 's Encouragement

This is the ideal tool for decision-making in many fields in marketing according to the conceptual models inserted...

Hence broad and specific managerial implications

Géraldine Michel, Professor IAE Sorbonne Paris

Next Steps

Next Steps

- Define a robust methodology / Framework

- Requirements
- Model Structure Alignment
- Reliable method for Standardized Direct Effects
- Distribution transport and Distribution Alignment
- ….

Next Steps

- Leverage Marketing Sciences Knowledge in the traditional Research Space

- From Fundamental Research
- From Research Agencies
- Meta Analysis Oriented

Next Steps

- Leverage Marketing Sciences Knowledge in the AI Space

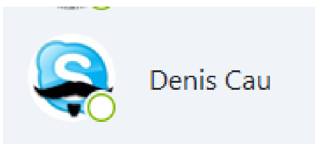
- Massive Use of API and techs
- Review of BN Combination Theory
- Combining with other AI technics (CNN, RNN, etc…)

Next Steps

- Build a Big (Open?) Bayesian Network Library
- Collaborate
- Collective Intelligence

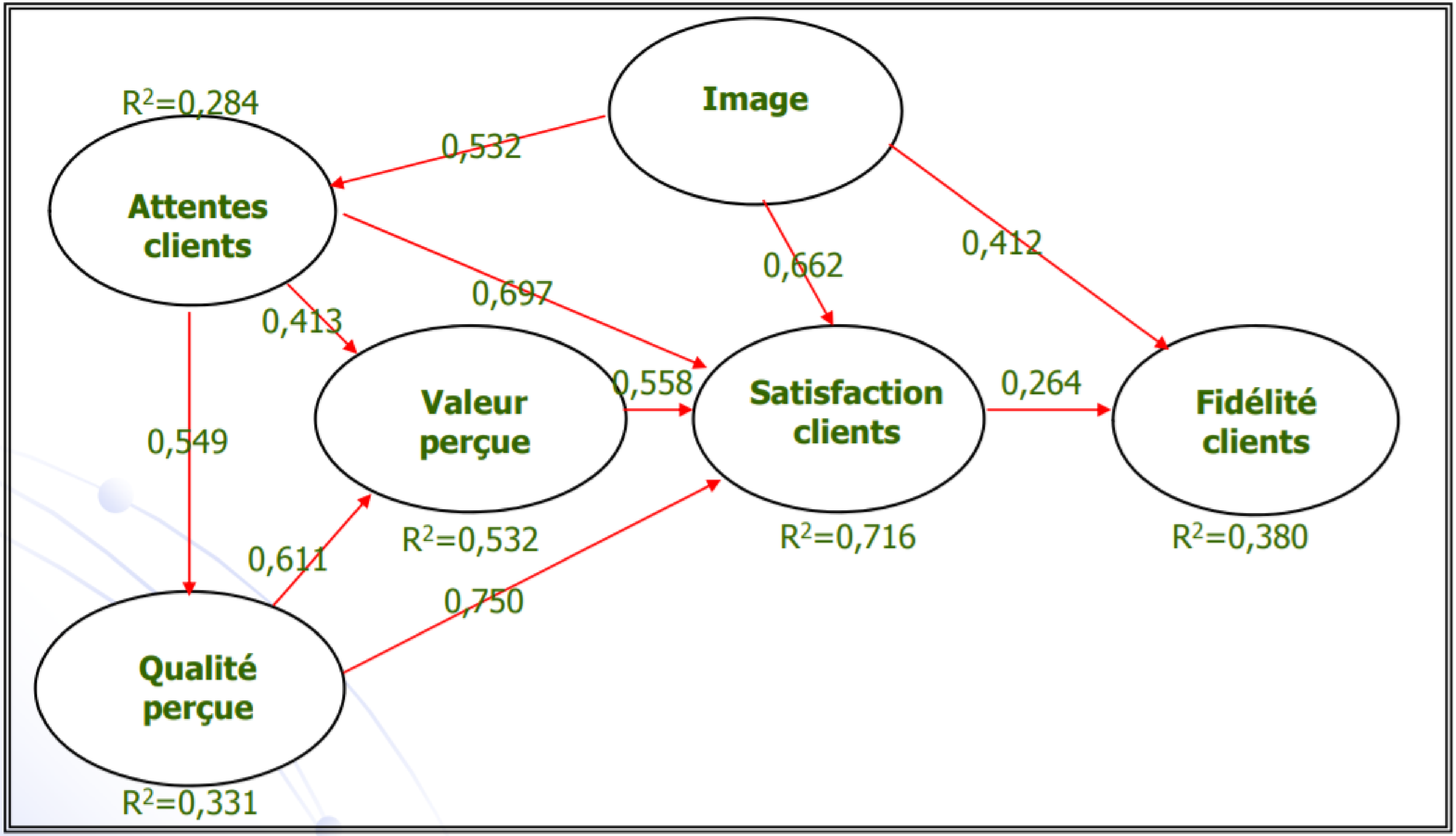
Thank you

This cool Benoit



Back-up

Schéma de causalité (R^2 et corrélations)



Application - Modèle interne pour la méthode LISREL

Schéma de causalité (R^2 et corrélations)