Using Path Analysis to Test a Hypothesis on the Process of Change in Hemoglobin A1c (HbA1c) Among Clients in a Culturally Tailored Diabetes Intervention for African Americans and Latino/as

Brandy R. Sinco, MS, Nicolaus R. Espitia, MSW, Michael S. Spencer, PhD, Edith Kieffer, PhD, Gloria Palmisano, MA, Melissa Valerio, PhD, Phillip L. Chapman, PhD

Disclosure Statement

I have no conflict of interest and am not involved in any off-label or experimental uses of a commercial product or service discussed in my presentation.

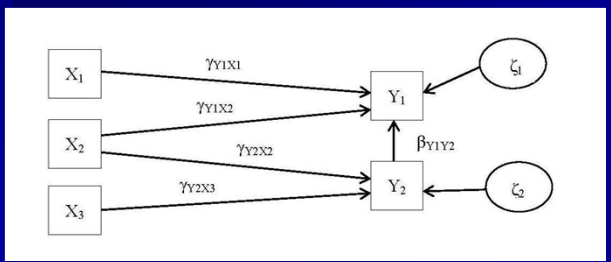
I do not own stock in SAS, IBM, Microsoft, nor in any software company.

Outline (Map)

- Basic Concepts of Path Analysis
- Brief description of the REACH-Detroit Project.
- Assessment of multivariate normality.
- Analyzing missing data.
- Results of fitting a path analysis model.
- Software comparison.
- Conclusions.

Definition of Path Analysis Model

- A Path Analysis model is a system of linear equations based on a diagram that specifies the relationships between the variables.
- Path Analysis is the sub-model of the structural equation model), in which all variables are observable or "manifest".
- Examples of manifest variables: weight, voltage, temperature.
- Exogenous variables analogous to X or independent variables.
- Endogenous variable are outcomes, Y in regression.



Design Equations and Matrices 1/2

- μ = Column vector of means of manifest variables, r × 1.
- Σ = Covariance matrix of manifest variables, r × r.
- **Goal: Estimate μ and Σ are based on model parameters.**
- $\bar{z}$ = Column vector of sample means of manifest variables, r × 1.
- S = Sample covariance matrix with (n – 1) denominator, r × r.
- $\hat{\mu}$ = Estimated mean vector of Z, based on path model.
- $\hat{\Sigma}$ = Estimated covariance matrix of Z based on path model.
- Ideal Model: $\hat{\mu} = \bar{z}; \quad \hat{\Sigma} = s.$

Design Equations and Matrices 2/2

- Use maximum likelihood to minimize F_{ML}, the discrepancy function.

$$F_{ML} = \ln\left(\left|\Sigma\right|\right) - \ln\left(\left|S\right|\right) + tr\left(S\Sigma^{-1}\right) + \left(\bar{z} - \mu\right)^{T} \Sigma^{-1}\left(\bar{z} - \mu\right) - r$$

- The model χ2 is given by $\chi_{ML}^{2} = (n - 1)\, F_{ML}$.

LISREL Equation for the Path Model:

- Y= α + YB + XΓ + ζ.
- A full SEM model would have 3 matrix equations.
- A path analysis model has only 1 matrix equation.

Goodness of Fit Indicators: Absolute fit, incremental fit, parsimony, prediction ability.

- **Absolute fit indices** are analogous to R^2 in linear regression.
- GFI (Joreskorg-Sorbom Goodness of Fit Index). Proportion of generalized variance explained by the model.
- (Klein, 2011; Joreskog & Sorbom, 1982) .
- GFI > .9 indicates a good absolute fit.

- **Incremental fit indices** compare the hypothesized model to the null model with no predictors ($Y_1 = \varepsilon_1, ..., Y_q = \varepsilon_q$).
- CFI (Bentler's Comparative Fit Index). A value of CLI from .90 - .95 is considered acceptable, while above .95 indicates a better incremental fit. (Klein, 2011; Bentler, 1990) .

$$CFI = 1 - \frac{\left(\chi^2_M - df_M\right)}{\left(\chi^2_B - df_B\right)}$$

Goodness of Fit Indicators

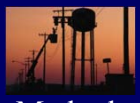
- **Parsimony adjusted indices** include penalty terms in their formulas for more complex models.
- RMSEA (Steiger-Lind Root Mean Square Error of Approximation) with a 90% confidence interval).
- RMSEA < .05 is considered ideal, .05 to .08 indicates acceptable parsimony, .08 to .10 is considered mediocre, and above .10 signals a poor fit. (Klein, 2011; Steiger, 1990)

$$RMSEA = \sqrt{\frac{\chi^2_M - df_M}{df_M\left(n-1\right)}}$$

- **Predictive fit indices** estimate model fit estimate the model's ability to make predictions for the population.
- SRMR (Standardized Root Mean Square Residual).
- SRMR < .10 is the goal; values < .08 indicate better predictive ability of the model. (Klein, 2011; Hu and Bentler, 1999).

Degrees of Freedom

- Let t = number of parameters estimated in a path model.
- t = # path coefficients + # variances + # covariances.
- df = degrees of freedom.
- df = r(r + 1)/2 – t.
- df does not change with n as in a linear regression model.
- Neither increasing nor decreasing the sample size will change the degrees of freedom, but will change the power.



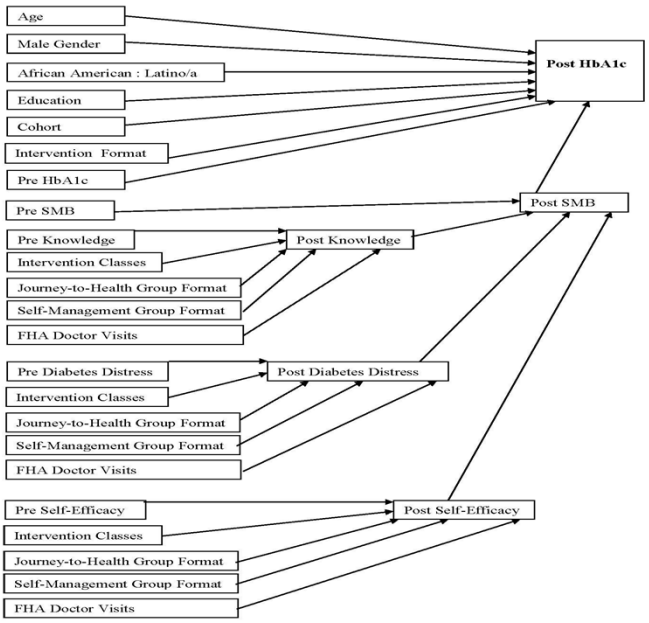
Power and Sample Size

- Method of MacCullum, Browne, and Sugawara (1996).
- For a well-fitting model, the χ^2 statistic will have a noncentrality parameter, λ, near zero.
- For a poorly fitting model, the χ^2 statistic will have a the same df, but with a larger non-centrality parameter.
- RMSEA $\leq$ .05 well-fitting model; $\geq$ .08 poor-fitting model.
- λ = Non-centrality parameter = (n-1) df ($RMSEA^2$).
- Null Hypothesis H0: $0 \leq \lambda \leq \lambda_0$; Alternative HA: $\lambda \geq \lambda_a$.
- For REACH-Detroit data, n=188 complete observations, 58 df.
- Lower bound for power is 0.79 because additional 138 observations with incomplete data included in estimation.

REACH-Detroit Partnership

"REACH is a national program that serves as the cornerstone of CDC's efforts to eliminate racial and ethnic disparities in health." www.reachdetroit.org, www.cdc.gov/reach

- Intervention = culturally tailored Diabetes curriculum over 11 sessions taught by PEER health educators, known as (FHAs) "Family Health Advocates".
- Part 1: Journey to Health; Part 2: Self-Management.
- FHAs accompany clients to at least one doctor visit.
- Combined two cohorts, N = 326, pre-intervention and post-intervention interviews and lab measurements.



Hypothesized Process of Change in HbA1c

- Improvement in diabetes self-management behavior would lead to reduction in HbA1c.
- Improvements in self-management behavior would be achieved through greater knowledge and self-efficacy, along with lower diabetes distress.
- Participation in the intervention would lead to improved knowledge and self-efficacy, and would reduce diabetes distress.
- Participation measured by the number of intervention classes, attendance in group versus one-on-one format, and being accompanied to at least one doctor appointment by a FHA.

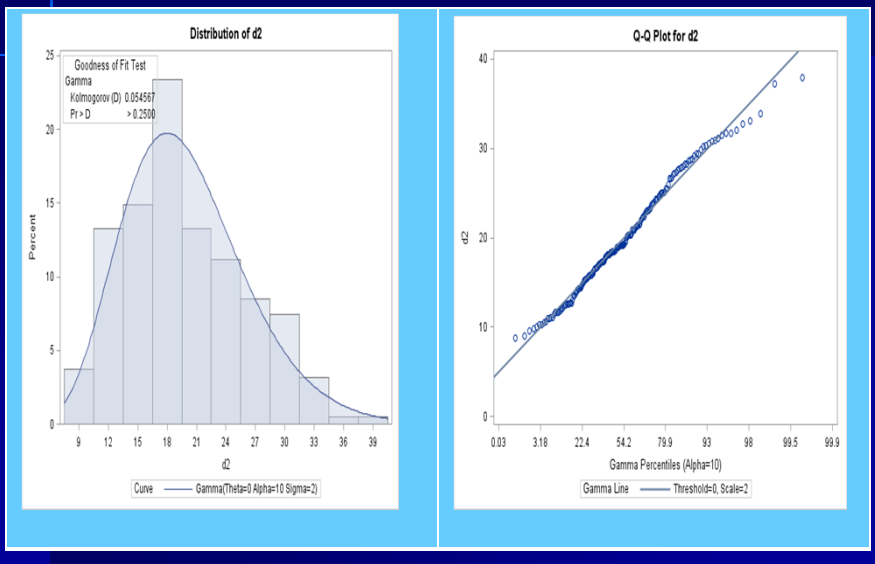
Univariate and Multivariate Normality

- Let Z_j be a single random variable with mean μ and variance σ^2.
- Standardized Skewness = $E[((Z_j - \mu)/\sigma)^3] = 0$.
- Standardized Kurtosis = $E[((Z_j - \mu)/\sigma)^4] - 3 = 0$.
- Assess Normality of Z_j by computing $(Z_j - \mu)/\sigma$ and comparing its histogram and qq-plot to a Normal(0,1) or by comparing histogram and qq-plot for $(Z_j - \mu)^2/\sigma^2$ to $\chi^2(1)$.
- For r-variate random sample of size n, Mahalanobis distance is analogous to $(Z_j - \mu)^2/\sigma^2$.
- $d_{(i)}^2$ = Mahalanobis distance of $Z_{(i)} = (Z_{(i)} - \mu^T)\,\Sigma^{-1}(Z_{(i)} - \mu^T)^T$.
- Compare histogram and qq-plot for $d_{(i)}^2$ to $\chi^2(r)$.

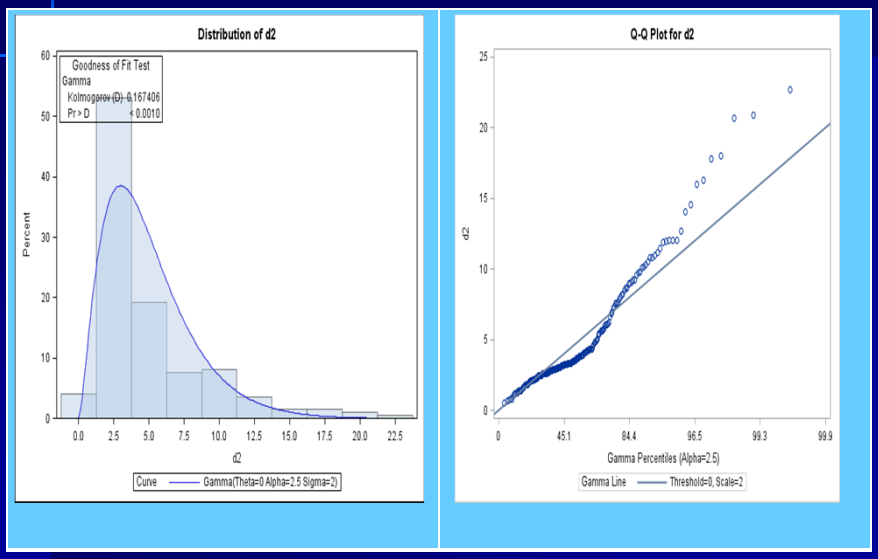
Mardia's Multivariate Skewness and Kurtosis (Mardia, 1970)

- Mardia generalized the formulas for univariate skewness and kurtosis to a r-variate distribution. He proved that the kurtosis for a r-variate standard normal variable would be r(r + 2).
- If r = 1, the kurtosis will be 3.
- Multivariate skewness evaluated with chi-square statistic; multivariate kurtosis with Z N(0, 1) statistic.

Histogram, QQ Plot for REACH-Detroit, All Variables (Some are Binary)



Histogram, QQ Plot for REACH-Detroit, Only Endogenous Variables



Mystery Solved

- Some of the variables are binary. So, how can all variables together produce better diagnostics for multivariate normality than only the endogenous variables?
- Binary variables can have kurtoses that are smaller than normal variables and the contribution of binary variables can lower the multivariate kurtosis. Including binary variables can lower overall kurtosis.
- Univariate skewness for Bernoulli variable with π = probability of event (0 if $\pi = 0.5$) $\dfrac{(1-2\pi)}{\sqrt{\pi(1-\pi)}}$
- Univariate kurtosis (0 if $\pi = 0.21$ or 0.79) $\dfrac{1-6\pi(1-\pi)}{\pi(1-\pi)}$

Conclusion on Multivariate Normality, REACH Data

- Structural Equation Model sensitive to multivariate kurtosis. REACH model has -0.03, which is << 1.96.
- Based on histogram and qq-plot, kurtosis fits with assumption.
- Although the model χ^2 derivation is based on the assumption that all variables in a SEM are multivariate normal, the exogenous variables do not have to be normally distributed.(Bollen, 1989).
- An adequate condition is that the endogenous variables, conditional on the exogenous variables, be multivariate normal.
- Bentler and Chou provided examples of exogenous variables, such as gender and race/ethnicity, that are clearly non-normal. (Bentler and Chou, 1987)

Missing Data Mechanisms

- M = indicator for missing data (1 = missing; 0 = complete).
- f(M) = probability density function for M.
-
- **MCAR (Missing Completely at Random).** Missingness does not depend on the values of variables in the data set. I.E., missingness does not depend on Y (outcome) or X (covariates). f(M | X, Y) = f(M).
- **MAR (Missing at Random).** Missing Y may depend on covariates, X, but not on Y. f(M | X, Y) = f(M | X).
- **MNAR (Missing Not at Random).** Missingness is related to unobserved data; also called "Non-Ignorable Missing".
- (Little & Rubin, 2002; Geldhof and Selig, 2007).

MAR (Missing At Random) Reasonable Assumption for REACH Data

- 188 of 326 clients have complete data.
-
- Pre-intervention means for all 5 endogenous variables (HbA1c, Knowledge, Diabetes Distress, Self-Efficacy, Self-Management) do not differ significantly by whether the post-intervention values are missing. Student t-test used to compare means.
- No differences in outcome nor demographic variables by withdrawal, only participation variables; makes perfect sense because people who withdrew weren't available to participate.

FIML (Full Information Maximum Likelihood)

- Missing data mechanism must be MAR or MCAR.
- The FIML algorithm is the same as the ML (Maximum Likelihood) algorithm, except that all available information is used. ML would exclude observation with data present on 9 out of 10 variables; FIML included observations with partial data
- Function minimized under ML:

$$F_{ML} = \ln\left(\left|\Sigma\right|\right) - \ln\left(\left|S\right|\right) + tr\left(S\Sigma^{-1}\right) + \left(\bar{z} - \mu\right)^{T}\Sigma^{-1}\left(\bar{z} - \mu\right) - r$$

- Function minimized under FIML (K_i is a constant).

$$F_{FIML} = \frac{1}{n}\sum_{i=1}^{n}\left(\ln\left(\left|\Sigma_i\right|\right) + tr\left(S_{ni}\Sigma_i^{-1}\right) + \left(\bar{z}i - \mu_i\right)^{T}\Sigma_i^{-1}\left(\bar{z}i - \mu_i\right) + \mathrm{K}_i\right)$$

- (SAS Institute, 2011; Yung and Zhang, 2011).

Multiple Imputation

- Multiple Imputation uses Markov Chain Monte Carlo simulation to estimate missing values in the data set.
- Key assumption - missing data mechanism is at least MAR.
- m = number of imputations, with the result being m datasets.
- Higher percentage of missing data ➔ more imputations.
- M datasets combined with serious of equations similar to ANOVA that account for variance between and within imputations.
- (Little and Rubin, 2002).

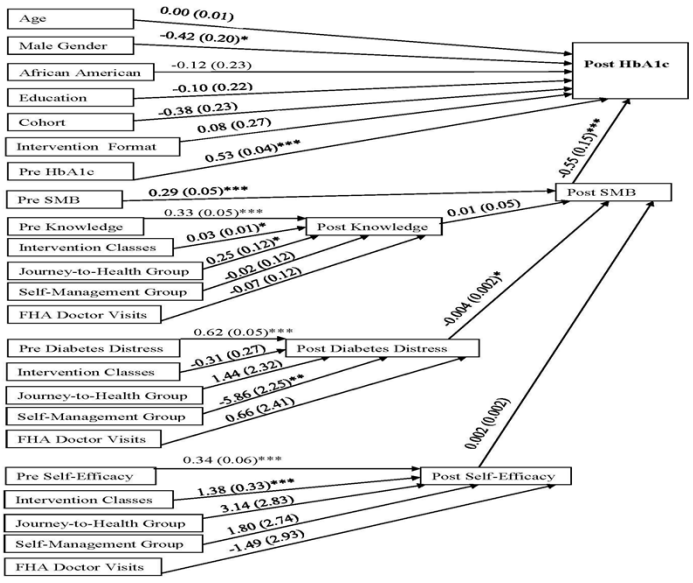
Comparison Between MI, FIML, ML

- According to the SEM literature, handling missing data with FIML is asymptotically equivalent to multiple imputation (Enders and Bandalos, 2001; Schafer and Olsen, 1998).
- Comparison by computing agreement ratio = (estimate by other method) / (estimate by FIML).
- Of the three estimation methods, FIML produced the most stable estimates.

	Coefficient Point Estimate MI / FIML	Coefficient Standard Error MI / FIML	Coefficient Point Estimate ML / FIML	Coefficient Standard Error ML / FIML
Average	0.98	1.13	1.14	1.18
Median	1.00	1.03	0.91	1.14
Min	0.10	0.90	0.14	1.00
Max	2.09	2.25	3.40	1.83

Fitting Path Model for REACH-Detroit

- **3 Issues:**
- Transform to code FHA-accompanied doctor visits. Based on AIC (Akaike Information Criteria), coding doctor visits as a binary variable (1 = 1+; 0 = none) fit data better than square root and {0, 1, 2, 3, 4+} coding.
- Direct path from participation measures to Post-Intervention HbA1c. Based on LRT (Likelihood Ratio Test), direct path not needed.
- Effect of removing demographics, participation measures. Based on LRT, removing demographics or doctor visits not significant. However, number of intervention classes and group versus one-on-one format are key variables.



REACH-Detroit Model Interpretation 1/3

- All post-intervention variables were strongly associated with pre-intervention values.
- **HbA1c.** A unit increase in self-management behavior was associated with -0.55 drop in post-intervention HbA1c ($p<.001$).
- Although the majority of REACH participants were women, male gender was associated with a lower post-intervention HbA1c by -0.42 ($p<.05$).
- **SMB (Self-Management Behavior).** In the equation for post-intervention smb, the only significant predictor was a drop in diabetes distress. I.E., a drop in diabetes-related distress was associated with an increase in self-management behavior.

REACH-Detroit Model Interpretation 2/3

- **Knowledge of Diabetes Management.** Higher post-intervention knowledge was associated with better class attendance and attending classes in the group, rather-than one-on-one, format ($p<.05$).
- Knowledge was measured on a scale of 1-to-5, with higher values indicating better knowledge. For each intervention class attended the average increase in knowledge was 0.03 ($p<.05$).
- Clients who received the intervention in group format had 0.25 greater increase in knowledge than clients who attended one-on-one with their FHAs.
- Therefore, if a client attended 10 classes and each class was in group format, the average increase in knowledge would be .55, which is approximately half a point on a four point scale.

REACH-Detroit Model Interpretation 3/3

- **Diabetes-Related Distress.** Attending the "self-management" section of the intervention in group format was associated with a -5.86 ($p<.01$) average drop in Diabetes distress.
- A six point drop in Diabetes distress on a 100 scale is considered a clinically significant, as well as a statistically significant improvement.
-
- **Self-Efficacy.** Post-intervention self-efficacy increased on the average of 1.38 ($p<.001$) for each intervention class attended. If a client attended 10 classes, average self-efficacy would increase by 13.8 on a 100 point scale.

REACH-Detroit Goodness of Fit Indices

- $\chi^2 = 142.96$, df = 58, $p<0.0001$.
- Although the χ^2 for the REACH SEM is significant, GFI = 0.9928.
- A GFI above .9 indicates a good absolute fit.
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- The SRMR (Standardized Root Mean Square Residual) measures predictive fit;SRMR<.10 is the goal. REACH SRMR = 0.0464.
- The RMSEA (Root Mean Square Error of Approximation) is a parsimony-adjusted index. For the REACH SEM, RMSEA is 0.0670, with a 90% confidence interval of (0.0533, 0.0810).
- CFI (Comparative Fit Index) is an incremental fit index; .90 - .95 is considered acceptable, above 0.95 ideal.
- For REACH, CLI is 0.9353.

Comparison Between SAS Proc CALIS, SPSS AMOS MODULE, AND MPLUS

- SAS version 9.3, SPSS version 19, Mplus version 6.1.
- CALIS (Covariance Analysis and Linear Structural Equations),
- AMOS (Analysis of Moment Structures).

- Agreement ratio = (estimate by other software) / (SAS estimate).
- Point estimates were nearly identical between SAS, SPSS, Mplus.
- Std. errors were slightly larger in AMOS and Mplus than in SAS.

	Coefficient Point Estimate SPSS / SAS	Coefficient Standard Error SPSS / SAS	Coefficient Point Estimate Mplus / SAS	Coefficient Standard Error Mplus / SAS
Average	1.00	1.03	1.01	1.07
Median	1.00	1.00	1.00	1.01
Min	0.99	0.93	0.17	0.96
Max	1.00	1.38	1.54	1.55

Conclusions

- Path Analysis is an effective method of modeling the process by which health outcome variables change in a behavioral intervention.

- One or more participation variables were associated with changes in knowledge, diabetes distress, and self-efficacy.

- When intervention format was significant, group format was always more beneficial than the one-on-one format.

- Estimates with FIML (Fulll Information Maximum Likelihood) close to those with MI (Multiple Imputation), but more stable with FIML.

Acknowledgements

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Contact Information

- Brandy R. Sinco, Statistician and Programmer/Analyst
- University of Michigan School of Social Work
- 1080 S. University St.
- Box 183
- Ann Arbor, MI 48109-1106
- Phone: 734-763-7784
- E-Mail: brsinco@umich.edu