CHAPTER-VI
STRUCTURAL EQUATION MODELING
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6.0 Introduction

The present study was an attempt to examine the relationship of personal growth initiative with self-efficacy, risk-taking behaviour and mental health among university postgraduates. One of the objectives of the study was to develop a model for personal growth initiative, self-efficacy, risk-taking behaviour and mental health. For the purpose of developing model, Structural Equation Modeling (SEM) with AMOS software was used. SEM to develop 'structural model' is used only if the 'measurement model' are found satisfactory. In chapter-III, the validity of all the four scales was established and was found to be satisfactory; therefore, valid structure of all the scales for the data supported that SEM can be used for developing model in the present data.

The term structural equation modeling conveys two important aspects of the procedure: (a) that the causal processes under study are represented by a series of structural (i.e., regression) equations, and (b) that these structural relations can be modeled pictorially to enable a clearer conceptualization of the theory under study (Byrne, 2010). SEM has become a popular methodology for non-experimental research, where methods for testing theories are not well developed (Bentler, 1980). SEM has advantages over other methods of analysis like multivariate analysis. Firstly, it takes confirmatory rather than exploratory approach to data analysis and is inferential in nature. Secondly, it is different from traditional multivariate procedures as these are incapable of either assessing or correcting for measurement error, SEM provides explicit estimates of these error variance parameters. Third, the former methods of analysis are based on observed measurements only, but SEM procedures can incorporate both unobserved (i.e., latent) and observed variables (Byrne, 2010). All these unique characteristics of SEM stimulated the adoption of this technique for analysis all over the world.

In the behavioral sciences, researchers are often interested in studying theoretical constructs that cannot be observed directly. These abstract phenomena are termed latent variables, or factors. Because latent variables are not observed directly,
therefore, the researcher must operationally define the latent variable of interest in terms of behavior believed to represent it. As such, the unobserved variable is linked to one that is observable, thereby making its measurement possible. Assessment of the behavior, then, constitutes the direct measurement of an observed variable, albeit the indirect measurement of an unobserved variable. It is important to note that the term behavior is used here in the very broadest sense to include scores on a particular measuring instrument. Thus, observation may include, for example, self-report responses to an attitudinal scale, scores on an achievement test, in vivo observation scores representing some physical task or activity, coded responses to interview questions, and the like. These measured scores (i.e., measurements) are termed observed or manifest variables; within the context of SEM methodology, they serve as indicators of the underlying construct which they are presumed to represent (Byrne, 2010).

Structural equation modeling (SEM) is analytical approach that combines these two components and considers them simultaneously. Thus, SEM is often described as combining factor analytic and regression models into a single data analysis tool. Using the language of SEM, latent variables (factors) represent the concepts of the theory, and data from measures (indicators) are used as input for statistical analyses that provide evidence about the relationships of the latent variables with their indicators and relationships among the latent variables (Williams, Vandenberg and Edwards, 2009). Structural equation modeling (SEM) is a series of statistical methods that allow complex relationships between one or more independent variables and one or more dependent variables. Though there are many ways to describe SEM, it is most commonly thought of as a hybrid between some form of analysis of variance (ANOVA)/regression and some form of factor analysis. In general, it can be remarked that SEM allows one to perform some type of multilevel regression/ANOVA on factors. SEM is a multivariate regression model that describes the relationships between a set of observed dependent variables and a set of continuous latent variables. The structural model describes three types of relationships in one set of multiple regression equations: the relationships among factors, the relationships among observed variables and the relationships between factors and observed variables that are not factor indicators. In the context of SEM, the relations between the latent variables (directed arrows) are called ‘the structural model’.
6.1 Structural Model

Typically, a researcher postulates a statistical model based on his or her knowledge of the related theory, on empirical research in the area of study, or on some combination of both. Once the model is specified, the researcher then tests its plausibility based on sample data that comprise all observed variables in the model. The primary task in this model-testing procedure is to determine the goodness-of-fit between the hypothesized model and the sample data. As such, the researcher imposes the structure of the hypothesized model on the sample data, and then tests how well the observed data fit this restricted structure. Because it is highly unlikely that a perfect fit will exist between the observed data and the hypothesized model, there will necessarily be a differential between the two; this differential is termed the residual. The model-fitting process can therefore be summarized as follows:

\[ \text{Data} = \text{Model} + \text{Residual} \]

Where

- **Data** represent score measurements related to the observed variables as derived from persons comprising the sample.
- **Model** represents the hypothesized structure linking the observed variables to the latent variables and, in some models, linking particular latent variables to one another.
- **Residual** represents the discrepancy between the hypothesized model and the observed data.

Structural equation models are schematically portrayed using particular configurations of four geometric symbols—a circle (or ellipse), a square (or rectangle), a single-headed arrow, and a double-headed arrow. By convention, circles (or ellipses; \( ) \) represent unobserved latent factors, squares (or rectangles; \( ) \) represent observed variables, single-headed arrows (\( \rightarrow \) ) represent the impact of one variable on another, and double-headed arrows (\( \leftrightarrow \) ) represent covariances or correlations between pairs of variables.

In building a model of a particular structure under study, researchers use these symbols within the framework of four basic configurations, each of which represents an important component in the analytic process. These configurations, each accompanied by a brief description, are as follows:
Path coefficient for regression of an observed variable onto an unobserved latent variable (or factor)

Path coefficient for regression of one factor onto another factor

Measurement error associated with an observed variable

Residual error in the prediction of an unobserved factor

Schematic representations of models are termed *path diagrams* because they provide a visual portrayal of relations which are assumed to hold among the variables under study (Byrne, 2010).

6.2 Model for Personal Growth Initiative, Self-Efficacy, Risk-Taking Behaviour and Mental Health among University Postgraduates

In the present study, the relationship of personal growth initiative with self-efficacy, risk-taking behaviour and mental health was investigated and the impact of self-efficacy, risk-taking behaviour and mental health on overall personal growth initiative and its four dimensions were studied. The model for personal growth initiative, self-efficacy, risk-taking behaviour and mental health among university postgraduates on the basis of causal relationships was developed through SEM with AMOS. (The model is given on next page)
6.3 Evaluating Model Fit

Only development of model is not enough, it has to be tested statistically. Most statistical methods only require one statistical test to determine the significance of analyses. However, in CFA and SEM, several statistical tests are used to determine how well the model fits to the data (Suhr, 2006). A good fit between the model and the data does not mean that the model is “correct”. A good model fit only indicates that
the model is plausible (Schermelleh-Engel, Moosbrugger and Muller, 2003). Though several varying opinions exist, Kline (2010) recommends reporting the Chi-Square, the RMSEA (Root Mean Square Error of Approximation) and the CFI (Comparative Fit Indices). The results of the SEM for the model are given below:

Table-6.1
Fit Indices for Structural Equation Model

<table>
<thead>
<tr>
<th>Indices Name</th>
<th>Indices Values</th>
<th>Recommended Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square</td>
<td>2.086</td>
<td>&lt;3</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.036</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>NNFI or TLI</td>
<td>0.849</td>
<td>&gt;0.9-good and &gt;0.8-permissible</td>
</tr>
<tr>
<td>CFI</td>
<td>0.864</td>
<td>&gt;0.9</td>
</tr>
<tr>
<td>IFI</td>
<td>0.867</td>
<td>&gt;0.9</td>
</tr>
</tbody>
</table>

Various fit indices like goodness and badness of fit were computed to find the fitness of the model for university postgraduates. From the goodness of fit indices, it can be concluded the values of CFI (0.864), IFI (0.867) and NNFI or TLI (0.849) values were somewhat lower than very good model fit (>0.9-Good,>0.8-Permissible) which indicated that model was permissible. Moreover, badness of fit indices were also computed i.e. the chi-square value was 2.086 (<3-Good) and RMSEA values was 0.036 (<0.05- Good) and these values were lower than the given values which meant that the model was showing lower badness of fit indices which indicated that model was good and permissible fit into the recommended values and showed good model fit for the data
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REFERENCES


