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APPLICATION OF ADVANCED MODELING IN SOCIAL WORK RESEARCH: A DEMONSTRATION OF MULTILEVEL PATH MODELING ANALYSIS BY MPLUS

Jerf W. K. YEUNG[1], *Evans LI*[2]

Abstract

Social work research has a crucial role in steering development, implementation and intervention of quality services and programs, in which application of more advanced statistical modeling analyses may redress the inaccuracy of findings and Type I error, that are mostly likely derived from conventional statistical procedures at individual-level analyses, such as ANOVA and OLS Regression. A multilevel path modeling analysis demonstrated by Mplus, an easy-to-use statistical program for advanced modeling, is suggested as a preliminary step to open up the window for other more sophisticated and useful statistical modeling procedures that are imperative for us to comprehend influences of multi-layer social situations on human behaviors and outcomes. Results showed that, in addition to knowledge on effects from a higher level, the multilevel path model increased explanatory power and rectify some augmented path parameters at individual level. Procedures and construction of model command syntaxes for the usage of Mplus are also reported in detail.

Keywords: social work research; multilevel path modeling; conventional statistical procedures; individual-level; cluster-level.

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Introduction

Social work research would be a driving engine to help to steer development, implementation, as well as intervention of frontline services and programs for the needs of its potential recipients. More than that, social work research, specific to those evaluation researches, would be imperative and indispensable from the relations to the improvement and optimalization of utility of resources and maintenance of service quality. As such, use of more sophisticated and fine-grained analytical models is needed (Gerdes, 2011; Thyer, 2010).

In the past, social work researches were predominantly focused on individual-level effects, which would glaringly bias the precision of findings (Geldof, 2010; Gerdes, 2011). As social work scholars reviewed the nature and characteristics of recent social work researches and pointed out that conventional statistical analyses, such as ANOVA, MANOVA, OLS regression, may easily ignore environmental and societal influences on human effects (Beddoe, 2011, Mitchell, 2010), because all these analytical methods are confined on tapping on subject-level phenomena, which are called, by the terms of Shek and Lee (2007), as micro studies rather than macro studies. However, in order to address environmental and societal influences on individuals, more advanced statistical techniques are needed to incorporate those higher-level effects on human behaviors and developments.

On the other hand, the confinement of using conventional statistical analyses is that these analyses cannot deal with multiple mediators and outcome variables simultaneously in a single modeling procedure. In fact, for many social situations and human activities, distal precursor predictors and proximal variables are concurrently interplayed to contribute to outcomes. However, conventional statistical models are difficult in portraying the in-between relationships of multiple variables in a single analytical model. For answering hypotheses that are involving both distal and proximal variables at once, a causal model is necessitated in dealing with these interlocked connections (Hoyle, 2011; Kline, 1998).

Apparently, the advance of multilevel modeling (MLM) and structural equation modeling (SEM) techniques are important in redressing the afore-mentioned demerits in studying complicated social situations and behavioral repertoires by conventional statistical analyses (Luke, 2004). For example, MLM has a capability of incorporating cluster-level effects, such as school-level and neighborhood-level impacts, on individual outcomes. Manifestly, most human behaviors and outcomes are not independent of greater societal influences, as we are all the "products of social structure" (Nezlek, 2011). However, data are being analyzed using traditional statistical procedures, such as multiple regression models, which recognize only the individuals as the units of analysis and ignore their grouping effects within the environmental surroundings. In some worse cases, the significant findings obtained from conventional statistical procedures may be substantially curtailed or even turn to be insignificant, after taking the cluster-level impacts into account. As such these findings would easily lead to Type I error (Nezlek, 2011).

Moreover, SEM can accommodate the situation, in which research questions involve interlinking a set of predictors to a number of outcomes in a structural fashion. In addition, measurement models in SEM could also preclude the problems of measurement errors. For this, it is capable of procuring more accurate results. The preponderance of SEM over conventional statistical analyses is that it can concurrently cope with multiple predictors, mediators and outcome variables in one time. In comparison, conventional statistical procedures are only able to look into a single outcome once in a time and not versatile in exploring the mediating relationships as well (Hoyle, 2011).

More than that, multilevel modeling is competent in investigating effects from an aggregated higher level, such as school-level impacts on students' outcomes, the term in which most educators would like to use, and neighborhood-level impacts on residents' outcomes, the term in which most sociologists would like to use (Luke, 2004). On the other hand, SEM could take account of incorporating multiple mediators and outcomes in a single model, plus reducing measurement errors by subsuming latent constructs as a measurement model (Hyle, 2011; Kline, 1998). Albeit, multilevel modeling incapacitates in dealing with multiple mediators and outcomes simultaneously, and SEM is not versed in coping effects exerted from an aggregated higher level. For this, multilevel SEM can be versatile in dealing with multiple predictors, mediators, as well as outcomes from different levels of analyses in a single inquiry (Nezlek, 2011).

Stated succinctly, multilevel path modeling constitutes the core part of multilevel SEM. There are concrete reasons why multilevel path modeling should be highlighted as a demonstration for social work research. First, a causal path model is the advanced version of those conventional statistical analyses, such as ANOVA and OLS regression, used in social work research, which can help to open the window for other higher-order analytical modeling procedures, such as SEM, Latent Growth Curve Modeling, and Mixture Modeling. Taken on the first reason, the second reason is that a grasp of the basic techniques of path modeling could expedite our comprehension about the knowledge of the aforementioned sophisticated statistical models, which could enhance our understanding for those more subtle social and behavioral phenomena influencing the outcomes of our service recipients.

Third, incorporation of multilevel techniques into path modeling analyses may take the advantage of accounting for the impacts from that of cluster-level, such as the aggregated school-level or neighborhood-level effects, on service recipients' outcomes. In fact, service outcomes of our clients are seldom the pure consequences of service or program interventions. Apparently, societal and cultural factors may play an important part in shaping these outcomes. Fourth, demonstration of a multilevel path model by the newly-developed Mplus statistical program could gain the benefit that analytical procedures in this statistical program is more flexible and easy-to-use, and it has the versatility in conducting other more advanced and complicated statistical modeling procedures just by commanding a set of simple model command syntaxes. For example, these complicated statistical modeling procedures include SEM with categorical outcomes, confirmatory factor analysis (CFA) with censored and count indicators, SEM with interactions between latent factors, linear growth curve models with censored or categorical outcomes. Fifth, more advanced motley statistical models can be developed by mingling different model building concepts used in Mplus. These advanced motley statistical models comprise of multilevel CFA mixture modeling, multilevel SEM analyses with a combination of categorical and continuous outcomes, growth mixture modeling with count outcomes. In fact, the application of these advanced kinds of statistical models would enhance our understanding of clients' needs and effects of our services and programs on those intended outcomes with accurate results in a multi-layer and sophisticate social environment, where precursor factors are all the times interlinked and interplayed together.

Construction of an Example multilevel Path Model

Throughout this paper, I did the analyses based the demonstration of a multilevel life satisfaction path model, which was constructed from an imitated dataset[3]. The dataset contains 8 variables, they are:

Neig (v1), ID (v2), NeigDv (v3), NeigRlg (v4), LS (v5), Rlg 96), SES (v7), Anx (v8)

The first variable Neig(v1) is a neighborhood-level code variable, which is used to identify participants coming from different neighborhood districts. In this demonstration study, participants are coming from 25 neighborhood districts, so that you can see the code number ranging from 1 to 25. The second variable ID(v2) is the individual-level code variable, which is used to identify the number of participants. In this study, each neighborhood district contains 20 participants, meaning that there are a total of 500 participants in the dataset.

[3] The dataset is titled mlm.sav, it is a SPSS file. If you wants to do analyses in Mplus, you should change to text file (dat file). The file can be located at http://cid-21fac83b41513769.office.live.com/self.aspx/%e6%96%b0%e8%b3%87%e6%96%99%e5%a4%be/mlm.sav

The remaining variables (variable 3 to variable 8) are the analytical variables, in which variable 3 NeigDv(v3) and variable 4 NeigRlg(v4) are the neighborhood-level variables, and variable 5 LS(v5), variable 6 Rlg(v6) , variable 7 SES(v7) , as well as variable 8 Anx(v8) are individual-level variables. For neighborhood-level variables, NeigDv(v3) connotes whether the neighborhood district is a rural (1), semi-developed industrial (2), or a highly-developed industrial (3) district. So as, you can treat this variable is an ordinal variable ranging from 1 to 3. NeigRlg(v4) connotes how religious the district is. In fact, residents living in a district may be more or less religious in aggregation in some sense, so as this neighborhood-level variable is a continuous variable.

For individual – level variables, variable 5 LS(v5) means individual life satisfaction, and variable 6 Rlg(v6) means a person's level of religiosity, and variable 7 Anx(v7) means personal anxiety levels, all of which are self-rated continuous variables. The last variable, variable 8 SES(v8) implies socio-economic status, which is ranked from lower social status (1), middle social status (2), to higher social status (3), so as it is an ordinal variable ranging from 1 to 3.

According to previous research, religious people would tend to be more satisfied about their lives and feel less anxious (Brkljacic & Lipovcan, 2010; Lim & Putnam, 2010; Yeung et al., 2007). In addition, a sense of anxiety would compromise life satisfaction (Norberg et al., 2008). Moreover, people with a higher socio-economic status would be less anxious about their lives and future (Ybrandt, 2008; Yeung & Chan, 2010), which would be an important contributor to life satisfaction through reducing anxiety (Brkljacic & Lipovcan, 2010; Gerber, & Puhse, 2007). However, the direct relation between socio-economic status and life satisfaction is much contradictory. Some studies showed that a higher socio-economic status may result in a higher level of life satisfaction (Moller & Huschka, 2008; Yeung et al., 2010); other research findings revealed that people with high socio-economic statuses would feel their lives less contented (Shek et al., 2005). For this, we expected that the contribution of SES to life satisfaction is more likely through the mediating effect of lessened anxiety. As such, we have the following hypotheses at individual-level.

H1: People with higher anxiety would negatively affect their life satisfaction.
H2: People with higher religiosity would beneficially contribute to their life satisfaction.
H3: People with higher religiosity would have lower levels of anxiety, which would in turn increase their life satisfaction.
H4: People with a high socio-economic status would have lower anxiety, which would in turn increase their life satisfaction.

More than that, both literature and research reported that people living in a neighborhood with higher district-level religiosity would feel more cohesive and less socially estranged, in which a higher level of life satisfaction is warranted (Brkljacic & Lipovcan, 2010; Mochon et al., 2011). Moreover, highly industrial-developed communities would be less religious than country sides where are more rustic, and residents in rural areas would be more satisfied about their lives in general (Lim, & Putnam, 2010; Mochon et al., 2011). As such, we have the following hypotheses for the neighborhood-level variables.

H5: A neighborhood district where has high level of aggregate religiosity would beneficially contribute to people's life satisfaction in the district.
H6: A neighborhood district where is more industrially developed would adversely affect to people's life satisfaction in the district.
H7: A neighborhood district where is more industrially developed would occasion to be less religious in the district.

With respect to the above hypotheses, a path model regarding H1-H4 at individual-level was first built, and the model fit and significant path parameters of this individual-level path model was tested first. This individual-level path model would defacto become the base for constructing our multilevel path model. Stated succinctly, if a model at individual level obtains a bed fit between the analytical dataset and the theoretical model, there is no means to justify the construction of a more complicated multilevel path model.

Methods and Procedures for the Demonstration

Model Command Profile

As mentioned above, all analyses in this demonstration paper would be based on the imitated multilevel life satisfaction dataset(mlm.sav). The dataset has 8 variables and contains 500 participants coming from 25 neighborhood districts. The statistical software program used to carry out the multilevel path modeling analyses was Mplus, which is versatile in conducting various modeling procedures with latent and observed variables. It offers users a wide range of choices of models, estimators, and algorithms with an easy-to-use interface. In addition, Mplus has the capability in modeling both continuous and categorical latent variables, and an interaction of them to predict an outcome that is a continuous, categorical, censored, or a count variable. It can also deal with cross-sectional, longitudinal, as well as complex survey dataset, and has capabilities in coping and generating missing data by its Monte Carlo simulation capabilities. The current demonstration would be only confined in showing an example of a multilevel path model, in which the individual-level life satisfaction variable as the outcome.

In Mplus, all modeling command syntaxes are under ten command titles. The ten commands of Mplus are:

1. TITLE*
2. DATA*
3. VARIABLE*
4. DEFINE
5. ANALYSIS
6. MODEL*
7. OUTPUT
8. SAVEDATA
9. PLOT
10. MONTECARLO

in which, the command titles with an asterisk are necessary while constructing an analytical model. For this, TITLE, DATA, VARIABLE, AND MODEL must appear in any modeling building procedure. The TITLE command is used to provide a title for the analysis, the DATA command is used to provide information about the dataset to be analyzed, and the VARIABLE command is used to provide information about the variables in the dataset to be analyzed, and finally the MODEL command is used to describe the model to be estimated (Muthen & Muthen, 2010).

For other non-required command titles, the DEFINE command is used to transform existing variables and create new variables, the ANALYSIS command is used to describe the technical details of the analysis, the OUTPUT command is used to request additional output, the SAVEDATA command is used to save the analysis data. In addition, the PLOT command is used to request graphical displays of observed data and analysis results, and the MONTECARLO command is used to specify the details of a Monte Carlo simulation study. For details of constructing any models by writing model command syntaxes, you can refer to the Mplus User's Guide that is downloadable with no charge in the official Mplus program website at http://www.statmodel.com/ugexcerpts.shtml.

Going back to our example multilevel life satisfaction path model; we would construct the relations among the variables by portraying a multilevel path model, in which Figure 1 depicts the whole structure of the current multilevel life satisfaction path model. The upper part of the figure represents the individual-level path model and the lower part of the figure is the neighborhood-level path model. As we can see the relations portrayed in the figure that correspond to the hypotheses mentioned before, except the covariance between the two exogenous variables at individual level, Religiosity and SES, which is the preconcerted practice in SEM modelling.

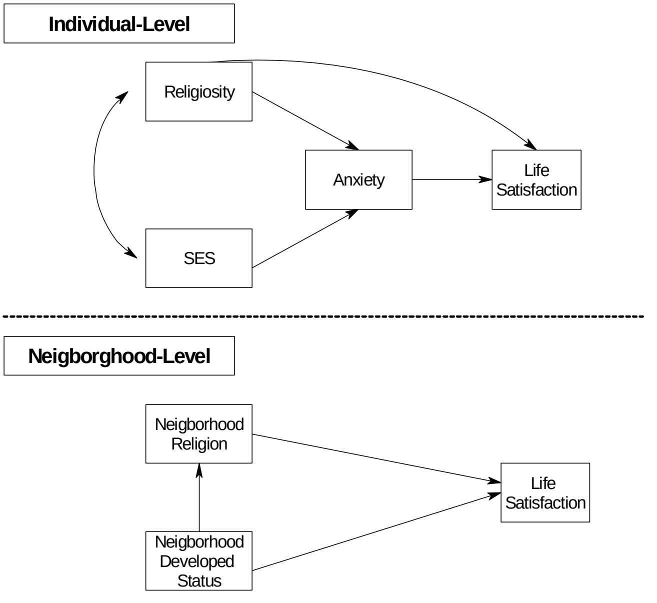


Figure 1. The Theoretical Multilevel Life Satisfaction Path Model

Model Building

Now, let's us start writing the command syntaxes for the individual-level path model, which is depicted at the upper part of Figure 1. After opening the Mplus program, we need to click on the "File" icon and then select "New" to enter the interface for writing command syntaxes. Figure 2 presents the interface, in which the model command syntaxes for the individual-level life satisfaction path model were completed.

Looking at the first part of the model command syntaxes that is "Title", describes the name of the path for identification purpose. The second part is "Data", which is important to tell the Mplus program where the dataset for analysis comes from. You can see that I put the dataset at the folder named Mplus Dataset in D Drive. The third part is named "Variable" that is crucial to tell the Mplus Program where the dataset contains how many variables. In this case, we have 8 variables for analysis, so we can see that there are v1-v8 under the "Names" in the "Variable" title. However, in our individual-level path model we only adopted 4 variables for analysis, so as we need to name these adopted variables for analysis (v5, v6, v7, and v8), under “Usevariables” to tell Mplus what variables we would like to use for analysis. The fourth part, Model, tells Mplus how to build this path model. We can see that the outcome variable, Life Satisfaction (v5), was regressed on the predictor variables of Anxiety (v7) and Religiosity (v6); and the mediator of Anxiety (v7) was regressed on the two exogenous variables, Religiosity (v6) and SES (v8). These simple command languages have portrayed the structure of our current individual-level life satisfaction path model. In the last part, that is “Output”, I have input the command of “Standardized(Stdyx)” that means the standardized format of output results is required, which is convenient for our interpretation of the results.

Once we have built the individual-level path model, we should do the analysis by pressing the icon  to obtain the analytical results of this individual-level life satisfaction path model. In this analysis we obtained a good model-fit between the data and the theoretical model, in which the model fit indexes are all desirable, X^2= 2.319, df=1, p=.127, CFI= .993, RMSEA= .052. An appendix 1 contains the results of the individual-level life satisfaction path model, and let’s discuss this analysis in the next section, Outputs and Findings, for details.

After we ensured the model fit of this individual-level path model, we could proceed to carry out the multilevel path modeling analysis. Based on the individual-level model command syntaxes displayed in Figure 2, we can start constructing the command syntaxes for the multilevel life satisfaction path model. Figure 3 shows the Mplus interface for the completed model command syntaxes of the multilevel life satisfaction path model in this demonstration. What should be highlighted in the Variable part of the command syntaxes is that the variables belonging to the individual-level and neighborhood-level are needed to be identified under the command syntax of “Within â” and “Between â” to address that v8, v7, and v6 are individual-level variables and v4 and v3 are neighborhood-level variables for identification purpose.

As you can see in the “Analysis” part of the command syntaxes, which is a newly added section. The “Type” command is necessary to tell Mplus that there is a two-level model. The “Estimator” command requires using Maximum Likelihood with Robust Stand Errors, so we input “Estimator â MLR”. In addition, by specifying “Algorithmâ Integration”, the estimation of Maximum Likelihood with Robust Stand Errors will adopt a numerical integration algorithm to take part in the estimation process, which is common in doing multilevel modeling. In the “Model” part, the model relations were built under the cover of “% Within %”, which means all the individual-level causal relations of the path model are constructed under the individual-level; and the model relations under the cover of “% Between %” connotes that all the causal relations are constructed under the neighborhood-level. Now, the results of both the individual-level and multilevel life satisfaction path models are discussed below in the section of Outputs and Findings.

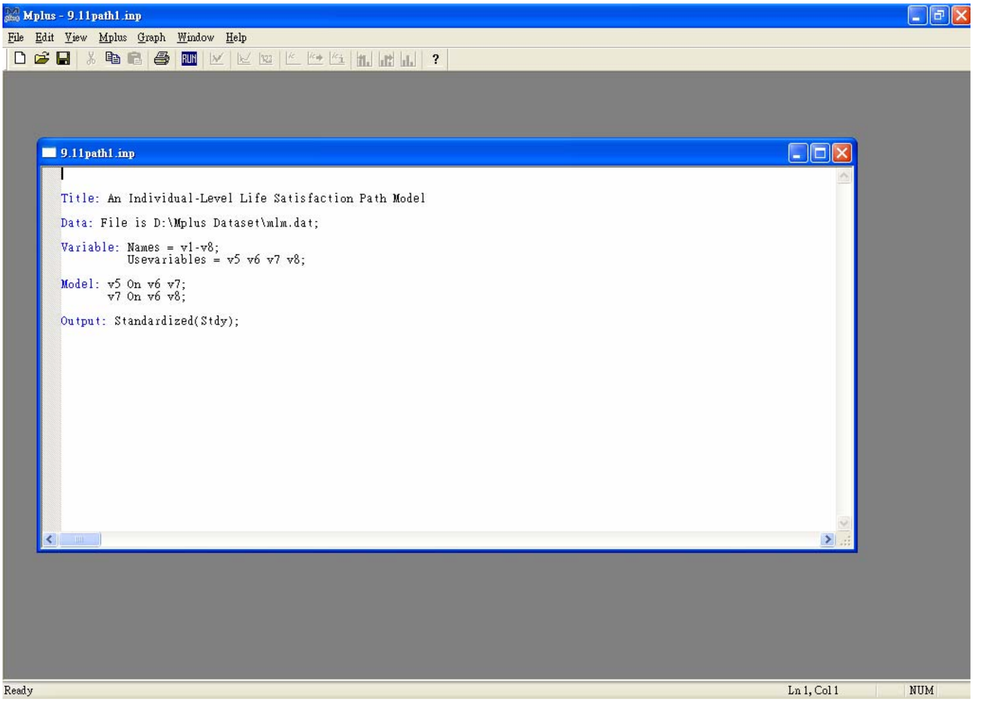
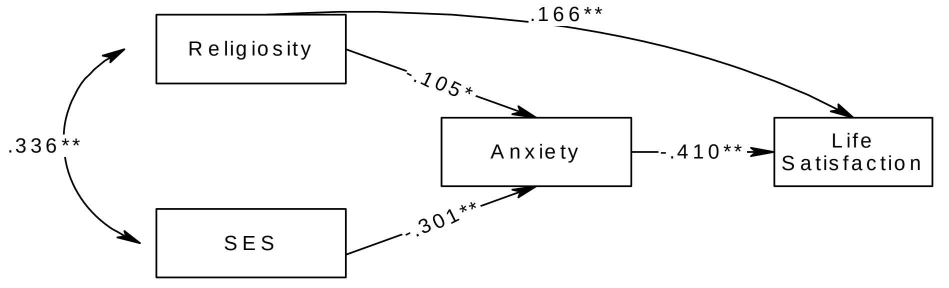


Figure 2. Command Syntaxes for the Life Satisfaction Path Model at Individual Level

Outputs and Findings

As mentioned before, we should first look at the model fit of the individual-level path model. All the analytical results of the individual-level life satisfaction path model are contained in Appendix 1. The first sentence "THE MODEL ESTIMATION TERMINATED NORMALLY", specifies that our model command syntaxes are appropriate for the analysis. In the part of "MODEL FIT INFORMATION", we could locate all the model-fit indexes to judge how well the data correspond to the theoretical path model. In this case, we have obtained an excellent model fit for our individual-level life satisfaction path model, X^2= 2.319, df=1, p=.127, CFI= .993, TLI= .965, RMSEA= .052, 95% CI-$_{RMSEA}$ = .000-.142, SRMR= .014. The third part is the "MODEL RESULTS", which contains the unstandardized analyses of model path parameters that are with little interest for us as its unstandardized nature.



X^2= 2.329 df= 1 p= .127, CFI= .993, TLI= .965, RMSEA=.052, RMSEA= .052, 95% CI_{RMSEA} = .000-.142, SRMR= .014. *p<.05, **p< .01

Figure 3. Standardized Results for the Individual-Level Life Satisfaction Path Model

In the last part of the outputs, "STANDARDIZED MODEL RESULTS", which shows the standardized forms of model path parameters, is of attention for us. Figure 3 shows the standardized path parameters of this path model, we may note that anxiety levels had much to do with the outcome variable life satisfaction, in which more anxiety levels would occasion less satisfaction about one's life, b= -.410, p<.001. On the other side, more religious people might have higher life satisfaction, b= .166, p<.001, and lower anxiety levels as well, b= -.105, p<.05. Besides, SES had a substantial negative effect on anxiety levels, b= -.301, p<.001, which implies that people with higher socio-economic statuses would have lower anxiety levels.

Based on the model command syntaxes of Figure 4, we have had the results for the multilevel life satisfaction path model. The outputs of the results are contained in Appendix 2. The first line of the outputs "THE MODEL ESTIMATION TERMINATED NORMALLY" utters that the running of the model command syntaxes proceeded successfully. However, in the heading of "MODEL FIT INFORMATION", you do not see any model fit indexes, e.g. CFI and REMSEA, because such kinds of indexes do not apply to multilevel SEM modeling. What we need to inspect are the H0 value of Loglikelihood . The lower score of this value compared to the former individual-level path model connotes the good model-fit of the multilevel path model. The Loglikelihood H_0 value of the multilevel path model is -2978.970, opposed to -2982.611 of the individual-level path mode, which bear out the good model-fit of the current multilevel path model.

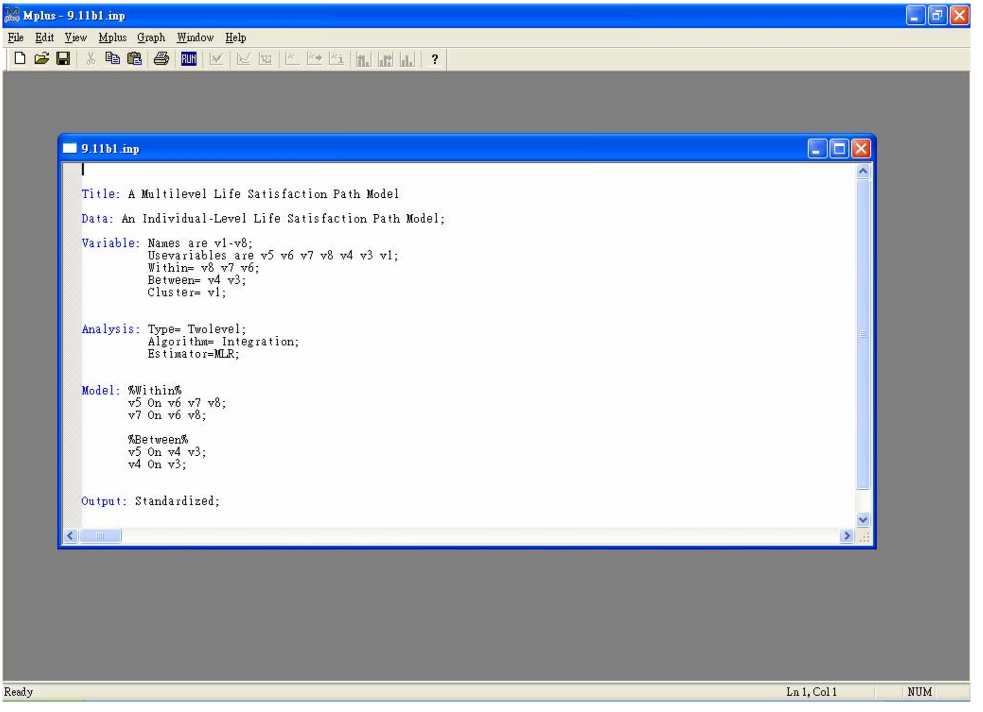


Figure 4. Command Syntaxes for the Multilevel Life Satisfaction Path Model

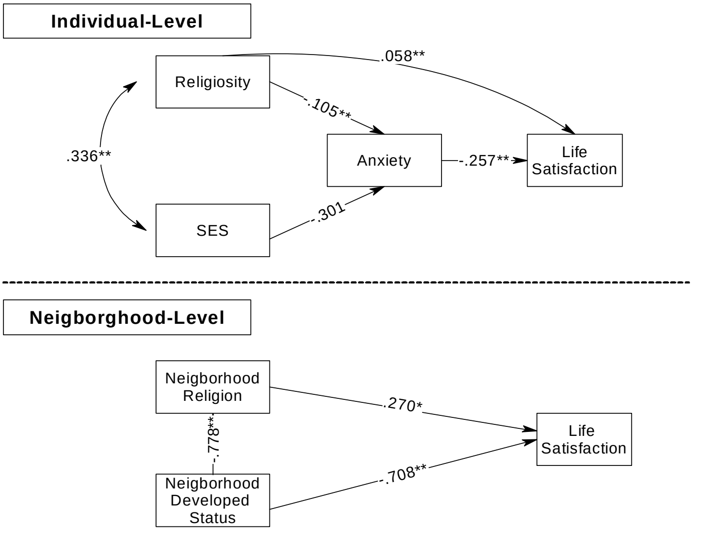


Figure 5. Standardized Results for the Multilevel-Level Life Satisfaction Path Model

Figure 5 shows the standardized path parameters of this multilevel life satisfaction path model; we can see that magnitude the standardized path coefficients from Religiosity to Life Satisfaction and from Anxiety to Life Satisfaction have shrunk substantially at the multilevel path model. The path parameter from Religiosity to Life Satisfaction is now .058, and from Anxiety to Life Satisfaction is now .257. However, they are all significant at $p< .01$. Moreover, other path parameters at the individual-level remain intact. For standardized path parameters at neighborhood-level, results revealed that a neighborhood district where was more industrially developed would have a substantially negative and concrete impact on people's life satisfaction there, $b= -.708$, $p<.01$, and the aggregate-level of religiosity at a neighborhood-level district with higher industrial development would be dampened, $b= -.778$, $p<.01$. In contrast, neighborhood districts with a higher aggregate- level of religiosity would be positively predictive of higher life satisfaction of their district residents $b= .270$, $p<.01$.

Discussion

The current imitated study demonstrated a multilevel life satisfaction path model, which is constituent of the core part for those more sophisticate and advanced multilevel SEM analyses. As we can see that mere adoption of an individual-level approach to investigate relationships in structural models would augment some path effects, which may be substantially shrunk if a higher level of analysis is imposed. In this mock study, the predictive power of anxiety to life satisfaction changed from $b=-.410$ to $b=-.257$, and the predictive power of religiosity to life satisfaction changed from $b=.166$ to $b=.058$. In addition, the significant path effects at the neighborhood-level shed light on the crucial consideration of influences of impacts from a higher level of impacts in structuralist nature. In social work research, it is indubitable that much of the change on outcomes for service recipients may not be only due to the consequences of interventions and individual factors. In fact, effects of a treatment outcome and human behaviors pertinent to that treatment are both kept within bounds of factors from a higher level, such as school effects on students' academic outcomes and neighborhood effects on residents' behavioral choices.

On the other hand, refereed to the Appendix 1, the current individual-level path model accounts for 22.4% of variance for the outcome of life satisfaction, $R^2= .224$, Standard Error= .033, $p< .01$. However, the explained variance of the life satisfaction outcome variable was dropped to 7.6% at individual-level in the multilevel path model, $R^2= .076$, Standard Error= .012, $p< .01$; and, on the other side, the neighborhood-level path model accounted for 87.3% of variance for life satisfaction, $R^2= .873$, Standard Error= .059, $p< .01$. As such, this imitated multilevel path model utters the importance of a higher-level effect on the outcome. If we only look at individual-level factors for outcome effects, we may ignore capaciously explanatory power of a test model, and may exaggerate or downplay the estimated effects at individual-level predictors, all of which may lead to inaccurate conclusions.

Stated succinctly, all human behaviors and choices are imbued in a higher-level societal structure that may have collective effects on the outcomes that we are looking for. Social work research should consider effects executed from a higher level to obtain more precise results, which may help to avoid unnecessarily overstated or understated conclusions based on a single-level model in analyzing effects of service and program interventions. In a long run, we could grip a more complicated causal fashion of those dismal and proximal factors that are influential of our service clients through these more advanced modeling procedures.

References

Beddoe, L. (2011). Investing in the Future: Social Workers Talk about Research. *British Journal of Social Work*, 41(3), 557-575.

Brkljacic, T., & Lipovcan, L. K. (2010). Life satisfaction and feeling of happiness among students. *Suvremena Psihologija*, 13(2), 189-201.

Geldof, D. (2010). New challenges for urban social work and urban social work research. *European Journal of Social Work*, 14(1), 27-39.

Gerber, M., Puhse, U. (2007). Psychosomatic complaints and psychological well-being among high-school students. *Psychologie In Erziehung Und Unterricht*, 54(3), 223-235.

Gerdes, K. E. (2011). Introduction: 21st-Century Conceptualizations of Empathy: Implications for Social Work Practice and Research. *Journal of Social Service Research*, 37(3), 226-229.

Hoyle, R. H. (2011). *Structural equation modeling for social and personality psychology*. London : Sage Publications

Kline, R. K. (1998). *Principles and practice of structural equation modeling*. London: Guilford Press.

Lim, C., & Putnam, R. D. (2010). Religion, Social Networks, and Life Satisfaction. *American Sociological Review*, 75(6), 914-933.

Luke, D. A. (2004). *Multilevel modeling*. Thousand Oaks, CA : Sage.

Mitchell, F., Lunt, N., & Shaw, I. (2010). Practitioner research in social work: a knowledge review. *Evidence & Policy*, 6, 7-31.

Mochon, D., Norton, M. I., & Ariely, D. (2011). Who Benefits from Religion? *Social Indicators Research*, 101(1), 1-15.

Moller, V., & Huschka, D. (Eds.) (2008). *Quality of life and the millennium challenge: Advances in quality-of-life studies, theory and research*. London: Springer.

Muthen L. K. & Muthen, B. O. (2010). *Mplus Statistical Analysis with latent variables: User's Guide*. Los Angels, CA: Muthen & Muthen.

Nezlek, J. B. (2011). *Multilevel modeling for social and personality psychology*. London: Sage, 2011.

Norberg, M. M., Diefenbach, G. J., & Tolin, D. F. (2008). Quality of life and anxiety and depressive disorder comorbidity. *Journal of Anxiety Disorders*, 22(8), 1516-1522.

Shek, D. T. L. & Lee, B. M. (2007). A comprehensive review of quality of life (QOL) research in Hong Kong. *TheScientificWorldJournal*, 7, 1222-1229.

Shek, D. T. L., Chan, Y. K., & Lee, P. S. N. (2005). *Quality-of-life research in Chinese, Western, and global contexts*. Norwell, MA : Springer.

Thyer, B. A. (2010). Introductory Principles of Social Work Research. In Bruce Thyer (Ed.), *The Handbook of Social Work Research Methods* (Pp. 1-24). Los Angeles: SAGE.

Ybrandt, H. (2008). The relation between self-concept and social functioning in adolescence. *Journal of Adolescence*, 31(1), 1-16.

Yeung, J. W. K., & Chan, Y. C. (2010). Family functioning of Chinese families on an impoverished neighborhood in Hong Kong. *Psychological Reports*, 107(3), 740-748.

Yeung, J. W. K., Cheung, C. K., & Chan, Y. C. (2007). Impacts of religious involvement on adolescent health and behavioral outcomes: Implications for local research in Hong Kong. *Journal of Youth Studies*, 10(2), 178-197.

Yeung, J. W. K., Kwok-Lai Y. C., & Chung, A. (2010). Correlates of Prevalence of Depression in Nursing Home Chinese Residents in Hong Kong and Implications for Services and Policy Intervention. *Ljetopis socijalnog rada: Annual of social work*, 17(3), 445-460.

Appendix 1. Outputs of the Individual-Level Life Satisfaction Path Model

THE MODEL ESTIMATION TERMINATED NORMALLY

```
MODEL FIT INFORMATION
Number of Free Parameters                13
Loglikelihood
        H0 Value                -2982.611
        H1 Value                -2981.446

Information Criteria
        Akaike (AIC)               5991.222
        Bayesian (BIC)             6046.011
        Sample-Size Adjusted BIC         6004.749
          (n* = (n + 2) / 24)

Chi-Square Test of Model Fit
        Value                      2.329
        Degrees of Freedom               1
        P-Value                    0.1270

RMSEA (Root Mean Square Error Of Approximation)
        Estimate                   0.052
        90 Percent C.I.              0.000  0.142
        Probability RMSEA <= .05          0.346

CFI/TLI
        CFI                        0.993
        TLI                        0.965

Chi-Square Test of Model Fit for the Baseline Model
        Value                    194.148
        Degrees of Freedom               5
        P-Value                    0.0000

SRMR (Standardized Root Mean Square Residual)
        Value                      0.014

MODEL RESULTS
                                            Two-Tailed
                 Estimate       S.E.  Est./S.E.    P-Value
V5       ON
   V6              0.265      0.064      4.119      0.000
   V7             -0.589      0.058    -10.179      0.000
V7       ON
   V6             -0.117      0.049     -2.357      0.018
   V8             -0.463      0.068     -6.758      0.000
V6       WITH
   V8              0.281      0.039      7.117      0.000

Means
   V6              2.916      0.048     60.620      0.000
   V8              1.602      0.035     46.108      0.000

Intercepts
   V5              4.397      0.300     14.638      0.000
   V7              4.358      0.157     27.706      0.000

Variances
   V6              1.157      0.073     15.811      0.000
   V8              0.604      0.038     15.811      0.000
```

Residual Variances

V5	2.292	0.145	15.811	0.000
V7	1.256	0.079	15.811	0.000

STANDARDIZED MODEL RESULTS
STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
V5 ON				
V6	0.166	0.040	4.162	0.000
V7	-0.410	0.037	-11.076	0.000
V7 ON				
V6	-0.105	0.044	-2.368	0.018
V8	-0.301	0.043	-7.043	0.000
V6 WITH				
V8	0.336	0.040	8.461	0.000
Means				
V6	2.711	0.097	28.037	0.000
V8	2.062	0.079	26.079	0.000
Intercepts				
V5	2.560	0.178	14.358	0.000
V7	3.642	0.138	26.431	0.000
Variances				
V6	1.000	0.000	999.000	999.000
V8	1.000	0.000	999.000	999.000
Residual Variances				
V5	0.776	0.033	23.649	0.000
V7	0.878	0.027	31.944	0.000

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
V5	0.224	0.033	6.807	0.000
V7	0.122	0.027	4.459	0.000

QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix 0.653E-02
(ratio of smallest to largest eigenvalue)

Appendix 2. Outputs of the Multilevel Life Satisfaction Path Model

```
HE MODEL ESTIMATION TERMINATED NORMALLY
MODEL FIT INFORMATION
Number of Free Parameters                19
Loglikelihood
        H0 Value                 -2978.970
        H0 Scaling Correction Factor     1.468
          for MLR
Information Criteria
        Akaike (AIC)              5995.940
        Bayesian (BIC)            6076.018
        Sample-Size Adjusted BIC       6015.711
          (n* = (n + 2) / 24)

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

Within Level

V5        ON
   V6          0.079     0.021      3.829      0.000
   V7         -0.315     0.036     -8.644      0.000
V7        ON
   V6         -0.117     0.022     -5.288      0.000
   V8         -0.463     0.062     -7.456      0.000
V6       WITH
   V8          0.281     0.091      3.098      0.002

Means
   V6          2.916     0.094     31.103      0.000
   V8          1.602     0.107     15.033      0.000

Intercepts
   V7          4.358     0.086     50.411      0.000

Variances
   V6          1.157     0.049     23.597      0.000
   V8          0.604     0.072      8.357      0.000

Residual Variances
   V5          1.983     0.104     19.033      0.000
   V7          1.256     0.008    157.810      0.000

Between Level
V5        ON
   V4          0.169     0.088      1.930      0.054
   V3         -0.712     0.140     -5.086      0.000
V4        ON
   V3         -1.250     0.205     -6.109      0.000

Intercepts
   V4          5.540     0.392     14.132      0.000
   V5          4.950     0.489     10.118      0.000

Residual Variances
   V4          0.488     0.175      2.784      0.005
   V5          0.062     0.027      2.289      0.022
```

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Within Level				
V5 ON				
V6	0.058	0.014	4.288	0.000
V7	-0.257	0.018	-14.202	0.000
V7 ON				
V6	-0.105	0.019	-5.495	0.000
V8	-0.301	0.050	-6.032	0.000
V6 WITH				
V8	0.336	0.081	4.122	0.000
Means				
V6	2.711	0.034	80.055	0.000
V8	2.062	0.014	145.835	0.000
Intercepts				
V7	3.642	0.032	113.360	0.000
Variances				
V6	1.000	0.000	999.000	999.000
V8	1.000	0.000	999.000	999.000
Residual Variances				
V5	0.924	0.012	76.720	0.000
V7	0.878	0.046	19.005	0.000
Between Level				
V5 ON				
V4	0.270	0.135	1.997	0.046
V3	-0.708	0.105	-6.749	0.000
V4 ON				
V3	-0.778	0.080	-9.678	0.000
Intercepts				
V4	4.978	0.437	11.391	0.000
V5	7.107	0.926	7.674	0.000
Residual Variances				
V4	0.394	0.125	3.151	0.002
V5	0.127	0.059	2.153	0.031

R-SQUARE

Within Level

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
V5	0.076	0.012	6.274	0.000
V7	0.122	0.046	2.653	0.008

Between Level

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
V4	0.606	0.125	4.839	0.000
V5	0.873	0.059	14.778	0.000

QUALITY OF NUMERICAL RESULTS
Condition Number for the Information Matrix -0.161E-15
(ratio of smallest to largest eigenvalue)