Building Structural Equation Models in JMP Pro

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Lively Tutorial

Building Structural Equation Models in JMP Pro

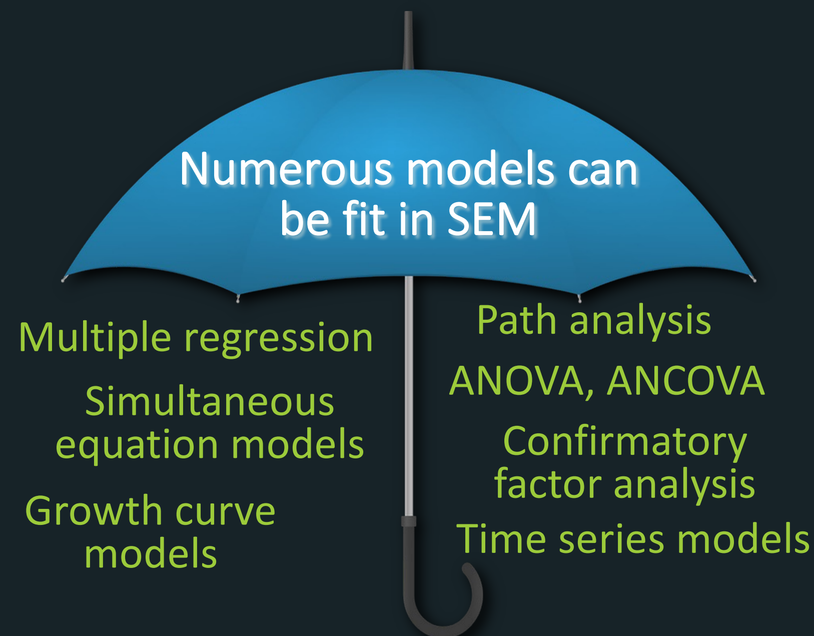
Outline

- What, why, and how of SEM
- Building blocks
  - Simple linear regression
  - Confirmatory factor analysis
- Multiple-Group Analysis
- Summarize key benefits of SEM in JMP Pro

What is SEM?

Definition

- General ***analysis framework*** for investigating associations between variables



- **Flexibility**: Model variances, covariances, and means in observed data

What is SEM?

Analogy

SEM

OLS Regression

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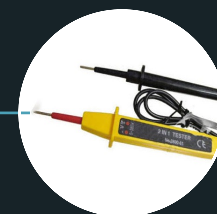
SEM in JMP Pro

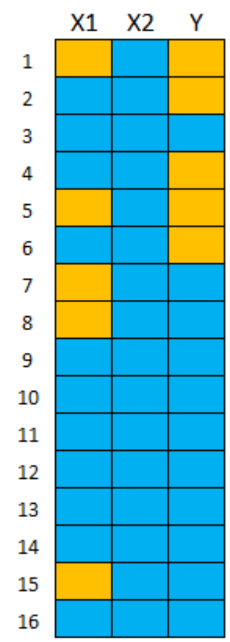


Why use SEM?

Even in the simplest cases: Missing data

SEM

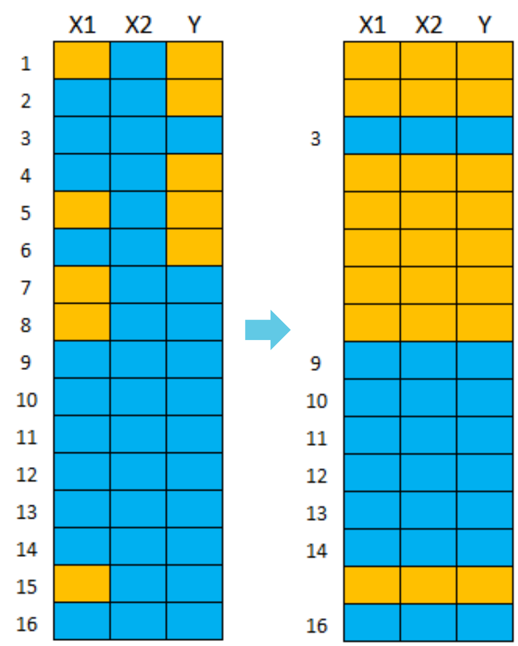
Sample Size = 16 (100%)

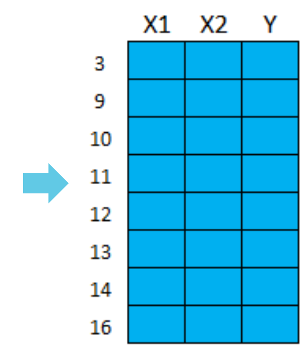


Use all available data:
- Greater power
- Less restrictive assumptions
- Done by default

OLS Regression

Sample Size = 8 (50%)





Listwise deletion:
- Reduced power
- Restrictive assumptions can lead to bias
- Or do multiple imputation

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Why use SEM?

SEM is particularly useful if you need to…

- Handle missing data with cutting edge methods without the hassle of multiple imputation
- Specify a model in which variables are both predictors and outcomes
  - Understand mechanisms by which things happen
- Test specific theories about the association of variables
  - Leverage your domain expertise
- Model variables that cannot be measured directly (aka latent variables)
- Model variables that have measurement error (and account for it)
- Diagrams that describe your statistical models intuitively

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Why use SEM?

SEM is particularly useful if you need to...

- Specify a model in which variables are both predictors and outcomes
  - Understand **mechanisms** by which things happen

Why use SEM?

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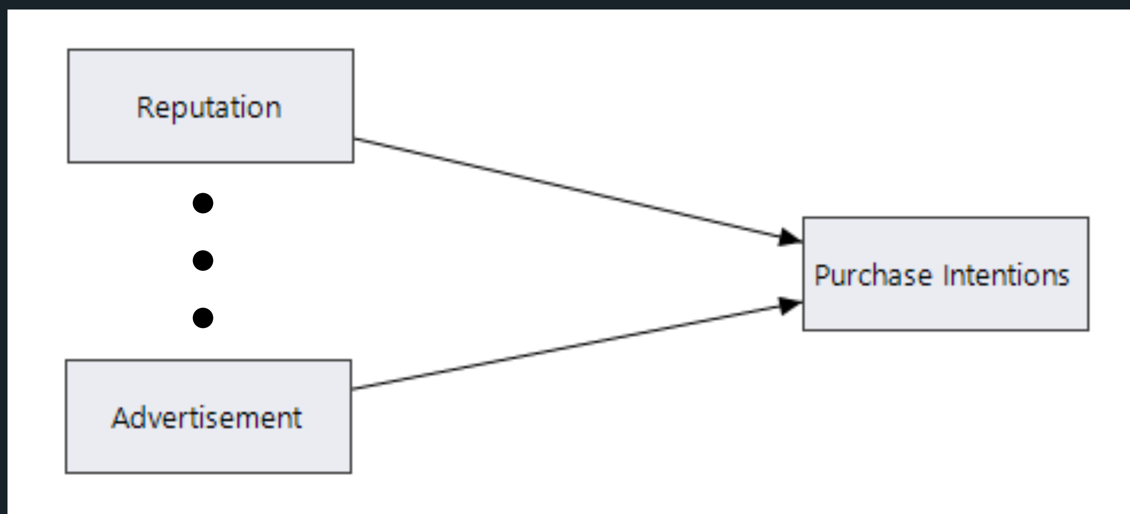
- Specify a model in which variables are both predictors and outcomes
  - Understand mechanisms by which things happen

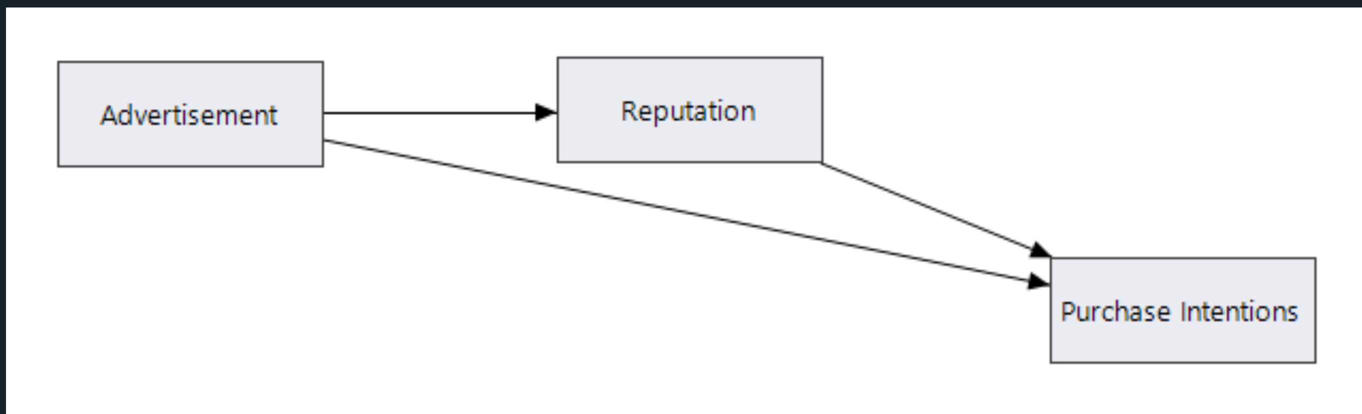


$$Purchase\ Intentions = \ B_0 + B_1 Reputation + \cdots + B_p Advertisement + e$$

Why use SEM?

SEM is particularly useful if you need to…

- Test specific theories about the association of variables
  - Leverage your **domain expertise**



Why use SEM?

SEM is particularly useful if you need to…

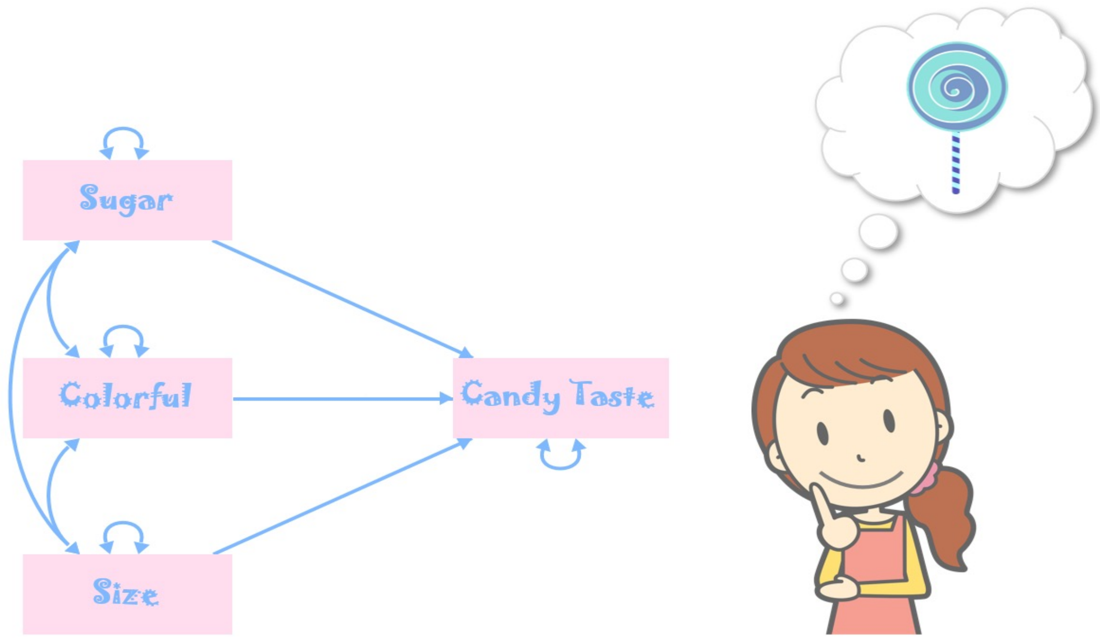
- Model variables that
  - Cannot be measured directly (aka **latent variables**)
  - Have **measurement error** (and account for it)

Why use SEM?

SEM is particularly useful if you need to…

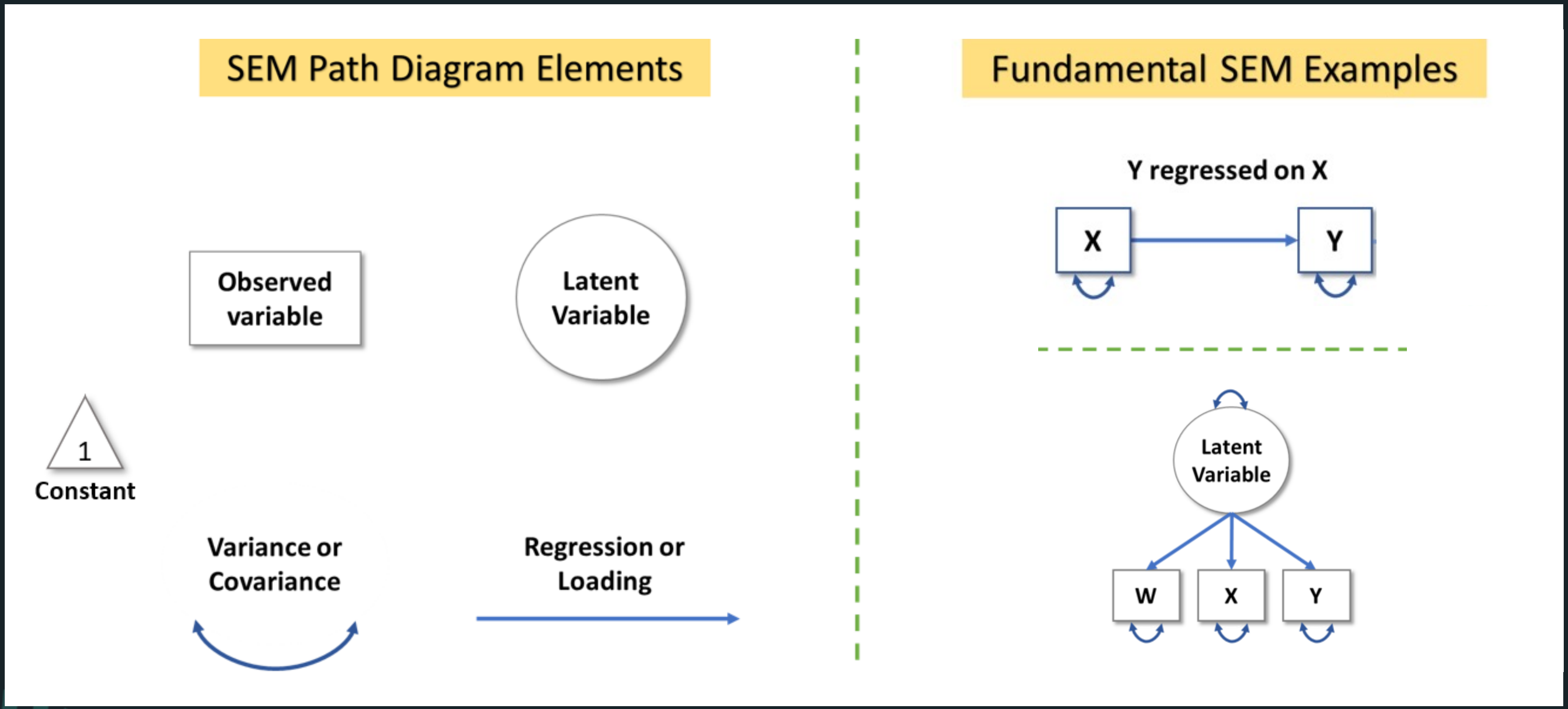
- **Diagrams** that describe your statistical models intuitively

$$CandyTaste_i = \tau_1 + \beta_1 Sugar_i + \beta_2 Colorful_i + \beta_3 Size_i + \varepsilon_{ci}$$
$$Sugar_i = \tau_2 + \varepsilon_{sui}$$
$$Colorful_i = \tau_3 + \varepsilon_{coi}$$
$$Size_i = \tau_4 + \varepsilon_{si}$$



Why use SEM?

Path Diagrams: Intuitive, Powerful, Represent Statistical Model



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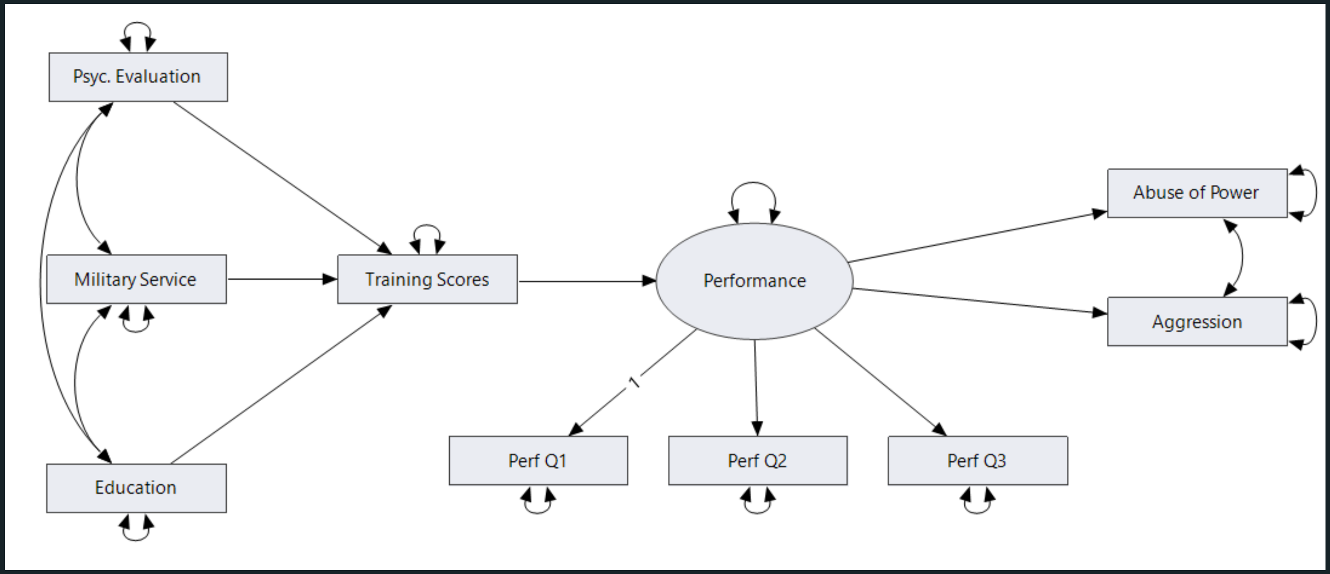
Undercover Agents

SEM for Improving Operations and Field Outcomes

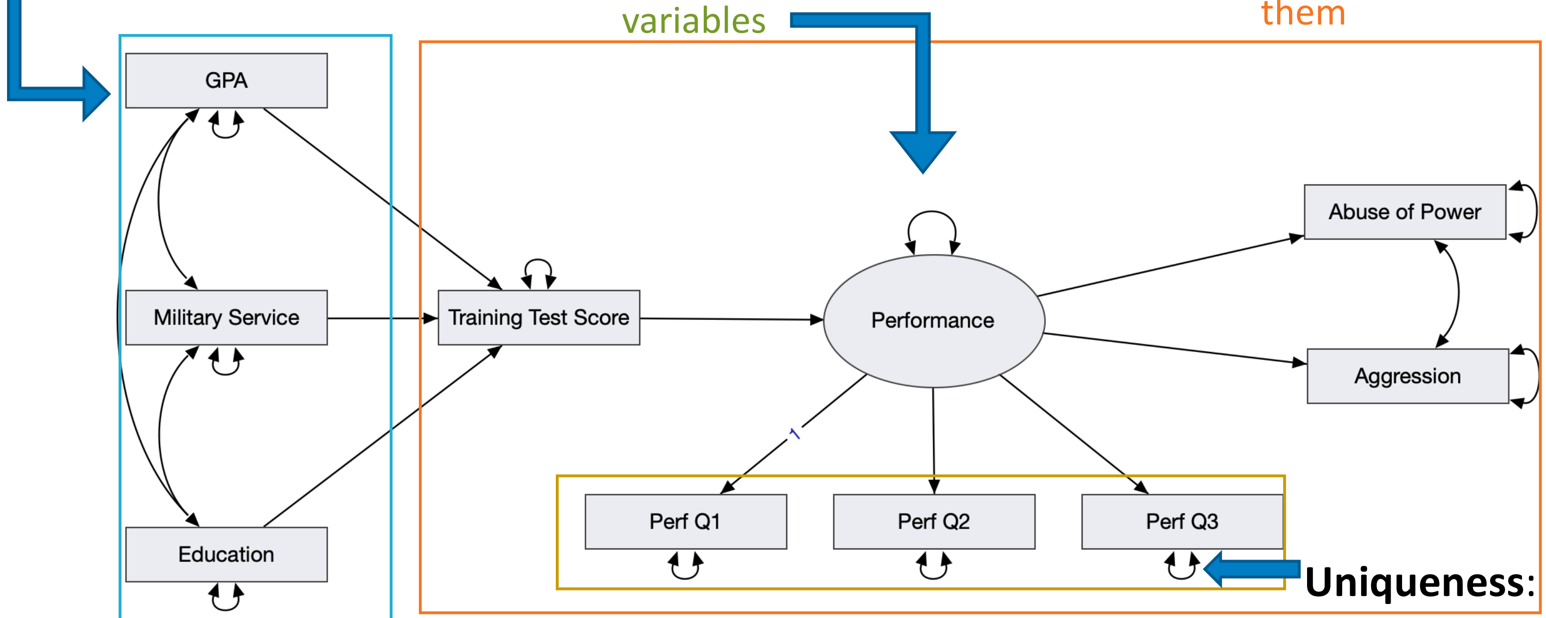


SEM Terminology

Manifest variables:
Measured/observed variables

Latent variables:
Unobserved causal variables

Endogenous variables:
Have variables predicting them



Exogenous variables:
Only predict other variables

LV Indicators:
Variables caused by unobserved variables

Uniqueness:
Variance not explained by LV: Systematic (unique to MV) plus measurement error

How does SEM work?

Shift in focus: from data table to covariance matrix

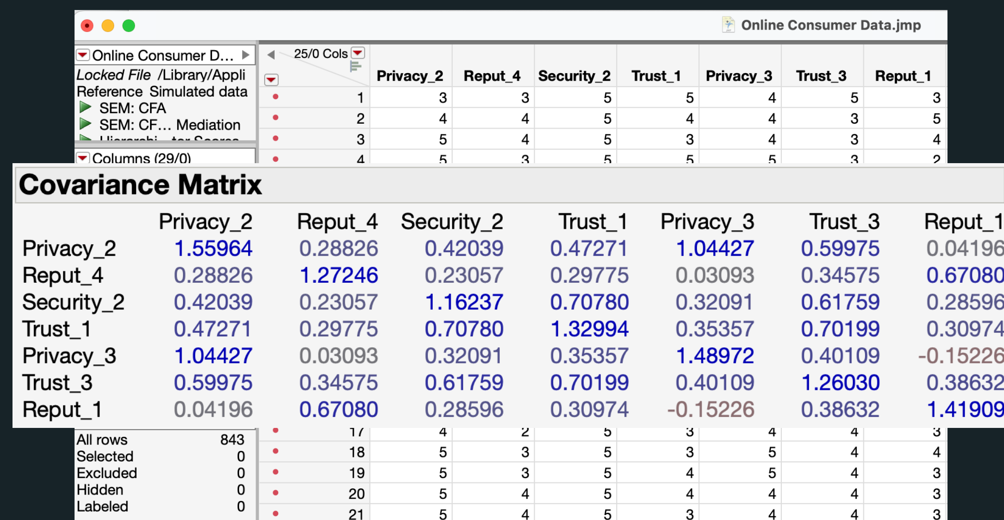
- Multivariate analysis of *covariance* structures (and means)
- Implications:
  - Data

    Variances and covariances (and means)
  - Residuals

    WRT variances and covariances (and means)
  - Degrees of freedom

    WRT variances and covariances (and means)

    df = knowns - unknowns



	Privacy_2	Reput_4	Security_2	Trust_1	Privacy_3	Trust_3	Reput_1
1	3	3	5	5	4	5	3
2	4	4	5	4	4	3	5
3	5	4	5	3	4	3	4
4	5	3	5	5	5	3	2
17	4	2	5	3	4	4	3
18	5	3	5	3	5	4	4
19	5	3	5	4	5	4	3
20	5	4	5	4	4	4	3
21	5	4	5	3	4	4	3

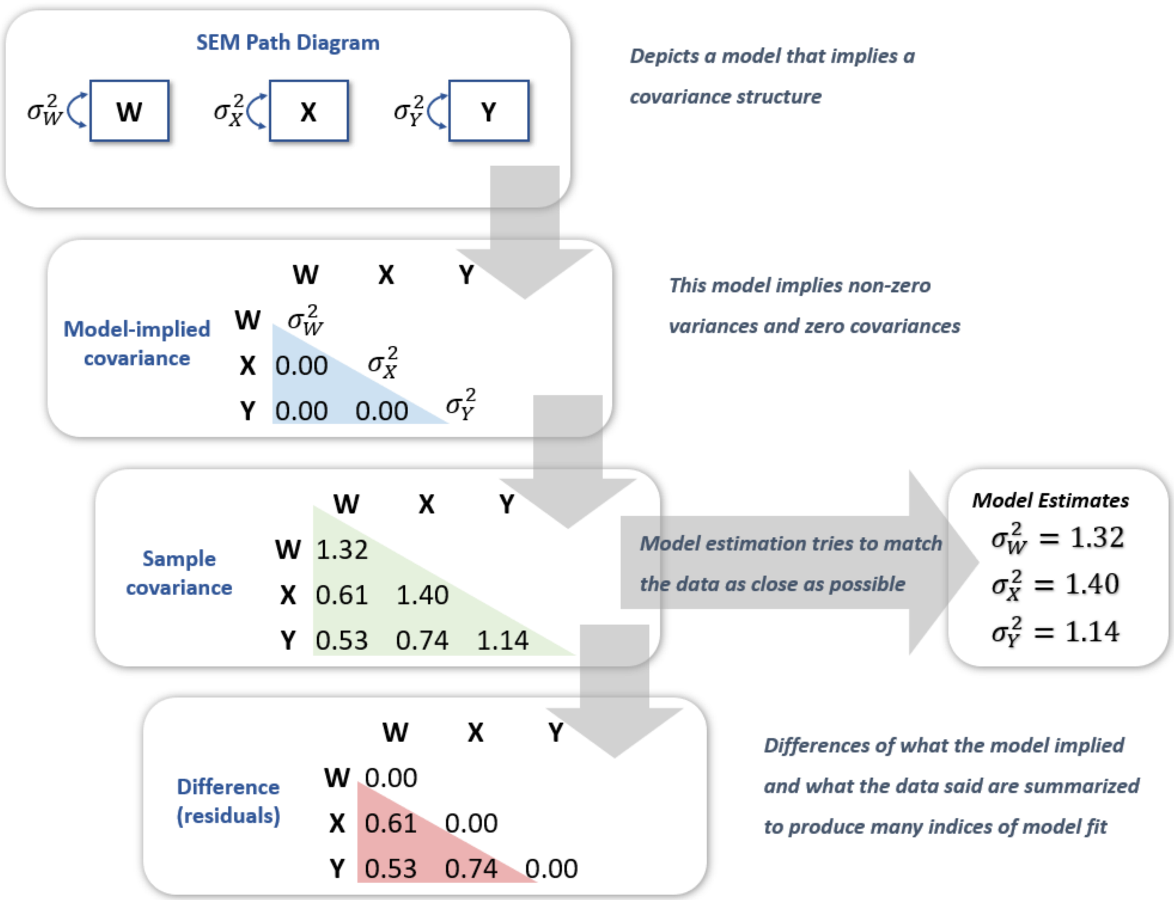
Covariance Matrix

	Privacy_2	Reput_4	Security_2	Trust_1	Privacy_3	Trust_3	Reput_1
Privacy_2	1.55964	0.28826	0.42039	0.47271	1.04427	0.59975	0.04196
Reput_4	0.28826	1.27246	0.23057	0.29775	0.03093	0.34575	0.67080
Security_2	0.42039	0.23057	1.16237	0.70780	0.32091	0.61759	0.28596
Trust_1	0.47271	0.29775	0.70780	1.32994	0.35357	0.70199	0.30974
Privacy_3	1.04427	0.03093	0.32091	0.35357	1.48972	0.40109	-0.15226
Trust_3	0.59975	0.34575	0.61759	0.70199	0.40109	1.26030	0.38632
Reput_1	0.04196	0.67080	0.28596	0.30974	-0.15226	0.38632	1.41909

Example: 7 variances + 21 covariances

df = 28 – unknowns (# of estimates)

How does SEM work?



Depicts a model that implies a covariance structure

This model implies non-zero variances and zero covariances

Differences of what the model implied and what the data said are summarized to produce many indices of model fit

How does SEM work?

- Model and path diagram imply
  - Covariance structure: Σ
  - Parameter vector: Θ
- We have sample covariance matrix: S
- We minimize a discrepancy function $F[S, \Sigma(\Theta)]$ to obtain $\widehat{\Theta}$
- We use:

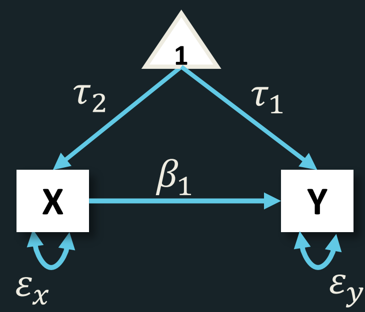
$$F_{ML}(\boldsymbol{S}, \boldsymbol{\Sigma}) = \ln|\boldsymbol{\Sigma}| - \ln|\boldsymbol{S}| + tr(\boldsymbol{S}\boldsymbol{\Sigma}^{-1}) - p$$

- Missing data: Full Information Maximum Likelihood

Building Block #1

Simple Linear Regression

Simple Regression Example

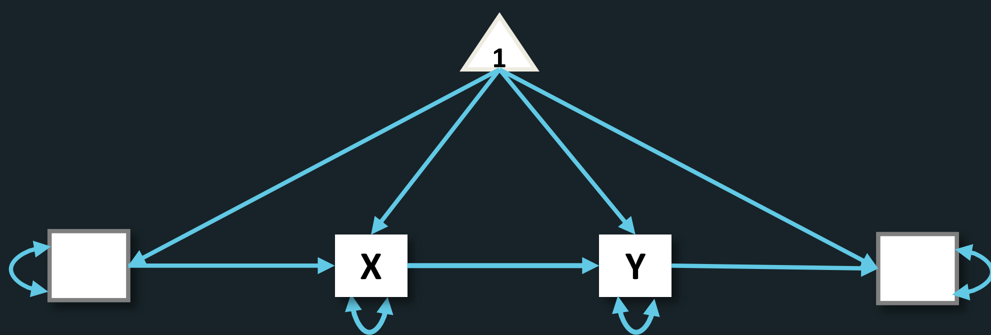


$$Y = \tau_1 + \beta_1 X + \varepsilon_y$$
$$X = \tau_2 + \varepsilon_x$$

Building Block #1

Regression + Regression +… + Regression = Path Analysis

Regression Building Block



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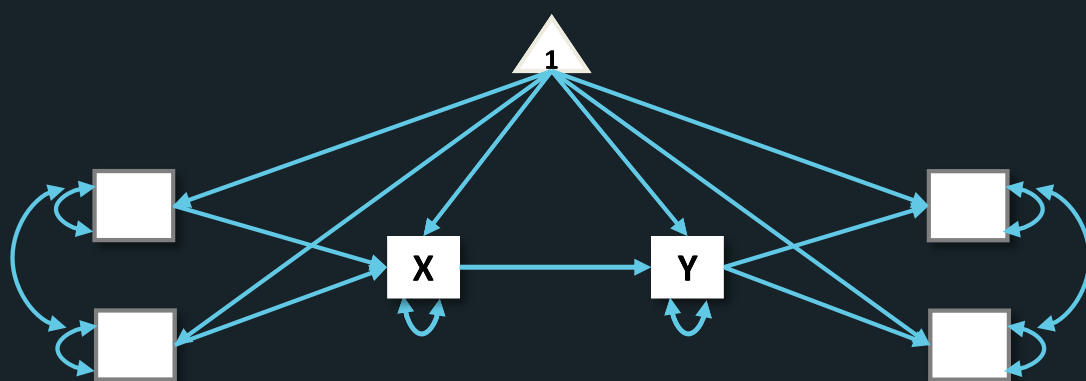
Building Block #1

Regression + Regression +… + Regression = Path Analysis

Regression Building Block

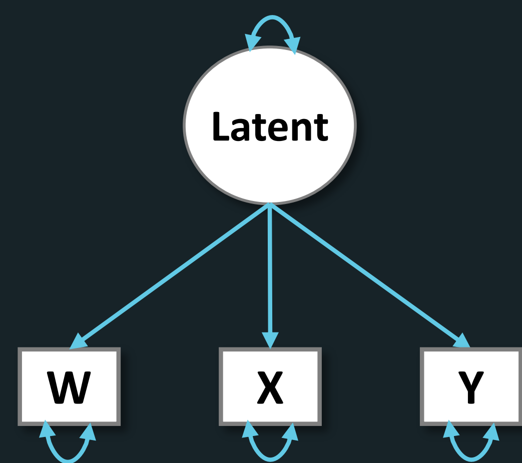


Building Block #1

DEMO

Building Block #2

Confirmatory Factor Analysis (CFA)



Reputation

versus

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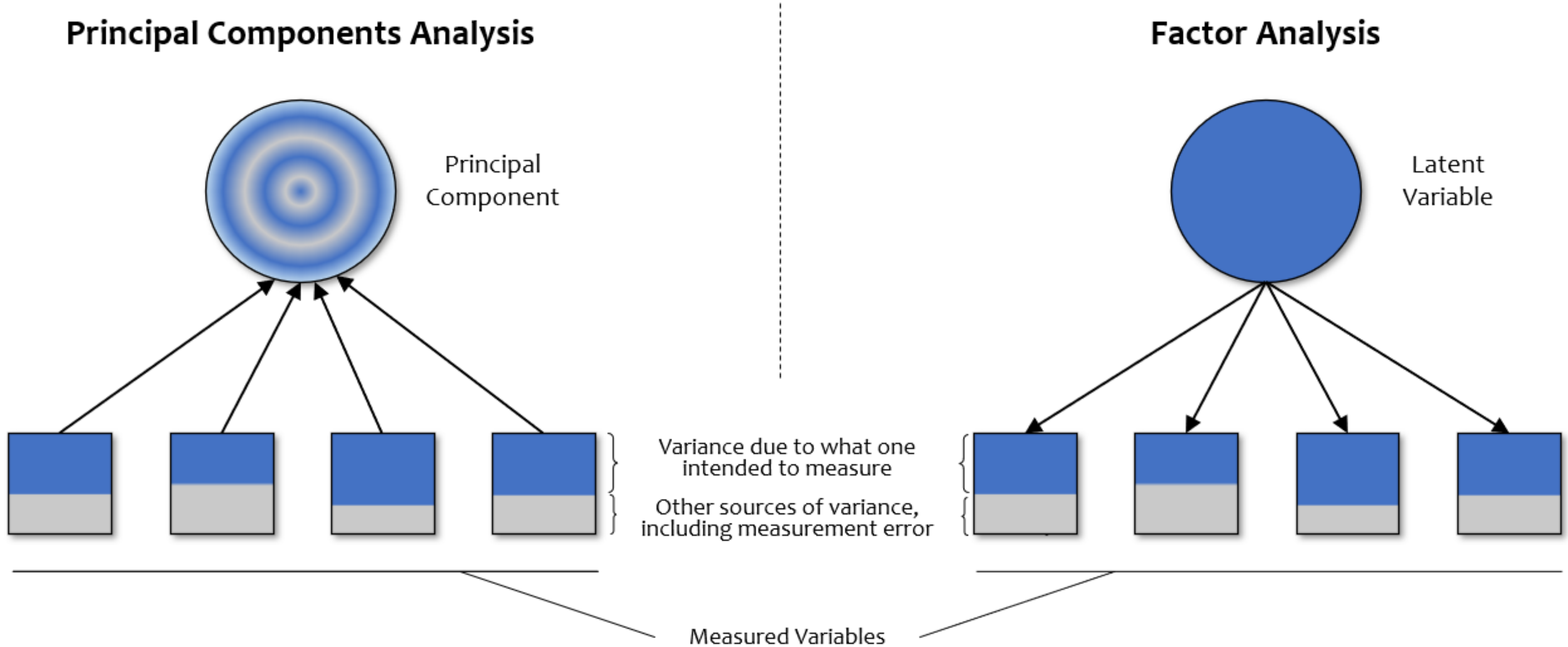
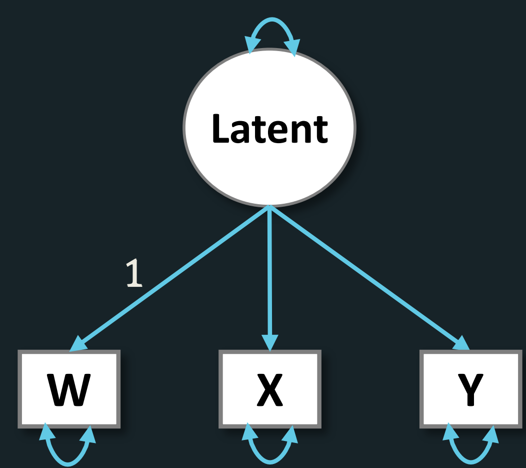
Latent Variable Definition



https://community.jmp.com/t5/JMP-Blog/Principal-components-or-factor-analysis/ba-p/38347

Building Block #2

Confirmatory Factor Analysis (CFA)



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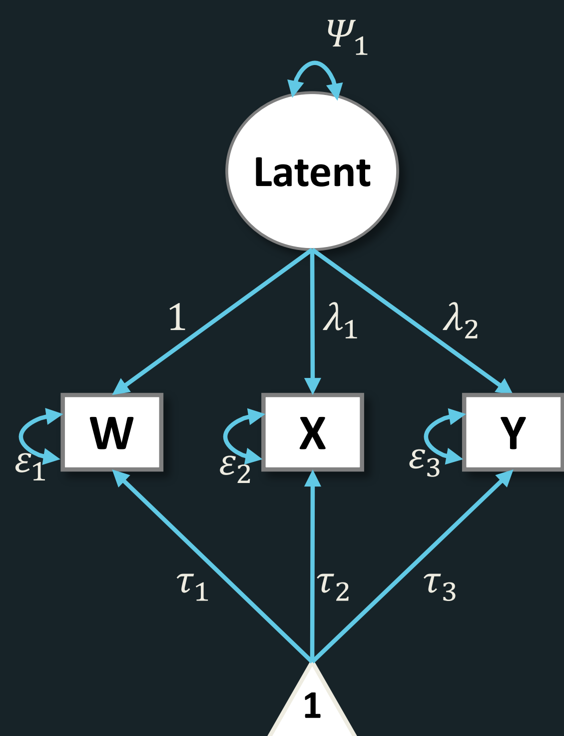
Building Block #2

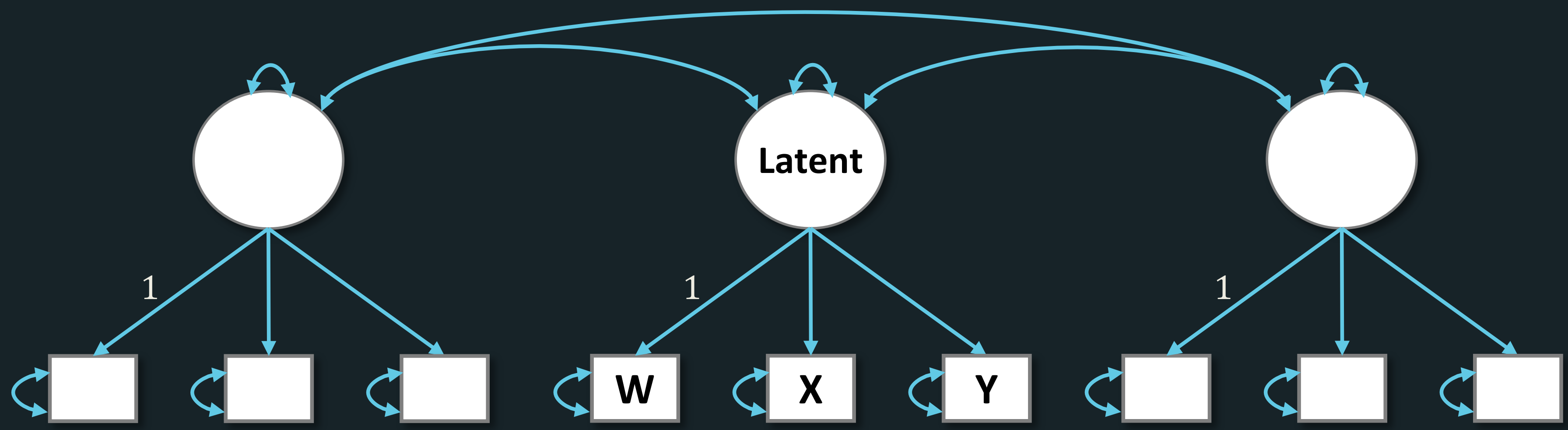
Confirmatory Factor Analysis (CFA)



$$W = \tau_1 + 1L + \varepsilon_1$$
$$X = \tau_2 + \lambda_1 L + \varepsilon_2$$
$$Y = \tau_3 + \lambda_2 L + \varepsilon_3$$

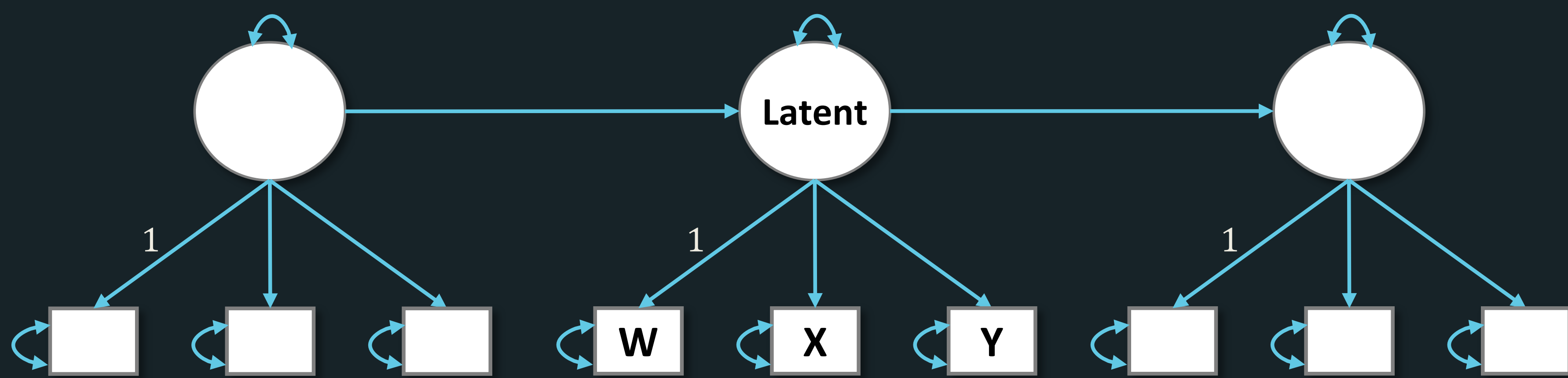
Building Block #2

CFA Building Block



Building Block #1 and #2

CFA + Regression Building Blocks



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SEM Research Examples in Law Enforcement

Police Practice and Research ›
An International Journal
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Police Personnel

Using structural equation modeling to explore the role of early strain on later stress responses and aggression by police officers

Don L. Kurtz & Vivian Hughes

Pages 355-369 | Received 22 Feb 2019, Accepted 07 Mar 2020, Published online: 19 Apr 2020
Download citation https://doi.org/10.1080/15614263.2020.1749623

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ABSTRACT

Policing is frequently identified as one of the most stressful professions and police officers are often exposed to dangerous situations and traumatic experiences on the job. Exposure to these traumatic experiences, also referred to as critical incidents, may negatively influence the

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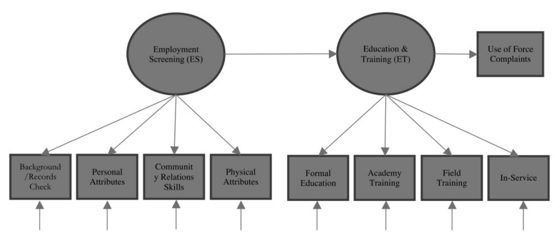

Published: 30 October 2007

Police Stress: A Structural Model

Risdon N. Slate, W. Wesley Johnson & Sharla S. Colbert

Journal of Police and Criminal Psychology 22, 102–112 (2007) | Cite this article

Abstract

A number of existing studies have identified various factors that contribute to stress among police officers. This analysis is unique among these insofar as it employs structural equation modeling to specify, in path model format, the influence of participation in workplace decision-making and other variables on employee stress levels. The findings of this analysis

Police visibility, trust in police fairness, and collective efficacy: A multilevel Structural Equation Model

Julia Yesberg, Ian Brunton-Smith and Ben Bradford View all authors and affiliations

OnlineFirst | https://doi.org/10.1177/14773708211035306

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Abstract

Areas high in collective efficacy – where residents know and trust one another and are willing to intervene to solve neighbourhood problems – tend to experience less crime. Policing is thought to be one antecedent to collective efficacy, but little empirical research has explored this question. Using three waves of survey data collected from London residents over three consecutive years, and multilevel Structural Equation Modelling, this study tested the impact of police visibility and police–community engagement on collective efficacy. We explored direct effects as well as indirect effects through trust in police. The findings showed levels of police visibility predicted trust in police. Trust in police fairness, in turn, predicted collective efficacy. There was a small *indirect* relationship between police visibility and collective efficacy, through trust in police fairness. In other words, police presence in neighbourhoods was associated with more positive views about officer behaviour, which in turn was associated with collective efficacy. The findings have important implications for

Restricted access | Research article | First published October 2006

Violence Between the Police and the Public: Influences of Work-Related Stress, Job Satisfaction, Burnout, and Situational Factors

Patrik Manzoni and Manuel Eisner View all authors and affiliations

Volume 33, Issue 5 | https://doi.org/10.1177/0093854806288039

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Abstract

Stress of police officers is assumed to be one of the causes for an increased use of force, but to date, very few studies have tested this relationship empirically. This study examines influences of perceived work-related stress, job satisfaction, organizational commitment, and burnout on the use of force by police officers in Zurich, Switzerland (n = 422). A new approach is developed by including the officer's routine activities (herein referred to as job profile) and victimization experiences as two situational controls and by capturing a continuum of self-reported force used in typical operational situations. Although bivariate

Victimization, stress and use of force among South Korean police officers

Jinseong Cheong, Ilhong Yun

Policing: An International Journal
ISSN: 1363-951X
Article publication date: 8 November 2011

Abstract

Purpose

This study aims to assess the direct and indirect impact of stress on police use of force among a sample of male South Korean frontline officers (n=574).

Design/methodology/approach

Largely drawing on a methodological approach adopted by Manzoni and Eisner the paper employs a structural equation modeling approach.

Related articles

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Building Block #2

DEMO

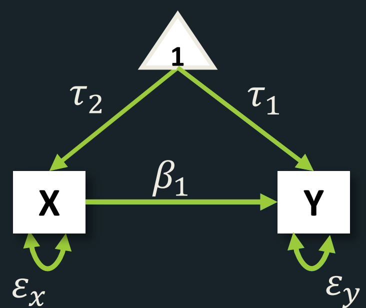
Multiple Group Analysis

SEM Technique

- Extends all models fit in SEM
- Investigate similarities and differences across populations
- Requires grouping variable (often with few levels)

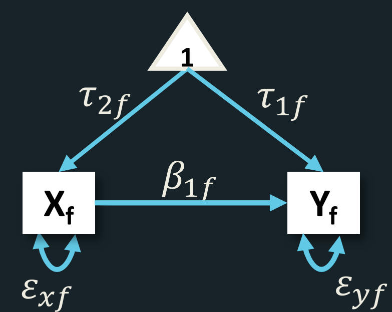
Multiple Group Analysis

Simple Regression Example

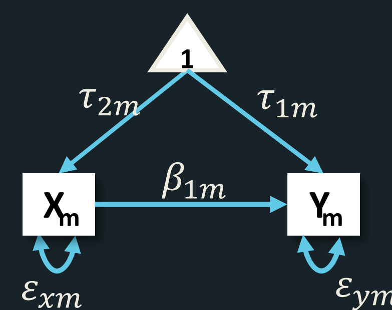


MGA Extension

Females



Males



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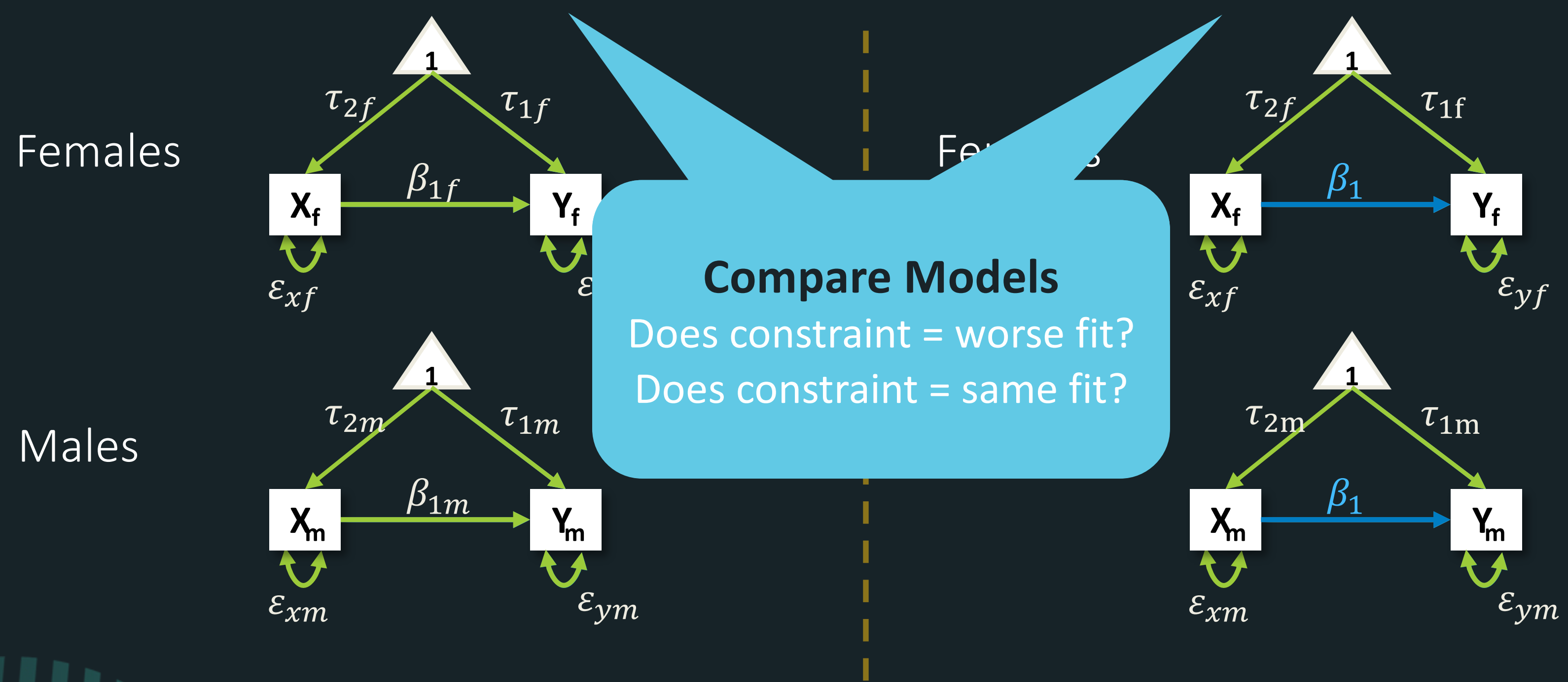
Multiple Group Analysis

MGA All Free (Model 1)

MGA Equal β (Model 2)



Multiple Group Analysis

DEMO

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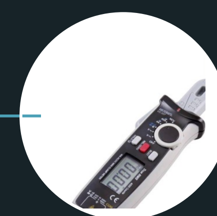
Summary

SEM in JMP Pro

- SEM: Many benefits
- JMP Pro: Reduces barriers



Thank you!

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