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Path analysis in Mplus: A tutorial using a conceptual model of psychological and behavioral antecedents of bulimic symptoms in young adults

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Abstract ■ Path analysis is a widely used multivariate technique to construct conceptual models of psychological, cognitive, and behavioral phenomena. Although causation cannot be inferred by using this technique, researchers utilize path analysis to portray possible causal linkages between observable constructs in order to better understand the processes and mechanisms behind a given phenomenon. The objectives of this tutorial are to provide an overview of path analysis, step-by-step instructions for conducting path analysis in Mplus, and guidelines and tools for researchers to construct and evaluate path models in their respective fields of study. These objectives will be met by using data to generate a conceptual model of the psychological, cognitive, and behavioral antecedents of bulimic symptoms in a sample of young adults.

Keywords ■ Path analysis; Tutorial; Eating Disorders. **Tools** ■ Mplus.

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Introduction

Path analysis (also known as causal modeling) is a multivariate statistical technique that is often used to determine if a particular a priori causal model fits a researcher's data well; however, path analysis is "not intended to discover causes but to shed light on the tenability of the causal models that a researcher formulates" (Pedhazur, 1997, pp. 769-770). Although causal models are tested, causation cannot be implied, since causation can only be inferred through experimental design. Path analysis is gaining popularity across various fields of research because of its unique properties of being able to assess the validity of multiple causal models for a single dataset; to examine "causal" inferences or linkages between variables of interest, including examining the predictive power of one predictor variable on more than one criterion variable; and to examine direct and indirect effects amongst all variables in the model simultaneously. Path analysis is a powerful statistical technique that can answer many types of research questions and is commonly employed for generating and evaluating causal models. This tutorial aims to provide basic knowledge in employing and interpreting path models, guidelines for creating path models, and utilizing Mplus to conduct path analysis. An a priori conceptual model of psychological and behavioral antecedents of bulimic symptomology in young adults will be utilized as an example path model.

Why take the path to path?

Path analysis is an extension of multiple regression but allows researchers to infer and test a sequence of causal links between variables of interest. It also allows researchers to examine the relationships between multiple predictor and criterion variables simultaneously. Path analysis is also considered a special case of structural equation modeling (SEM). SEM is a general technique that is used to generate inferences about measurement error in latent constructs (psychological constructs that cannot be measured directly) and causal links between multiple predictor and criterion variables (Bollen, 1989b; Kline, 1998). Similar to regression, this technique operates by examining the relationship between estimated parameters and the variance-covariance matrix of observed or latent variables; however, SEM can be used to derive additional inferences regarding which parameters and how many parameters "best fit" the data. Although path analysis operates under SEM framework, they are distinct analyses and differ in two ways: Path analysis examines the relationships between observed variables, not latent variables, and does not allocate additional error to the path coefficient, since it assumes that there are no errors in how variables of interest are defined or measured, which is similar to regression.

Although path analysis can be utilized to evaluate various types of conceptual models, it is best to adopt an a priori conceptual model-testing framework, as it is designed to test and capture multiple complex "causal" relationships between variables of interest. Path analysis is especially useful to compare *a priori* models against "gold standard" models because they can add to current existing models, a new conceptual model of the phenomenon can be proposed, or existing theoretical framework can be tested. Path analysis models represent processes, in which researchers propose how variables are correlated. Thus, researchers propose the mechanisms that lead to many observable phenomena, which is better approached by path analysis than by multiple regression, since path analysis can generate many indices of best fit that can be used to compare multiple models for a single dataset.

In this tutorial, path analysis will be used to test an *a priori* model that is based on theoretical framework, Self-Determination Theory (SDT; Deci & Ryan, 2000), a leading theory in human motivation, in Mplus (Muthén & Muthén, 2010). This conceptual model will be applying SDT to examine key psychological and behavioral determinants of bulimic symptoms in young adult women. More specifically, the researchers will be examining how the fulfillment (satisfaction) and depletion (frustration) of essential psychological resources, or psychological needs (e.g., for autonomy, competence, and relatedness), may differentially predict bulimic symptoms in women through two key mediators, endorsement of society's beliefs about thinness and obesity and body inflexibility. According to SDT, psychological needs are universal essential nutriments, which affect an individual's ability to self-regulate and cope with everyday life demands and may render individuals vulnerable to ill-being if their psychological needs are frustrated (Vansteenkiste & Ryan, 2013). Need frustration may be more psychologically depleting than lack of need satisfaction, since frustration may be caused by an environment that is directly impeding the satisfaction of these needs and, thus, may be perceived as more controlling. Individuals whose needs are frustrated may engage in unhealthy compensatory behaviors in order to regain short-term feelings of need satisfaction. Need frustration also renders individuals vulnerable to endorsing cultural ideals, since personal resources to reject these ideals are depleted (Pelletier & Dion, 2007).

The conceptual model that will be tested proposes that women whose psychological needs are frustrated will endorse more problematic societal ideals about thinness and obesity than women whose psychological needs are satisfied. Need frustration will also be predictive of inflexible body schemas and bulimic symptoms, since need frustration has been shown to lead to body image disturbance and pathological eating behaviors (Boone, Vansteenkiste, Soenens, Van der Kaap-Deeder, & Verstuyf, 2014). This model also proposes that higher endorsement of societal beliefs about thinness and obesity will be predictive of heightened inflexible body schemas and, on its own, will be predictive of bulimic symptoms.

This tutorial will guide readers through the coding procedures and techniques for generating and evaluating 1) a path model and model specification, 2) model fit, and 3) direct and indirect effects in path models.

Mplus

Since modelling techniques, such as SEM, have become more widely used, many statistical packages have been created to employ these techniques. Mplus (Muthén & Muthén, 2010) is a suitable program for conducting all SEM techniques and is a highly flexible program, such that users can perform any SEM technique by either manually inputting code, using a language generator to input code, or constructing a diagram of the proposed model. For example, Mplus has two possible interfaces: A diagrammer (a visual representation of the model that can be created by drawing the model via drop down tabs of illustration options) or syntax (code-based or using the language generator drop down tabs to begin coding syntax to generate the model). Often, both interfaces are used simultaneously, such that the diagram of the model can be requested through a drop-down tab on the syntax interface as the model is being estimated. Furthermore, Mplus allows users to choose various techniques for model estimation, which can be employed simultaneously; however, this program is costly, like many other licensed statistical packages, and is not readily compatible with SPSS. Other statistical packages, such as AMOS (IBM Corp., 2011) or R (R Core Team, 2018), are capable of employing SEM techniques, such as path analysis; however, AMOS is the most highly used due to its widespread availability, high compatibility with SPSS, and its diagramming interface. One drawback of AMOS is its inability to deal with non-normal data utilizing robust model estimation techniques (view Savalei, 2014, for more information about robust techniques commonly used in SEM for non-normal data). R has similar capabilities as Mplus in conducting path analysis and is a syntax-based program; however, this tutorial will focus on utilizing Mplus, since it is also a widely used and accessible SEM statistical package.

Although Mplus is highly versatile, it requires that the data reside in an external file with a file extension of either ".dat" or ".txt". This file also has limited capacity, such that a single file cannot contain more than 500 variables and/or exceed 5000 characters (Byrne, 2013). This file must also only comprise numbers; researchers must remember the order of the variables when coding. This tutorial will provide a step-by-step guide for preparing data for path analysis using Mplus before estimating the model fit. The data that is stored in SPSS (IBM Corp., 2013) will be converted to an external file that is appropriate for running path analysis in Mplus.

Path analysis terminology

In path analysis, the observed variables in the model are either referred to as endogenous variables or exogenous variables. *Exogenous* variables are those that have arrows emerging from them, not directed toward them, which means that these variables are not caused by any variables in the model but are caused by other extenuating variables outside of the model (Streiner, 2005). If there is more than one exogenous variable in the model, these variables will be connected by a curved arrow, which insinuates a correlation between them (see Figure 1). This is only appropriate if they are thought to share a common cause or if they are inherently related, based on a theoretical framework. *Endogenous* variables are those that have arrows directed toward them, and possibly emerging from them, such that they can be both outcome variables and predictor variables in different path relationships. These variables are thought to be influenced by other variables in the model.

The strength of the relationships between variables is represented by path *beta coefficients*, which represent both the strength and the direction of the relationship between two variables and its associated *error* (variance that cannot be explained). This is analogous to the beta coefficient obtained by running a simple regression. Each relationship between a variable is represented by a straight arrow, which represents a unidirectional "causal" relationship between variables, or a curved arrow, which represents an association between two or more variables; however, only exogenous variables are permitted to have these relationships. In addition, only unidirectional/non-recursive relationships between variables are permitted in path analysis; therefore, bidirectional/recursive relationships cannot be examined or inferred.

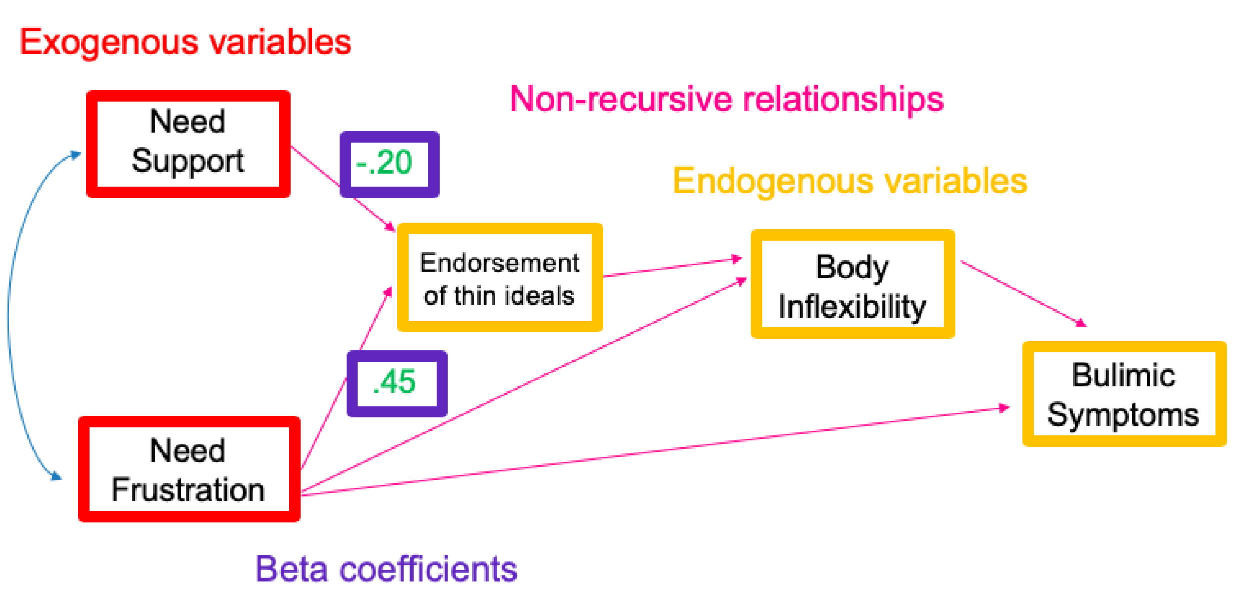
In the conceptual model that is being proposed, need frustration and need satisfaction are exogenous variables, since it is proposed that they are not caused by variables in the model, while endorsement of societal beliefs about thinness and obesity, body inflexibility, and bulimic symptoms are endogenous variables, since it is proposed that they are caused by a variable, or variables, in the model. Figure 1 demonstrates the hypothesized model and outlines the nomenclature used in path analysis, demonstrated by variables in the proposed model.

Relationships between exogenous and endogenous variables can be simple or quite complex, such that an exogenous variable may influence an endogenous variable directly (e.g., need frustration directly influences body inflexibility) or indirectly through another endogenous mediating variable in the model (e.g., need frustration indirectly influences body inflexibility through the mediator endorsement of societal beliefs about thinness and obesity). These are referred to as direct and indirect effects. Direct effects are the effects of a predictor variable on a criterion variable, while not accounting for effects from a mediating variable in the relationship. This is illustrated by the c' path in Figure 2. Indirect effects are determined by subtracting the direct effects from the total effects, which is the sum of the direct and indirect effects (Bollen, 1987; Muller & Judd, 2005). A total effect (e.g., body inflexibility) is represented by a beta coefficient and can be determined by multiplying the beta coefficient of the exogenous variable (e.g., need frustration) by the beta coefficient of the mediating variable (e.g., endorsement of societal beliefs about thinness and obesity). Indirect effects are represented in the a and b paths in Figure 2. A popular method to infer mediation is to use bootstrapping (Shrout & Bolger, 2002, 4), in which a mean indirect effect is computed using a specified re-sampling method (e.g., 5000 iterations). This method generates a p-value, confidence intervals, and a standard error, which is used to interpret mediation. Typically, if the confidence interval does not include 0, one may conclude that the indirect effect is different from 0 and is statistically significant at the 0.05 level (Kenny, 2018).

Parameters: What are they and why do they matter for causal modelling?

Parameters in the data are represented by the number of covariances and variances observed, which ultimately represent how much information can be estimated (or inferred) by a causal model. The number of variables in the data dictates how many parameters exist in the data: The number of parameters equals $n(n+1)/2$ (Streiner, 2005). The number of parameters in the model is esti-

Figure 1 ■ Hypothesized conceptual model with path analysis nomenclature



mated by summing the number of variables and relationships (curved and straight arrows) proposed in the model. The objective of causal modelling is to estimate an appropriate number of parameters that best reflects the observable parameters in the raw data, which also involves estimating accurate fixed and free parameters.

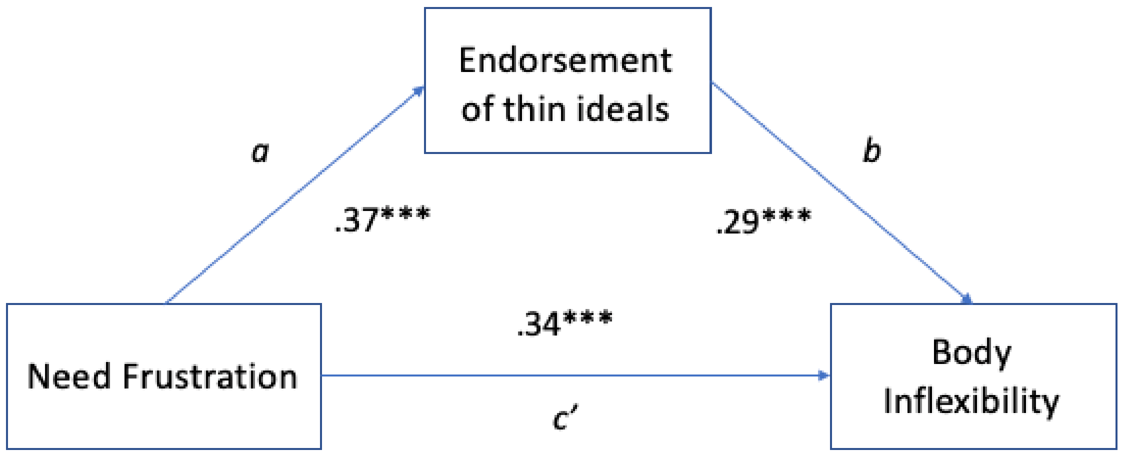
Parameters are considered fixed if the value of the parameter is assumed to be estimated from the data, whereas parameters that are free are thought to be influenced by other parameters in the data (Suhr, 2006). In the proposed model, a fixed parameter will be represented by a curved arrow (correlation) between need frustration and need satisfaction; this parameter will not be estimated or influence the model fit, since potential parameters that could influence these variables exist outside of the model. All of the other endogenous variables and paths (arrows) are considered fixed parameters.

The objective of path analysis is to propose sufficiently accurate parameters that best reflect the parameter estimates in the raw data; however, the same number of parameters that exist in the data cannot be proposed. Parameters represent how much information can be explained; therefore, if the same number of parameters that exist in the data are estimated, there is no information left to explain. The number of parameters proposed in a causal model compared to the number that exists in the observable data not only affects overall model fit, but also affects model specification, which is an index of the relative validity of the model.

Parameters and model specification

Model fit indices represent how well a causal model represents the data, while model specification determines the appropriateness of interpreting relative model fitness. There are three categories of model specification: Over-identified, identified (also known as saturated), and under-identified. Over-identified models are those that propose fewer parameters, or information, than what can be estimated (collected) in the raw data. The parameters are also highly reflective of what is occurring in the raw data (e.g., variances observed in the data are reflected well by proposed relationships between variables). Over-identified models are considered the most valid type of model. Identified, or saturated models, propose the same number, or a similar number, of parameters that can be estimated, such that there is little or no information left to be predicted. Often, these models have perfect fit indices by default, although this is not always the case, and can be identified by examining the degrees of freedom obtained from the chi-square goodness of fit test. These models usually have 0 or 1 degree of freedom, which means that there is either 0 or 1 parameter (e.g., covariances, variances) that can be predicted by the model. Interpreting this model warrants caution, since it has little predictive power; however, it could be modified to increase its validity or it could be used to compare against alternative models (MacCal-

Figure 2 ■ Example of a simple mediation model



lum, 1995). Under-identified models represent a variety of model-building errors, such that the misspecification of the model may impede the ability for it to be evaluated or statistically tested in Mplus. Often, this misspecification occurs if a researcher omits key influential variables that could best represent covariances in the raw data or has failed to reflect the covariances observed in the data through proposed causal relationships between variables in the model (MacCallum, 1995).

Parameters and model specification are essential concepts to comprehend in order to interpret the validity and relative fit of proposed causal models. In this tutorial, a step-by-step guide for proposing an over-identified model, the most specified type of model, in Mplus will be presented.

Methodology

Participants and measures

The sample included 192 female and male participants from the community and undergraduate students from the University of Ottawa, Canada who were between the ages of 17 and 67 years old ($M = 21.20$, $SD = 6.89$). Most participants were female (88.3%), had normal BMI (64.6%), and identified as Caucasian/White/European-Canadian (66.1%). Most of the participants indicated that high school (63.5%) was the highest level of education that they had completed, and most of the participants had a low yearly income (40.6% of the participants had an income of less than $5,000 per year).

Participants were recruited through online Kijiji advertisements or through the Integrated System of Participation in Research at the University of Ottawa. Informed consent was obtained electronically before participation. The study was approved by the University of Ottawa's research ethics board.

Four psychosocial self-report measures were administered through an online questionnaire to assess participants' body image flexibility (Body Image-Acceptance and Action Questionnaire; Sandoz, Wilson, Merwin, & Kellum, 2013), the extent to which participants internalize society's beliefs related to thinness and obesity (Endorsement of Society's Beliefs Related to Thinness and Obesity; Boyer, 1991), participants' psychological need satisfaction and frustration (Basic Psychological Needs Satisfaction and Frustration Scale; Chen et al., 2015), and bulimic symptomology (Eating Disorders Inventory-2 – Bulimic Symptomology Subscale; Garner, 1991).

Procedure

Assumptions of path analysis. Before running a path analysis in Mplus (Version 8; Muthén & Muthén, 2010), six assumptions must be met. Assumptions can be checked and handled in many statistical packages; this tutorial will use SPSS (IBM Corp., 2013). If any of the following assumptions are violated, note the extent of the problem and how it was handled (Weston & Gore, 2006).

1. Type of data: Endogenous variables must be continuous or categorical data, which includes scale, interval, ordinal, or nominal data (Iacobucci, 2010).
2. Missing data: The method of handling missing data should be determined by the randomness of the missing data (whether the data is missing at random, missing completely at random, or not missing at random; see Field, 2013 for more information about determining the type of missing data). The same sample size is

required for all regressions used to calculate the path model, so the missing data must be deleted or imputed (Garson, 2008).

3. Normality: Normal univariate and multivariate distributions are required. To determine whether there is univariate normality, examine each variable's distribution for skewness and kurtosis. An absolute skew value larger than 2 or smaller than -2 or an absolute kurtosis value larger than 7 or smaller than -7 may indicate non-normality (Kim, 2013). To increase normality, the non-normal data can be deleted or transformed (e.g., square root, logarithm, inverse transformations). To address this, maximum likelihood robust (MLR) estimator correction can be used, which is robust to non-normality (Muthén & Muthén, 2010). Deleting or transforming univariate and multivariate outliers also enhances multivariate normality.
4. Outliers: There should be no univariate or multivariate outliers in the data. Univariate outliers can be handled by transforming the data or changing the data to the next most extreme score (winsorizing), depending on the normality of the data (see Reifman & Keyton, 2010, for more information about winsorizing univariate outliers). A multivariate outlier is determined using Mahalanobis distance cut-off values, which are determined by the degrees of freedom in the model. If data exceeds this cut-off value, they are multivariate outliers. If there are multivariate outliers, remove them (Weston & Gore, 2006).
5. Collinearity: Path analysis requires low collinearity between the variables. If variables with multicollinearity are included, the variables might be measuring the same construct (similar to adding the same variable multiple times in the model). To check for multicollinearity, screen the bivariate correlations: $r = .85$ and above indicates multicollinearity (Kline, 2005). To address multicollinearity, remove one of the variables (Weston & Gore, 2006).
6. Sample size: In previous research, the rule of thumb was to include at least ten participants, but preferably twenty participants, per parameter (e.g., a path model with twenty parameters should contain no fewer than 200 participants, but preferably 400 participants), with 200 participants minimum (Kline, 1998).

Coding. Before running a path analysis, researchers must create models to test *a priori* hypotheses about the possible relationships/paths between variables of interest. Path analysis will measure how well a model fits the data. Once the hypotheses are determined, one can begin preparing the data and coding a model.

First, researchers choose the variables in SPSS and change each variable name to an abbreviated string of up to four letters; for example, the variable names in the hypothesized model were changed from "Body Inflexibility" to BFLX, "Endorsement of Societal Beliefs about Thinness and Obesity" to END, "Mean Need Satisfaction" to MNS, "Mean Need Frustration" to MNF, and "Bulimic Symptoms" to BULS. Then researchers must save the SPSS file as a ".dat" file and open it in a text editor application, such as TextEdit in Mac OS systems or NotePad in Windows systems. In the text editor application, the file must be opened and the characters that represent the names of the variables must be erased. Then the .dat file and SPSS file should be saved in the same folder as the Mplus application.

Now, the Mplus application (text editor) can be opened and researchers can begin entering "main commands" and "subcommands" in the syntax field. In Mplus, main commands represent headings where appropriate codes, subcommands, are organized. Each main command must be completed with a colon and each subcommand must end with a semi-colon. Popular main commands include `TITLE`, `DATA`, `VARIABLE`, `ANALYSIS`, `MODEL`, `MODEL INDIRECT`, and `OUTPUT`. Popular subcommands include `NAMES ARE`, `USEVARIABLES ARE`, `TYPE =` general, `BOOTSTRAP =` *(the number of iterations)*, `WITH`, `ON`, `VIA`, `IND`, `SAMPSTAT`, `TECH4`, `STDYX`, `CINTERVAL`, and `(BCBOOTSTRAP)` *residual*. See brief descriptions of their functions in Table 1.

The first command is `TITLE:`, which is the title of the model. The next command is `DATA:`, which tells the program where to find the .dat file that contains the data. The exact location of the .dat file must be written. The `VARIABLE` command is next. This command is used to describe the variables in the dataset. Under this command, the subcommand `NAMES ARE` is used to list all of the variables in the dataset in the order they appear in the .dat file, the subcommand `USEVARIABLES ARE` is used to list the variables that will be used from the dataset. The next command is `ANALYSIS`, which is used to determine the type of model or analysis that will be run. To do a general path analysis, type in the subcommand `TYPE=` *general*. In order to produce confidence intervals for direct and indirect effects, type the subcommand `BOOTSTRAP =` *(the number of iterations)*; to use bootstrapping. See Listing 1 for an example of how to input these commands and subcommands.

Next, researchers can determine the relationships between the variables by using the main command `MODEL:`. To denote variables as exogenous variables, the variable names should be listed using the with subcommand, to indicate correlation (e.g., MNF and MNS will be exogenous variables, so type the subcommand `MNF with MNS;`). To input the regression relationships (i.e., direct effects), researchers must code every relationship backwards with

Table 1 ■ Brief descriptions of popular main commands and subcommands in Mplus

Main commands and subcommands	Description
TITLE	Title of the model
DATA	Location of .dat file
VARIABLE	Activating variables in .dat file
NAMES ARE	List of variables in .dat file
USEVARIABLES ARE	List of variables used in the model
ANALYSIS	Type of analysis
TYPE = general	General path analysis
BOOTSTRAP = (number of iterations)	Confidence intervals for direct and indirect effects
MODEL	To determine relationships between the variables in the model
WITH	Correlational relationship
ON	Predictive relationship (i.e. "regressed on")
MODEL INDIRECT	To conduct mediation or moderation analyses
VIA	Variables involved in the mediation or moderation analyses
IND	Denotes which variables are mediators or moderators
OUTPUT	Generates model results
Sampstat	Generates descriptive statistics
tech4	Generates means, covariances, and correlations for variables in the model
stdyx	Generates standardized estimates
cinterval	Generates confidence intervals for regressed relationships, including indirect effects
(BCBOOTSTRAP) residual	Must be used with the subcommands cinterval and BOOSTRAP = to generate confidence intervals for all analyses

the subcommand `ON`, which indicates "regressed on". For example, if it is hypothesized that MNS predicts END, the relationship must be inputted as `END ON MNF;`. To examine the indirect effects, use the main command `MODEL INDIRECT:`. First, researchers must state which variables will be included in the indirect pathways that will be analyzed by using the subcommand VIA. Then the variables included in the indirect path must be inputted. Again, the variables must be inputted in the opposite order of the hypothesis and the subcommand `IND` must be used. For example, if it is hypothesized that MNF predicts BULS through the mediators END and BFLX, `BULS VIA BFLX END MNF;` will be written. Notice that the exogenous variable, MNF, is inputted last and that the mediators are inputted opposite of what is hypothesized (the first mediator in the hypothesized model is END and the second mediator is BFLX, but these are written backwards in the subcommand).

Finally, to generate the output, researchers must use the command Output: and the subcommands `sampstat` for sample statistics, `tech4` for estimated means, covariances and correlations for the latent/observed variables, `stdyx` to get standardized values, `cinterval` for confidence intervals, and `(BCBOOTSTRAP) residual;`. Model fit indices will always appear. See Listing 2 for an example of how to input these commands and subcommands.

Results

Preliminary analyses

Data were cleaned and screened for missing and out-of-range values, univariate and multivariate normality, and normality in SPSS (IBM Corp., 2013). Missing data were imputed using EM algorithm multiple imputation analysis (Little, 1989). Data were considered univariate outliers if their z-scores exceeded the cut-off of $z = \pm 3.29$, which means they are significant at $p < .001$ (Field, 2013). Univariate outliers were winsorized (Field, 2013). Data were considered multivariate outliers if their Mahalanobis Distance exceeded $\chi^2 = 18.47$ at $p < .001$ (Field, 2013). After the data were cleaned, standardized kurtosis and skewness values were obtained. Variables were considered non-normally distributed if they exceeded a kurtosis value larger than 7 or smaller than -7 and/or a skew value larger than 2 or smaller than -2 (Kim, 2013).

Means scores, standard deviations, and ranges of the variables included in the model were examined and are presented in Table 2. The mean scores for body inflexibility, endorsement of societal beliefs about thinness and obesity, need frustration and bulimic symptoms are mid-range. Mean scores for need satisfaction are higher than

Listing 1 ■ Examples of commonly used commands and subcommands in Mplus (Version 8). BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

```
TITLE: Tutorial Data
DATA: FILE IS C:\Users\kheana\Desktop\Tutorial_Data.dat;
VARIABLE:
NAMES ARE
MNT MNS END BULS BFLX;
USEVARIABLES ARE
END BFLX BULS MNT MNS;
ANALYSIS: Type = general;
Bootstrap = 5000;
```

Listing 2 ■ Examples of commonly used commands and subcommands in Mplus (Version 8). BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

```
MODEL:
MNF with MNS;
END on MNF;
END on MNS;
BFLX on END;
BULS on BFLX;
BULS on MNF;
BFLX on MNF;
MODEL INDIRECT:
BULS via END BFLX MNF,
BFLX IND END MNF,
BULS IND BFLX END MNF,
OUTPUT: sampstat tech4 stdyx clnterval(BCBOOTSTRAP)residual;
```

need frustration, meaning that participants reported perceiving more basic psychological need support than frustration.

Correlations between the variables included in the model were also examined and are presented in Table 3. As expected, body inflexibility, endorsement of society's beliefs about thinness and obesity, need frustration and bulimic symptoms are significantly positively associated with each other, while need satisfaction is significantly negatively associated with each variable.

Testing the hypothesized model

In the model, the exogenous variables were need satisfaction and need frustration and the endogenous variables were body inflexibility, endorsement of society's beliefs about thinness and obesity and bulimic symptoms. Fit indices and the percentage of variance accounted for in the model were used to evaluate the hypothesized model's fit.

Fit indices. Fit indices, such as chi-square (χ^2), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Standardized Root Mean Square Residual (SRMR) index, and the Root Mean Square Error of Approximation (RMSEA) index, will be used to determine the hypothesized model's fit. See Figure 3 for the Mplus (Version 8) output of the hypothesized model's fit indices.

Chi-square (χ^2) test. A chi-square test is an absolute fit index, so it directly assesses how well a model fits the data (Bollen, 1989a). The chi-square test compares the hypothesized model's covariance matrix and mean vector to the covariance matrix and mean vector of the observed data. A significant χ^2 value suggests that the path model does not fit the data, while a non-significant χ^2 value ($p > .05$) is indicative of a path model that fits the data well (Shah, 2012).

A chi-square test is the most commonly reported absolute fit index; however, two limitations exist with this statistic: 1) It tests whether the model is an exact fit to the

Table 2 ■ Descriptive statistics of the variables included in the hypothesized model. BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

Variables	Mean	Standard deviation	Range
BFLX	3.55	1.62	1-7
END	3.49	1.19	1-7
MNS	3.83	0.67	1.92-5
MNF	2.45	0.75	1-4.5
BULS	3.03	1.42	1-7

Table 3 ■ Correlations between the variables included in the hypothesized model. BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms.

Variables	1	2	3	4	5
1. BFLX	-	.44**	-.41**	.55**	.63**
2. END	-	-	-.37**	.45**	.44**
3. MNS	-	-	-	-.71**	-.39**
4. MNF	-	-	-	-	.47**
5. BULS	-	-	-	-	-

Note. **: $p < .001$

data, but finding an exact fit is rare; and 2) it is affected by sample size – larger sample sizes increase power, resulting in a significant χ^2 value with small effect sizes (Henson, 2006).

Comparative fit index (CFI). The CFI is an incremental fit index that compares the fit of the hypothesized model to the fit of the independence (null) model. In path analysis, the independence model assumes that there are no relationships between any of the variables in the model (Bentler, 1990). CFI indicates by how much the hypothesized model fits the data better than the independence model. CFI values range from 0 to 1, with higher values indicating better model fit. A CFI value of .95 or higher means that the hypothesized model has acceptable fit (Bentler, 1990).

Tucker-Lewis index (TLI). The TLI is a non-normed incremental fit index that attempts to determine the percentage of improvement of the hypothesized model over the independence model and adjusts this improvement by the number of parameters in the hypothesized model (Cangur & Ercan, 2015). The TLI penalizes researchers for creating more complex models, since model fit is improved by adding parameters. TLI values range from 0 to 1 or higher (values higher than 1 are treated as a 1). A TLI value of .95 or higher indicates acceptable model fit (Hu & Bentler, 1999).

Standardized root mean square residual (SRMR) index. The SRMR index is a standardized absolute fit index that is used to evaluate the model's residuals. The SRMR index is the absolute mean of all differences between the hypothesized and observed correlations, which is an overall measure of discrepancies between a hypothesized model and patterns in the raw data (Bentler, 1995). A mean of 0 indicates no difference between the correlations of the observed data and the hypothesized model, so an SRMR value of 0 indicates perfect model fit; an SRMR value of .05 indicates acceptable model fit. Furthermore, small SRMR values indicate that the variances, covariances and means of the model fit the data well.

Root mean square error of approximation (RMSEA). The RMSEA is a measure of approximate model fit: It corrects for a model's complexity and indicates the amount of unexplained variance (Steiger, 1990). Lower RMSEA values are desirable: A RMSEA value of 0 indicates perfect model fit. RMSEA values of .05 or lower indicate good model fit, while RMSEA values of .06 to .08 indicate acceptable model fit for continuous data and values of .06 or lower indicate acceptable model fit for categorical data. The RMSEA index also includes a 90% confidence interval (CI), which incorporates the sampling error associated with the estimated RMSEA (Steiger & Lind, 1980).

Model fit. The final path analysis is presented in Figure 4. The fit indices indicate that the model fits the data well: $\chi^2(3) = 4.97$, $p = 0.17$, CFI = .99, TLI = .98, SRMR = .02, RMSEA = .06, 90% CI = 0.000 to 0.146 (See Figure 3 for the Mplus output). When writing up the results, standardized beta coefficients and their p-values should be included. In this paper, standardized beta coefficients will

Figure 3 ■ Mplus (Version 8) output of the model's fit

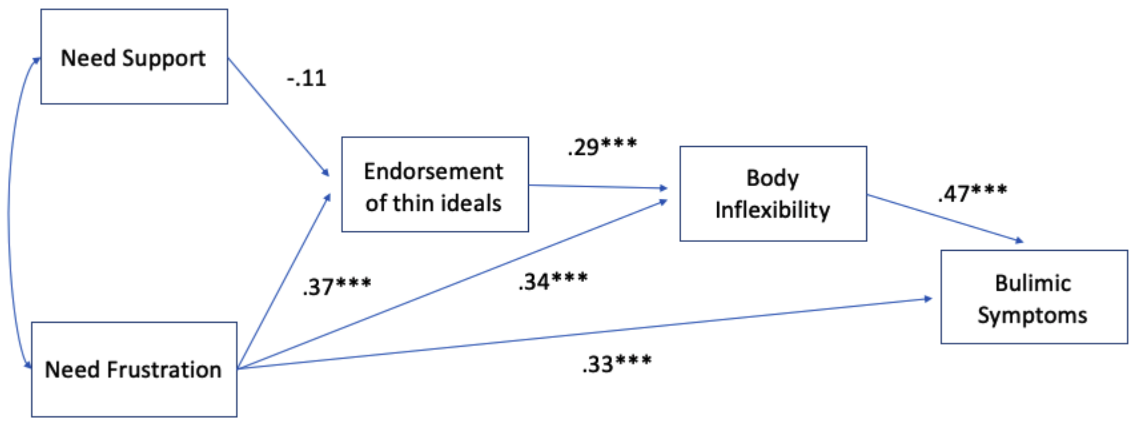
```
MODEL FIT INFORMATION

Number of Free Parameters                        17

Loglikelihood

      H0 Value                       -1246.606
      H1 Value                       -1244.120

Information Criteria

      Akaike (AIC)                    2527.212
      Bayesian (BIC)                  2582.677
      Sample-Size Adjusted BIC        2528.826
        (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

      Value                              4.972
      Degrees of Freedom                     3
      P-Value                           0.1739

RMSEA (Root Mean Square Error Of Approximation)

      Estimate                           0.058
      90 Percent C.I.                    0.000  0.146
      Probability RMSEA <= .05           0.347

CFI/TLI

      CFI                                0.992
      TLI                                0.975

Chi-Square Test of Model Fit for the Baseline Model

      Value                            241.996
      Degrees of Freedom                     9
      P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)

      Value                              0.022
```

be represented by the Greek symbol β. Standardized 90% CIs should also be included when writing up the indirect effects. Standardized 90% CIs may also be included when writing up the direct effects by using the delta method; however, this is beyond the scope of this paper (for more details, see Ham & Woutersen, 2011). The percentage of variance explained in the model (Pearson correlation r-values) should also be included.

Direct effects. As the researchers hypothesized, need frustration is significantly positively associated with endorsement of society's beliefs about thinness and obesity ($\beta = .37$, $p < .001$, $90\% CI = .329$ to $.851$); however, need satisfaction is negatively associated with endorsement of society's beliefs about thinness and obesity, but the relationship is non-significant ($\beta = -.11$, $p = .31$). This partially supports the researchers' hypotheses since the relationship between need satisfaction and endorsement of society's beliefs about thinness and obesity is negative; however, it was non-significant. Need frustration is also significantly positively associated with body inflexibility ($\beta = .34$, $p < .001$) and bulimic symptoms (β = .33, p < .001), as hypothesized by the researchers. Endorsement of society's beliefs about thinness and obesity is significantly positively associated with body inflexibility ($\beta = .29$, $p < .001$) and body inflexibility is significantly positively associated with bulimic symptoms ($\beta = .47$, $p < .001$). An Mplus output of the direct effects, their standardized beta coefficients, and associated p-values is presented in Figure 5.

Indirect effects. In this model, three indirect effects were tested: 1) The mediating effect of endorsement of society's beliefs about thinness and obesity on the relationship between need frustration and body inflexibility; 2) the mediating effect of body inflexibility on the relationship between need frustration and bulimic symptoms; and 3) the mediating effects of two mediators, endorsement of society's beliefs about thinness and obesity and body inflexibility, on the relationship between need frustration and bulimic symptoms. For the first indirect effect, the indirect effect of endorsement of society's beliefs about thinness and obesity as a mediator in the relationship between need frustration and body inflexibility was significant, $\beta = .11$, ($p = .005$, $90\% CI = .044$ to $.172$). The indirect effect of

Figure 4 ■ The final structural model with standardized path coefficients ($n = 192$)



body inflexibility as a mediator in the relationship between need frustration and bulimic symptoms was also significant, $\beta = .16$ ($p < .001$, $90\% CI = .093$ to $.227$). Finally, the indirect effect of need frustration to bulimic symptoms through two mediators, endorsement of society's beliefs about thinness and obesity and body inflexibility, was significant ($\beta = .05$, $p = .014$, $90\% CI = .017$ to $.085$). Standardized beta coefficients, their associated p-values and standardized 90% CIs of the hypothesized model's indirect effects are presented in Figures 6 and 7.

Percentage of variance explained in the model. The relationships proposed in the model explains 20% of the variance in endorsement of society's beliefs about thinness and obesity ($r = .20$), 29% of the variance in body inflexibility ($r = .29$), and 47% of the variance in bulimic symptoms ($r = .47$). See R-SQUARE estimates in Figure 8.

Discussion

This tutorial provided an overview of path analysis, a specific type of SEM modeling; guidelines for constructing an *a priori* conceptual model; and a step-by-step guide for preparing data for path analysis and conducting and evaluating a path model using Mplus. Path analysis is a suitable multivariate technique to examine causal links between observable measures. This tutorial also demonstrated how to create and evaluate an over-identified model, the most specified type of model. More specifically, a conceptual path model of the psychological and behavioral antecedents of bulimic symptomology in young adults was constructed and evaluated.

In the proposed model, the researchers examined how the fulfillment (satisfaction) and depletion (frustration) of essential psychological needs could potentially differentially predict bulimic symptoms in women via two mediators, the endorsement of society's beliefs about thinness and obesity and body inflexibility. Results demonstrated that the proposed model fit the data well: $\chi^2(3) = 4.97$, $p = 0.17$, $CFI = .99$, $TLI = .98$, $SRMR = .02$, $RMSEA = .06$, $90\% CI = 0.000$ to 0.146. When examining the direct effects, most of the researchers' hypotheses were supported, such that need frustration was significantly positively associated with higher endorsement of societal beliefs about thinness and obesity, positively associated with higher body inflexibility, and positively associated with bulimic symptoms. Also in line with the researchers' hypotheses, higher endorsement of these ideals was significantly positively associated with higher body inflexibility, which, in turn, was significantly positively associated with bulimic symptoms. Although need satisfaction was not significantly negatively associated with endorsement of societal beliefs about thinness and obesity ideals, the relationship was still negative, which partially supports the researchers' hypotheses.

When examining the indirect effects, the relationship between need frustration and body inflexibility was significantly mediated by endorsement of societal beliefs about thinness and obesity, such that need frustration indirectly influences body inflexibility through higher endorsement of cultural ideals. The relationship between need frustration and bulimic symptoms was significantly mediated by body inflexibility, such that need frustration indirectly influences bulimic symptoms by increasing body-inflexible cognitions. Finally, the two proposed mediators, endorsement of societal ideals about thinness and obesity and body inflexibility, significantly mediated the relationship between need frustration and bulimic symptoms, such that need frustration indirectly influences bulimic symptoms by increasing endorsement of societal ideals about thin-

Figure 5 ■ Mplus (Version 8) output of the hypothesized model's direct effects. BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

```
MODEL RESULTS
                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 END      ON
    MNF                0.593      0.158      3.745      0.000
    MNS               -0.193      0.182     -1.059      0.290

 BFLX     ON
    END                0.350      0.092      3.799      0.000
    MNF                0.642      0.141      4.558      0.000

 BULS     ON
    BFLX               0.541      0.073      7.410      0.000
    MNF                0.707      0.141      5.015      0.000

 MNF      WITH
    MNS               -0.359      0.041     -8.716      0.000

 Means
    MNF                2.453      0.054     45.212      0.000
    MNS                3.829      0.048     79.821      0.000

 Intercepts
    END                2.771      1.025      2.704      0.007
    BFLX               0.226      0.318      0.710      0.478
    BULS               0.175      0.261      0.672      0.501

 Variances
    MNF                0.567      0.052     10.987      0.000
    MNS                0.454      0.040     11.413      0.000

 Residual Variances
    END                1.128      0.109     10.319      0.000
    BFLX               1.432      0.145      9.864      0.000
    BULS               1.378      0.129     10.651      0.000

STANDARDIZED MODEL RESULTS

                      StdYX
                    Estimate

 END      ON
    MNF                0.374
    MNS               -0.109

 BFLX     ON
    END                0.294
    MNF                0.340

 BULS     ON
    BFLX               0.473
    MNF                0.328

 MNF      WITH
    MNS               -0.708
```

ness and obesity, and, in turn, body inflexibility.

Limitations

As mentioned previously, the objective of path analysis is to test the tenability of a theory-based model to see how well the hypothesized model fits the data, or how well it reflects the process, or mechanism, behind a phenomenon of interest. Although the fit indices of the model suggest a good fit and the model was over-identified, the researchers cannot infer that the model best represents the process of the phenomenon of interest, bulimic symptomology. A major limitation of any statistical modeling technique is that it can only be interpreted in comparison with other models, and many of these comparative models are derived from a single dataset. For example, CFI and TLI are comparative fit indices that evaluate improved fitness from the independence model (null model). For this reason, it is encouraged to create multiple theory-based models and compare their relative fit.

Another limitation of path analysis is related to sample size. Users of path analysis should be aware of its sensitivity to sample size, especially when interpreting fit indices derived from a single dataset. Large sample sizes are more likely to produce significant fit indices, while small sample sizes are likely to produce non-significant fit indices, regardless of the proposed relationship between the variables (Streiner, 2005). As stated earlier, sample size should be no fewer than ten participants per parameter, but required sample size is subject to each study's individual power needs and hypotheses.

Figure 6 ■ Mplus (Version 8) output of the hypothesized model's indirect effects. BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

```
STANDARDIZED TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS

STDYX Standardization

                                                    Two-Tailed
                      Estimate       S.E.  Est./S.E.    P-Value

Effects from MNF to BFLX

Sum of indirect          0.110      0.039      2.815      0.005

Specific indirect

  BFLX
  END
  MNF                    0.110      0.039      2.815      0.005


Effects from MNF to BULS

Sum of indirect          0.052      0.021      2.469      0.014

Specific indirect

  BULS
  BFLX
  END
  MNF                    0.052      0.021      2.469      0.014
```

Although path analysis is often referred to as a "causal" modeling technique, and many researchers may use language that infers causality, causation cannot be implied. Similar to regression, predictor variables only have predictive, not causal, properties, such that the path coefficients denote the strength and direction of the prediction of a criterion variable. Causal relationships between variables can only be achieved through study design, such as experimental manipulation, not statistical analyses.

Conclusion

Although the primary objective was to provide a tutorial on conducting path analysis in Mplus, the researchers hope that this paper will also provide insight and tools for researchers to evaluate and interpret path models in their respective fields of study. The researchers also hope that this tutorial will encourage the use of *a priori* theory-derived models, rather than empirically-derived models. Using path analysis in Mplus will afford researchers flexibility in generating path models and allow them to explore and evaluate various conceptual health and disease models.

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References

Bentler, P. M. (1990). Comparative fit indices in structural models. *Psychological Bulletin*, *107*, 238–246.

Bentler, P. M. (1995). *Eqs structural equations program manual*. Encino, CA: Multivariate Software.

Bollen, K. A. (1987). Total, direct, and indirect effects in structural equation models. *Sociological Methodology*, *17*, 37–69. doi:10.2307/271028

Bollen, K. A. (1989a). A new incremental fit index for general structural equation models. *Sociological Methods & Research*, *17*, 303–316.

Bollen, K. A. (1989b). *Structural equations with latent variables*. New York, NY: Wiley.

Boone, L., Vansteenkiste, M., Soenens, B., Van der Kaap-Deeder, J., & Verstuyf, J. (2014). Self-critical perfectionism and binge eating symptoms: A longitudinal test of the intervening role of psychological need frustration. *Journal of Counseling Psychology*, *61*(3), 363–373.

Boyer, H. (1991). *Analyses d'équations structurales des facteurs socio-culturels cognitifs sous-jacents à la*

Figure 7 ■ Mplus (Version 8) output of the standardized 90% confidence intervals of the indirect effects in the hypothesized model. BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

```
CONFIDENCE INTERVALS OF STANDARDIZED TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT,
AND DIRECT EFFECTS

STDYX Standardization

                    Lower .5%  Lower 2.5%   Lower 5%   Estimate    Upper 5%  Upper 2.5%   Upper .5%

Effects from MNF to BFLX

Sum of indirect      0.009       0.033       0.046       0.110       0.174       0.186       0.210

Specific indirect

  BFLX
  END
  MNF                0.009       0.033       0.046       0.110       0.174       0.186       0.210


Effects from MNF to BULS

Sum of indirect     -0.002       0.011       0.017       0.052       0.087       0.093       0.106

Specific indirect

  BULS
  BFLX
  END
  MNF               -0.002       0.011       0.017       0.052       0.087       0.093       0.106
```


boulimie [structural equation analyses of cognitive sociocultural factors of bulimia]. Ottawa, ON: Doctoral dissertation. University of Ottawa.

Byrne, B. M. (2013). *Structural equation modeling with mplus: Basic concepts, applications, and programming*. New York, NY: Routledge.

Cangur, S., & Ercan, I. (2015). Comparison of model fit indices used in structural equation modeling under multivariate normality. *Journal of Modern Applied Statistical Methods*, *14*, 152–167. doi:10.22237/jmasm/1430453580

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., ... Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four countries. *Motivation and Emotion*, *32*, 216–236. doi:10.1007/s11031-014-9450-1

Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*, 227–268.

Field, A. (2013). *Discovering statistics using ibm spss statistics (4th ed.)* Sussex, UK: Sage Publications.

Garner, D. M. (1991). *Eating disorder inventory-2: Professional manual*. Odessa, FL: Psychological Assessment Resources.

Garson, D. (2008). Path analysis. Retrieved from https://www.scribd.com/document/323656506/Garson-2008-PathAnalysis-pdf

Ham, J., & Woutersen, T. (2011). Calculating confidence intervals for continuous and discontinuous functions of estimated parameters. Retrieved from https://d-nb.info/1013249933/34

Henson, R. K. (2006). Effect-size measures and meta-analytic thinking in counseling psychology research. *The Counseling Psychologist*, *34*, 601–629.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1–55. doi:10.1080/10705519909540118

Iacobucci, D. (2010). Structural equations modeling: Fit indices, sample size, and advanced topics. *Journal of Consumer Psychology*, *20*, 90–98. doi:10.1016/j.jcps.2009.09.003

IBM Corp. (2011). Ibm spss amos, version 20.0 (Version 20).

IBM Corp. (2013). Ibm spss for mac (Version 23). Retrieved from https://www.ibm.com/us-en/marketplace/spss-statistics-gradpack/details#product-header-top

Kenny, D. A. (2018). Mediation. Retrieved from http://davidakenny.net/cm/mediate.htm

Kim, H.-y. (2013). Statistical notes for clinical researchers: Assessing normal distribution using skewness and

Figure 8 ■ Mplus (Version 8) output of the percentage of variance explained in the hypothesized model. BFLX – Body Inflexibility, END – Endorsement of Societal Beliefs about Thinness and Obesity, MNS – Mean Need Satisfaction, MNF – Mean Need Frustration, BULS – Bulimic Symptoms

```
Means
   MNF                 3.258
   MNS                 5.685

Intercepts
   END                 2.321
   BFLX                0.159
   BULS                0.108

Variances
   MNF                 1.000
   MNS                 1.000

Residual Variances
   END                 0.791
   BFLX                0.708
   BULS                0.522


R-SQUARE

   Observed
   Variable         Estimate

   END                 0.209
   BFLX                0.292
   BULS                0.478
```

kurtosis. *Restorative Dentistry and Endontics*, *38*, 52–54. doi:10.5395/rde.2013.38.1.52

Kline, R. B. (1998). *Principles and practice of structural equation modeling*. New York, NY: Guilford.

Kline, R. B. (2005). *Principles and practice of structural equation modeling (2nd ed.)* New York, NY: Guilford.

Little, R. J. A. (1989). The analysis of social science data with missing values. *Sociological Methods Research*, *18*(2-3), 292–326. doi:10.1177/0049124189018002004

MacCallum, R. C. (1995). Model specification: Procedures, strategies, and related issues. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 16–29). Thousand Oaks, CA: Sage.

Muller, D., & Judd, C. M. (2005). Direct and indirect effects. *Encyclopedia of Statistics in Behavioral Science*, *1*, 490–492. doi:10.1002/0470013192.bsa173

Muthén, L. K., & Muthén, B. O. (2010). *Mplus user's guide (6th ed.)* Los Angeles, CA: Muthén & Muthén.

Pedhazur, E. J. (1997). *Multiple regression in behavioral research*. New York, NY: Wadsworth.

Pelletier, L., & Dion, S. (2007). An examination of general and specific motivational mechanisms for the relations between body dissatisfaction and eating behaviors. *Journal of Social and Clinical Psychology*, *26*(3), 303–333.

R Core Team. (2018). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria. Retrieved from https://www.R-project.org/

Reifman, A., & Keyton, K. (2010). Winsorize. In N. J. Salkind (Ed.), *Encyclopedia of research design* (pp. 1636–1638). Thousand Oaks, CA: Sage.

Sandoz, E. K., Wilson, K. G., Merwin, R. M., & Kellum, K. K. (2013). Assessment of body image flexibility: The body image-acceptance and action questionnaire. *Journal of Contextual Behavioral Science*, *2*(1-2), 39–48. doi:10.1016/j.jcbs.2013.03.002

Savalei, V. (2014). Understanding robust corrections in structural equation modeling. *Structural Equation Modelling: A Multidisciplinary Journal*, *21*(1), 149–160. doi:10.1080/10705511.2013.824793

Shah, R. B. (2012). A multivariate analysis technique: Structural equation modeling. *Asian Journal of Multidimensional Research (*, *4*, 73–81.

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, *7*, 422–445. doi:10.1037//1082-989X.7.4.422

Steiger, J. H. (1990). Structural model evaluation and modification: An internal estimation approach. *Multivariate Behavioral Research*, *25*, 173–180.

Steiger, J. H., & Lind, J. C. (1980). Statistically based tests for the number of common factors, Iowa City, IA: Paper presented at the annual meeting of the Psychometric Society.

Streiner, L. D. (2005). Finding our way: An introduction to path analysis. *Research Methods of Psychiatry*, *50*(2), 115–122.

Suhr, D. ((2006). The basics of structural equation modeling. Retrieved from https://www.lexjansen.com/wuss//tutorials/TUT-Suhr

Vansteenkiste, M., & Ryan, R. M. (2013). On psychological growth and vulnerability: Basic psychological need satisfaction and need frustration as a unifying principle. *Journal of Psychotherapy Integration*, *3*, 263–280.

Weston, R., & Gore, P. A. (2006). A brief guide to structural equation modeling. *The Counseling Psychologist*, *34*(5), 719–751. doi:10.1177/0011000006286345

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