How to Conduct Path Analysis and Structural Equation Model for Health Research

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What is Path Analysis/ SEM?

• Path Analysis is the statistical technique based upon a linear equation system used to examine causal relationships between two or more variables.

• It is just a series of regressions applied sequentially to data.

• In a regression model, each Independent Variable (IV) has direct on the Dependent Variable (DV)

• In a path analysis model, in addition to direct effect there is also indirect effect of an Independent Variable (IV), via an mediating variable, on the Dependent Variable (DV)
History of Path Analysis

• Path analysis was first developed by Sewall Wright in the 1930s for use in phylogenetic studies.
• Gained popularity in 1960, when Blalock, Duncan, and others introduced them to social science (e.g. status attainment processes).
• The development of general linear models by Joreskog and others in 1970s (“LISREL” models, i.e. linear structural relations)
Path Analysis is AKA (Also Known As)

- SEM – Structural Equation Modeling
- CSA – Covariance Structure Analysis
- Causal Models
- Simultaneous Equations
- Path Analysis
- Confirmatory Factor Analysis

Note:
- Path analysis and confirmatory factor analysis (CFA) are components of SEM
- SEM is an extension of Path Analysis
SEM vs. Other Approaches

- Similar to standard approaches based on linear model
- Based on statistical theory
- Conclusions valid only if assumptions are met
- Not a magic test of causality
- Statistical inference compromised if post hoc tests performed

- Different from standard approaches
- Requires formal specification of model
- Allows latent variables
- Statistical tests and assessment of fit more ambiguous
- Can seem like less of a science; more of an art
Path Analysis/ SEM

1. A comprehensive statistical approach to testing hypotheses about relations among observed and latent variables (Hoyle, 1995)

2. A methodology for representing, estimating, and testing a theoretical network of (mostly) linear relations between variables (Rigdon, 1998).

3. Tests hypothesized patterns of directional and non-directional relationships among a set of observed (measured) and unobserved (latent) variables (MacCallum & Austin, 2000).

4. Path is like SEM but has no latent variables
Difference Between Path Analysis and SEM

• Path analysis is a special case of SEM
• Path analysis contains only observed variables (no latent variable as SEM)
• Path analysis assumes that all variables are measured without error
• SEM uses latent variables to account for measurement error
• Path analysis has a more restrictive set of assumptions than SEM (e.g. no correlation between the error terms)
Difference Between Path Analysis and SEM

- Path analysis is a subset of Structural Equation Modeling (SEM), a multivariate procedure.
- Path analysis as defined by Ullman (1996) "allows examination of a set of relationships between one or more independent variables, either continuous or discrete, and one or more dependent variables, either continuous or discrete."
- SEM deals with measured and latent variables.
- SEM is a combination of multiple regression and factor analysis.
- Path analysis deals only with measured variables.
A measured variable is a variable that can be observed directly and is measurable.

Measured variables are also known as observed variables, indicators or manifest variables.
A latent variable is a variable that cannot be observed directly and must be inferred from measured variables. Latent variables are implied by the covariances among two or more measured variables. They are also known as factors (i.e., factor analysis), constructs or unobserved variables.
Components of SEM

- Structural equation modeling (SEM), as a concept, is a combination of statistical techniques
  1. Confirmatory factor analysis
  2. Path analysis
Example of SEM with Some Indicators in Each Latent Variables

Figure 2.1. Illustrative Model of Relationships Among Depression, Immune Function, and Illness

Source: Hoyle 1995
Path Analysis (No Latent Variables)

[Diagram showing relationships between variables, including Measured variables: Allocated OR Time, Estimated Elective Cases, Actual Elective Cases, Estimated Add-on Cases, Actual Add-on Cases, Mean 1st Case Delay, Mean Turnover Duration, and others.]
Factor Analysis

- Estimate a construct ($\eta$) underlying values on various related indicator variables ($y_1 - y_3$)

Multiple Regression

- Estimate $x \rightarrow y$ (parameter $\beta$) while controlling for confounders $z_1$, $z_2$, $z_3$ that are related to $x$ and to $y$

Path Analysis

- Estimate relations (parameters $\beta_1$, $\beta_2$, $\beta_3$) between various constructs ($x$, $y$, $z$) at the same time
The Goals of Path/ SEM

1. To understand the patterns of correlation/covariance among a set of variables
2. To explain as much of their variance as possible with the model specified

(Kline, 1998)
SEM Process

• SEM process centers around two steps:
  – Validating the measurement model: accomplished primarily through confirmatory factor analysis (CFA)
  – Fitting the structural model: accomplished primarily through path analysis with latent variables.
The Purposes of CFA and Path Analysis

1. Confirmatory factor analysis (CFA)
   - Tests models of relationships between latent variables (LVs or common factors) and MVs which are indicators of common factors.
   - A test of the meaningfulness of latent variables and their indicators, but the researcher may wish to apply traditional tests (ex., Cronbach's alpha)

2. Path analysis (e.g., regression)
   - Tests models and relationships among MVs.
Confirmatory Factor Analysis

• Confirmatory factor analysis (CFA) may be used to confirm that the indicators sort themselves into factors corresponding to how the researcher has linked the indicators to the latent variables.
• Confirmatory factor analysis plays an important role in structural equation modeling.
• CFA models in SEM are used to assess the role of measurement error in the model, to validate a multifactorial model, and to determine group effects on the factors.
Some Definitions

• Model: Statement about relationships between variables
• Specification: Act of formally stating a model
• Examples:

- zero-order correlation: 2 variables are related (but no direction specified)
  \[ A \leftrightarrow B \]
- multiple regression: predictors have directional relationship with outcome variable
  \[ P1 \rightarrow P2 \rightarrow P3 \rightarrow O \]
More Definitions

• Parameters:
  – Parameters are constants
  – Indicate the nature and size of the relationship between two variables in the population
  – Can never know the true value of a parameter, but statistics help us make our best guess

• Parameters in SEM
  – Can be specified as “fixed” (to be set equal to some constant like zero)
  – “free” (to be estimated from the data)

• Parameters in other techniques
  – Pearson correlation: one parameter is estimated (r)
  – Regression: regression coefficients are estimated
Indicators

• Indicators are observed variables, sometimes called manifest variables or reference variables.
• For example, items in a survey instrument.
• Four or more is recommended, three is acceptable and common practice,
• Two is problematic, and with one measurement, error cannot be modeled.
• Models using only two indicators per latent variable are more likely to be under-identified and/or fail to converge.
• Error estimates may be unreliable.
Caution About Indicators

- Indicator variables cannot be combined arbitrarily to form latent variables.
- For instance, combining gender, race, or other demographic variables to form a latent variable called "background factors" would be improper.
- Because it would not represent any single underlying continuum of meaning.
Latent Variable

- Latent variables are the unobserved variables or constructs or factors which are measured by their respective indicators.
- Latent variables include both independent, mediating, and dependent variables.
Diagram Elements

• Single-headed arrow $\rightarrow$
  – This is prediction
  – Regression Coefficient or factor loading

• Double headed arrow $\leftrightarrow$
  – This is correlation

• Missing Paths
  – Hypothesized absence of relationship
  – Can also set path to zero
Exogenous vs Endogenous Variables, Latent vs Measured Variables
Disturbances

- Every endogenous variable has a disturbance (aka. noise)
- These represent all omitted causes, plus any random or measurement error, i.e., all variance that predictors didn’t predict.
- Also called residuals or error terms “error term” implies that there are no omitted causes (only error variance).
- Disturbances can be conceptualized as unmeasured (latent) exogenous variables.
- They allow us to compute a percent variance explained for each endogenous variable.
Types of Associations

• Association:
  – Non-directional relationship
  – The type evaluated by Pearson correlation

• Direct:
  – A directional relationship between variables
  – The type of association evaluated in multiple regression or ANOVA
  – The building block of SEM models

• Indirect:
  – Two (or more) directional relationships
  – V1 affects V2 which in turns affects V3
  – Relationship between V1 and V3 is mediated by V2

• Total:
  – Sum of all direct and indirect effects
Multiple Regression and SEM

- Can run regression analyses using SEM software
- Mathematics/computer algorithm used by SEM is different, but
- Parameter estimates will be identical or very close
- Note that fit will be perfect (number of observations and number of parameters are equal)
- Running in SEM buys nothing but, nice analysis to start with
- SEM allows multiple DVs
- SEM allows two-group (or multi-group) comparisons
Multiple Regression Diagram

\[ X_1 \rightarrow Y_1 \]
\[ X_2 \rightarrow Y_1 \]
\[ X_3 \rightarrow Y_1 \]
\[ X_4 \rightarrow Y_1 \]

\[ e_1 \rightarrow Y_1 \]
Multiple Regression Diagram with SEM
Some examples of path models.
Data Type

• Both IV’s and DV’s can be continuous, discrete, or even dichotomous.
• If DV is continuous, can use model similar to regression analysis → can employ SPSS AMOS
• If DV is dichotomous, can use model similar to regression analysis → can employ Stata GSEM (generalized structural equation model)
• Independent variables are usually considered either predictor or causal variables because they predict or cause the dependent variables (the response or outcome variables).
The relationships between the theoretical constructs are represented by regression or path coefficients between the factors.
Diagram Elements

• Single-headed arrow →
  – This is prediction
  – Regression Coefficient or factor loading

• Double headed arrow ↔
  – This is correlation

• Missing Paths
  – Hypothesized absence of relationship
  – Can also set path to zero
Assumed Causal Relation in Path and SEM

• Just as in path analysis, the diagram for the SEM shows the assumed causal relations.
• If the parameters of the model are identified, a covariance matrix or a correlation matrix can be used to estimate the parameters of the model
• One parameter corresponds to each arrow in the diagram.
Estimated Sample Size Requirement

1. df (degree of freedom) ≥0
2. 200 subjects for small to medium sized model
3. At least, 10-20 subjects per estimated parameter
4. No less than 5 subjects per estimated parameter
   – For example:
     5 estimated parameter = 5 x 20 subjects = 100 subjects
SEM Limitations

• Biggest limitation is sample size:
  – It needs to be large to get stable estimates of the covariances/correlations
  – Requirement for large sample size $n < 100$: small; 100-200: medium.
  – A minimum of 10 subjects per estimated parameter
  – Also affected by effect size and required power
5 Steps in Path Analysis

1. Model specification
2. Model identification
3. Model fit
4. Coefficient estimates
5. Model re-specification (if necessary)
Path Model is Specified Based on Theory of Planned Behavior (Icek Ajzen)

Model Specification
Model Identification

• Model will be unidentified if $\#\text{Parameters} > \#\text{Observations}$

• Note: In PA and SEM, the number of observations is not based on the sample size, but rather, on the number of variables in the model ($k$).

• The specific formula is:

$$\text{Number of observations} = \left[ k(k + 1) \right]/2$$
Theory of Planned Behavior depicted in path diagram
Theory of Planned Behavior depicted in path diagram

Two regression analyses:
1. Behavior = Behavior intention + Perceived Behavior control
2. Behavior intention = Attitude toward act or behavior + subjective norm + perceived behavior control

For each endogenous (DV) variable, a regression analysis is performed.
Two regression analyses:
1. Behavior = Behavior intention + Perceived Behavior control
2. Behavior intention = Attitude toward act or behavior + subjective norm + perceived behavior control

Theory of Planned Behavior depicted in path diagram

Source: Ajzen (1991)
Path Analysis

– Path coefficients are standardized (´Beta´) or unstandardized (´B´ or (´β´) regression coefficients.

• Strength of inter-variable dependencies are comparable to other studies when standardized values (z, where \( M = 0 \) and \( SD = 1 \)) are used.
• Unstandardized values allow the original measurement scale examination of inter-variable dependencies.

\[
SD = \sqrt{\frac{\sum (x - \bar{x})^2}{N - 1}} \quad z = \frac{(x - \bar{x})}{SD}
\]
Interpretation of Unstandardized Path Coefficients

• They are not correlation coefficients.
• Suppose we have a network with a path connecting from variable A to variable B.
• With the unstandardized path coefficient B of 0.81:
  – If variable A increases by one unit, variable B would be expected to increase by 0.81 unit, while holding all other relevant variables constant.
• With a path coefficient B of -0.16:
  – If variable A increases by one unit, variable B would be expected to decrease by 0.16 unit, while holding all other relevant variable constant.
Interpretation of Standardized Path Coefficients

- They are not correlation coefficients.
- Suppose we have a network with a path connecting from variable A to variable B.
- The meaning of the standardized path coefficient Beta (e.g., 0.81):
  - If variable A increases by one standard deviation from its mean, variable B would be expected to increase by 0.81 its own standard deviations from its own mean while holding all other relevant variables constant.
- With a path coefficient Beta of -0.16:
  - If variable A increases by one standard deviation from its mean, variable B would be expected to decrease by 0.16 its own standard deviations from its own mean while holding all other relevant variable constant.
Path Analysis

– Path coefficient \( p_{DV,IV} \) indicates the direct effect of IV to DV.

– If the model contains only one IV and DV variable, the path coefficient equals to correlation coefficient.
  
  • In those models that have more than two variables (one IV and one DV), the path coefficients equal to partial correlation coefficients.
    
    – The other path coefficients are controlled while each individual path coefficient is calculated.
1. How many measured variables are in this path analysis diagram?
2. How many exogenous variables are in this path analysis diagram? Which are exogenous?
3. How many endogenous variables are in this path analysis diagram? Which are endogenous?
4. Is this model identified?
1. How many measured variables are in this path analysis diagram? 5
2. How many exogenous variables are in this path analysis diagram?
3. Which are exogenous? Attitude towards act or behavior, subjective norm, and perceived behavior control
3. How many endogenous variables are in this path analysis diagram? 3. Which are endogenous? Behavioral intention and behavior
4. Is this model identified?
• How many measured variables are in this path analysis diagram? 5

• Note: In PA and SEM, the number of observations is not based on the sample size, but rather, on the number of variables in the model (k).
• The specific formula is: Number of observations = \[k (k + 1)/2\]
• Number of observation= \[5(5+1)]/2= 15
• Is this model identified?
  df = degree of freedom = #observation - #parameter

  \[ df = 0 \Rightarrow \text{just identified} \]
  \[ df > 0 \Rightarrow \text{over-identified} \]
  \[ df < 0 \Rightarrow \text{under-identified} \]

  Path analysis model is executable if \( df \geq 0 \)
• Is this model identified?
  
  df = degree of freedom = #observations - #parameter
  
  # observations = ((#rectangles) * (#rectangles + 1))/2
  
  = (5 * (5+1))/2 = 15
  
  # parameters = (# arrows + #error terms + #exogenous variables
  
  = 8 + 2 + 3 = 13
  
  df = 15 - 13 = 2 → path analysis is executable
• Is this model identified?
  
  \[ df = \text{degree of freedom} = \#\text{observation} - \#\text{parameter} \]
  
  # observations = \((\#\text{rectangles}) \times (\#\text{rectangles} + 1))/2\]
  
  \[ = (5 \times (5 + 1))/2 = 15 \]
  
  # parameters = (# arrows + # error terms + # exogenous variables)
  
  \[ = 8 + 2 + 3 = 13 \]
  
  \[ df = 15 - 13 = 2 \rightarrow \text{path analysis is executable} \]
Model Fit

Absolute fit indices

- Absolute fit indices determine how well an a priori model fits the sample data (McDonald and Ho, 2002)
- They demonstrate which proposed model has the most superior fit.
- Provide the most fundamental indication of how well the proposed theory fits the data.
- Unlike incremental fit indices, their calculation does not rely on comparison with a baseline model.
- Instead, a measure of how well the model fits in comparison to no model at all (Jöreskog and Sörbom, 1993).
- Included in this category are the Chi-Squared test, RMSEA, GFI
Chi Square Statistic

The Chi-Square (CMIN) value:

- The traditional measure for evaluating overall model fit
- Assesses the magnitude of discrepancy between the sample and fitted covariances matrices” (Hu and Bentler, 1999)
- A good model fit would provide an insignificant result at a 0.05 threshold (Barrett, 2007)
- Chi-Square statistic is often referred to as a “badness of fit” (Kline, 2005)
Root Mean Square Error of Approximation (RMSEA)

- A cut-off value of RMSEA close to 0.06 (Hu and Bentler, 1999) or 0.07 (Steiger, 2007) seems to be the general consensus.
Goodness-of-Fit (GFI)

- Traditionally an omnibus cut-off point for GFI of 0.90 has been recommended.
- When factor loadings and sample sizes are low, a higher cut-off of 0.95 is more appropriate (Miles and Shevlin, 1998).
Adjusted Goodness-of-Fit Statistic (AGFI)

• Based upon degrees of freedom, with more saturated models reducing fit (Tabachnick and Fidell, 2007).
• More parsimonious models are preferred while penalized for complicated models.
• AGFI tends to increase with sample size.
• Values for the AGFI also range between 0 and 1
• Values of 0.90 or greater indicate well fitting models.
Incremental Fit Index

- Incremental fit indices, also known as comparative (Miles and Shevlin, 2007) or relative fit indices (McDonald and Ho, 2002), are a group of indices that do not use the chi-square in its raw form but compare the chisquare value to a baseline model.
- For these models the null hypothesis is that all variables are uncorrelated (McDonald and Ho, 2002).
Normed-fit Index (NFI)

- Values for this statistic range between 0 and 1
- Bentler and Bonnet (1980) recommend NFI values greater than 0.90 indicating a good fit.
- More recent suggestions state that the cut-off criteria should be $NFI \geq 0.95$ (Hu and Bentler, 1999).
Normed-fit Index (NFI)

Drawback:

- Sensitive to sample size
- Underestimate fit for samples less than 200 (Mulaik et al, 1989; Bentler, 1990)
- Not recommended to be solely relied on (Kline, 2005).
The Comparative Fit Index (CFI)

• First introduced by Bentler in 1990, a revised form of the NFI (Bentler, 1990)
• Takes into account sample size (Byrne, 1998)
• Performs well even when sample size is small (Tabachnick and Fidell, 2007).
• A cut-off criterion of CFI of ≥ 0.90 is recommended
• A value of CFI ≥ 0.95 is presently recognized as indicative of good fit (Hu and Bentler, 1999).
Unstandardized Estimate of Path Coefficient

• Unstandardized parameter estimates:
  1. Retain scaling information of variables involved
  2. Can only be interpreted with reference to the scales of the variables
Standardized Estimate of Path Coefficient

1. Transformations of unstandardized estimates that remove scaling information
2. Can be used for informal comparisons of parameters throughout the model.
3. Standardized estimates correspond to effect-size estimates
Interpretation of Standardized Estimates

- Interpretation of standardized path coefficient estimate:
  1. Standardized path coefficients with absolute values less than 0.10 may indicate a “small” effect
  2. Values around 0.30 indicate a “medium” effect
  3. Values greater than 0.50 indicate a “large” effect
Statistical Significance Test of the Estimated Parameter (P Value)

• The significance statistic is the ratio of each parameter estimate to its standard error, which is distributed as a z statistic
• Significant at the 0.05 level if its value exceeds 1.96
• At the 0.01 level if its value exceeds 2.56 (Hoyle, 1995).
• Results of significance tests reflect:
  1. Absolute magnitudes of path coefficients
  2. Sample size
  3. Inter-correlations among the variables
Model Modification (Model Re-Specification)

- Adjusts a specified and estimated model by either freeing parameters that were fixed or fixing parameters that were free.

- There are two strategies to take in the process of re-specifying a model:
  1. Test a priori, theoretically meaningful complications and simplifications of the model
  2. Use empirical tests (e.g., modification indices and standardized residuals) to respecify the model.
Model Modification (Model Re-Specification)

• All respecifications should be theoretically meaningful and ideally a priori.
• Too many empirically based respecifications likely lead to capitalization on chance and over-fitting (unnecessary parameters added to the model).
• Ideally, if many respecifications are made, a replication of the model should be undertaken.
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Unnamed project: Group number 1: Input

Group number 1

Default model

Unstandardized estimates
Standardized estimates
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The diagram presents a model with the following components:

- **Attitude**
- **Subjective Norm**
- **Intention**
- **Behavior**
- **Perceived Behavior Control**

The relationships between these components are depicted with arrows, indicating cause-and-effect or influence directions.
The relationships between the theoretical constructs are represented by regression or path coefficients between the factors.
Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments: 15
Number of distinct parameters to be estimated: 13
Degrees of freedom (15 - 13): 2

Result (Default model)

Minimum was achieved
Chi-square = .847
Degrees of freedom = 2
Probability level = .655
### Model Fit Summary

#### CMIN

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#### RMR, GFI

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### Baseline Comparisons

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80
## FMIN

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## RMSEA

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## AIC

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<td>54.074</td>
<td>67.074</td>
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<tr>
<td>Saturated model</td>
<td>30.000</td>
<td>33.396</td>
<td>61.415</td>
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<tr>
<td>Independence model</td>
<td>144.142</td>
<td>145.274</td>
<td>154.614</td>
<td>159.614</td>
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</table>
Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>S.E.</th>
<th>C.R.</th>
<th>P</th>
<th>La</th>
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</thead>
<tbody>
<tr>
<td>Intent &lt;-- Attitude</td>
<td>.444</td>
<td>.062</td>
<td>7.150</td>
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<tr>
<td>Intent &lt;-- PBC</td>
<td>-.064</td>
<td>.058</td>
<td>-1.097</td>
<td>.273</td>
<td></td>
</tr>
<tr>
<td>Intent &lt;-- SubNorm</td>
<td>.029</td>
<td>.030</td>
<td>.971</td>
<td>.332</td>
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</tr>
<tr>
<td>Behavior &lt;-- Intent</td>
<td>1.520</td>
<td>.516</td>
<td>2.944</td>
<td>.003</td>
<td></td>
</tr>
<tr>
<td>Behavior &lt;-- PBC</td>
<td>.734</td>
<td>.260</td>
<td>2.829</td>
<td>.005</td>
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</tbody>
</table>

Standardized Regression Weights: (Group number 1 - Default model)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intent &lt;-- Attitude</td>
<td>.807</td>
</tr>
<tr>
<td>Intent &lt;-- PBC</td>
<td>-.126</td>
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<tr>
<td>Intent &lt;-- SubNorm</td>
<td>.095</td>
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<td>Behavior &lt;-- Intent</td>
<td>.350</td>
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<td>Behavior &lt;-- PBC</td>
<td>.336</td>
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</table>
Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

Variances: (Group number 1 - Default model)

Regression Weights: (Group number 1 - Default model)
### Table for Reporting Path Analysis Results

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Independent variable</th>
<th>Unstandardized coefficient</th>
<th>p</th>
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</thead>
<tbody>
<tr>
<td>Indirect effect</td>
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<td></td>
<td></td>
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<tr>
<td>Behavior intention</td>
<td>Attitude</td>
<td>0.44</td>
<td>&lt;0.001</td>
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<tr>
<td></td>
<td>Perceived behavior control</td>
<td>0.06</td>
<td>0.273</td>
</tr>
<tr>
<td></td>
<td>Intent</td>
<td>0.03</td>
<td>0.332</td>
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<tr>
<td>Direct effect</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Behavior</td>
<td>Intent</td>
<td>1.52</td>
<td>0.003</td>
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<tr>
<td></td>
<td>Perceived behavior control</td>
<td>0.73</td>
<td>0.005</td>
</tr>
</tbody>
</table>

N observation = 60

Model fit:

- \( \chi^2 \) (CMIN) - 0.847, \( p = 0.655 \)
- GFI = 0.99, NFI = 0.99, CFI = 1.00
- RMSEA = <0.001
Thank You