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14

Longitudinal Mediation Analysis of Training Intervention Effects

Lijuan Wang, Zhiyong Zhang, and Ryne Estabrook

14.1 INTRODUCTION

Intervention research constitutes a broad research category, encompassing a large number of experimental, psychological, and medical research designs. While this type of research can build on rather simple designs and few variables, multivariate longitudinal designs allow for tests of more complex treatment assignments and models, as well as mediation. The focus of this chapter is on models and methods for evaluating longitudinal intervention effects in the presence of mediation: that is, the methods for analyzing the longitudinal impact of an intervention or treatment when that impact is mediated by one or more other variables.

We explore the concept of mediation and its application to longitudinal intervention research. First, we review the history and basic ideas of mediation analysis, including developments in longitudinal mediation analysis. Second, we present a variation of the longitudinal mediation model (Cole & Maxwell, 2003) for intervention and training research, highlighting the features of the nonrepeated training interventions, the repeatedly measured mediation and output variables, and the estimation methods of the model. Finally, we apply this new model to data from the Advanced Cognitive Training for Independent and Vital Elderly (ACTIVE) study (Jobe et al., 2001) to demonstrate the capabilities of the model.

14.2 MEDIATION ANALYSIS

Mediation analysis has been widely used in psychological research to develop theories on whether there exists a third variable that accounts for the relationship between an input variable and an output variable (Baron & Kenny, 1986; Cole & Maxwell, 2003; Judd & Kenny, 1981a, 1981b; MacKinnon, Fairchild, & Fritz, 2007; Shrout & Bolger, 2002). For example, Salthouse (1996, p. 403) developed the theory that "increased age in adulthood is associated with a decrease in the speed with which many processing operations can be executed and that this reduction in speed leads to impairments in cognitive functioning" (see also, Salthouse, 1991, 1993).

The simplest and most widely used mediation model is the three-variable model or the single-mediator model portrayed in Figure 14.1. For the purpose of simplification, here we only look at the covariance structure without the means. In Figure 14.1, Y, X, and M represent the dependent or output variable, the independent or input variable, and the mediation variable, respectively. e_M and e_Y are residuals or measurement errors with variances σ^2_{eM} and σ^2_{eY}. The mediation models can be expressed by two regression equations,

$$M = aX + e_M, \qquad Y = c'X + bM + e_Y, \tag{14.1}$$

where a, c', and b are regression coefficients. Thus, a represents the relation between X and M. c' represents the relation between X and Y adjusted for M and b represents the relation between M and Y adjusted for X. c' is also called the direct effect of X on Y and ab is called the indirect effect of

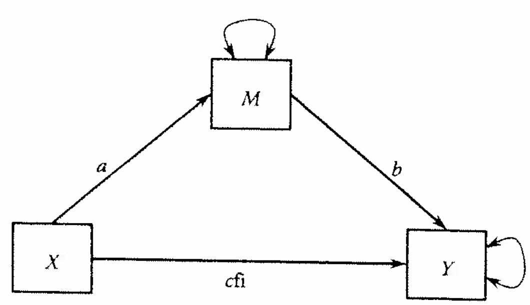

FIGURE 14.1 Path diagram of a single mediator model.

X on Y through mediation of M. The implied model without mediatio effects is $Y = cX + e_Y$. When mediation effects have occurred, the indirec effect, ab, or the difference in the direct effect, $c' - c$, should be significantl different from 0 (e.g., Baron & Kenny, 1986; MacKinnon & Dwyer, 199 Shrout & Bolger, 2002; Sobel, 1982).

Statistical approaches to estimating and testing mediation effects for th single mediator model have been discussed extensively in the psychologi cal literature (e.g., Baron & Kenny, 1986; Bollen & Stine, 1990; MacKinno et al., 2007; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; Shrou & Bolger, 2002). There are two common ways of testing mediation effects The first and perhaps most widely used method is the approach outline in Baron and Kenny's (1986) work, where the mediation parameters ar tested in a regression framework. This single sample method (named afte MacKinnon et al., 2002) is based on a large-sample normal approxima tion test provided by Sobel (1982, 1986), which is easy to implement an understand but may have low statistical power in some situations such a studies with small sample sizes (e.g., MacKinnon et al., 2002). The secon approach may be called the resampling method, which is based on the boot strap resampling procedure (e.g., Bollen & Stine, 1990; Efron, 1979, 1987 Preacher & Hayes, 2004; Zhang & Wang, 2008). The resampling metho does not require the large sample size assumption and could be mor accurate and more powerful than the single sample method under certai conditions such as studies with small size and/or skewed outcome problem (e.g., MacKinnon et al., 2007; Shrout & Bolger, 2002; Zhang & Wang, 2008)

Although the single mediator model is widely used, many complex exten sions have been developed (see the review by MacKinnon et al., 2007). Fo example, models with multiple mediators have been investigated and use (e.g., Cheung, 2007; MacKinnon, 2000; Rutter & Hine, 2005). Multileve mediation models have also been developed and used to accommodate dependent observations that are nested within groups (e.g., Bauer, Preacher & Gil, 2006; Kenny, Bolger, & Korchmaros, 2003; Krull & MacKinnon 1999, 2001). Another important extension is the development of longitudinal mediation models (e.g., Cheong, MacKinnon, & Khoo, 2003; Cole & Maxwell, 2003; Collins, Graham, & Flaherty, 1998).

The application of longitudinal mediation models is an important conceptual development. Collins et al. (1998) defined the mediated process as a reaction chain in which the input variable first affects the mediator, which, in turn, affects the output variable over time. This definition is different from the one given by Baron and Kenny (1986), which focuses on whether the relation between the input variable and the output variable can be explained by means of a mediator. For Baron and Kenny (1986), the data from the input variable, the mediator, and the output variable can be collected at the same time when the mediation effects are tested. To operate the method in Collins et al. (1998), one needs to obtain the input variable, the mediator, and the output variable at different occasions such as $X_{t-2} \rightarrow M_{t-1} \rightarrow Y_t$. Most modern definitions of mediation are more in line with Collins et al. (1998). And the Collins' definition can be operated in a longitudinal study conveniently. However, it is possible that sometimes the mediation occurs so quickly that the concurrent relationship among the input, mediator, and output variances might be observed. In this case, the definition of Baron and Kenny (1986) can still operate in a meaningful way.

Figure 14.2 portrays the path diagram for a longitudinal mediation model discussed by Cole and Maxwell (2003). In this model, the input variable, the mediator, and the output variable are measured multiple times. One form of this model can be written as

$$X_t = \beta_X X_{t-1} + e_{X_t},$$
$$M_t = \beta_M M_{t-1} + aX_{t-1} + e_{M_t}, \quad t = 3, \ldots, T, \qquad (14.2)$$
$$Y_t = \beta_Y Y_{t-1} + bM_{t-1} + cX_{t-2} + e_{Y_t},$$

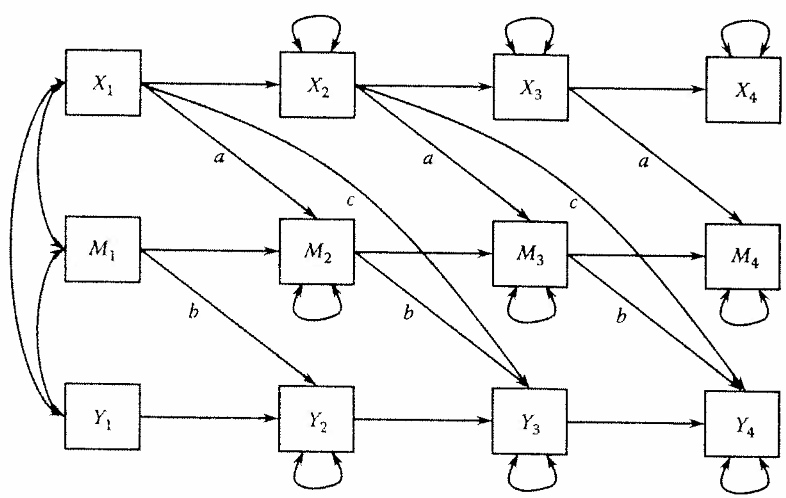

FIGURE 14.2 Path diagram of a longitudinal mediation model (see also Cole & Maxwell, 2003).

where X_t, M_t, and Y_t represent the observed data for X, M, and Y at tin t, respectively; and e represents residual errors for each regression equ tion at time t. Notice that, in investigating mediation effects, M_{t-1} is fir controlled before predicting M_t and Y_{t-1} is also controlled before predic ing Y_t. This is because they are confounds and without controlling ther one may obtain spuriously inflated estimates of mediation effects (Cole Maxwell, 2003). This model also implies that the unknown coefficients a invariant across time.

The model discussed by Cole and Maxwell (2003) is only one variety longitudinal mediation models. This model is also called the autoregre sive mediation model and a similar idea has been previously discussed b Gollob and Reichardt (1991), Judd and Kenny (1981b), and MacKinnc (1994). Cheong et al. (2003) proposed to use the latent growth curve moc els to analyze mediation effects where an input variable affects the growt (e.g., change from time 1 to time T) of the output variable through i influence on the growth (e.g., change from time 1 to time T) of the med ator. The autoregressive mediation model and the mediation model in tł growth curve modeling framework have very different emphases. The fo mer focuses more on the time-related relationship between the input an the output variables through a mediator variable, while the latter focuse on the effects of an input variable on the change of an output variabl through the change of a mediator variable. Therefore, the former can b more easily applied to analyze lag effects and predict long-term effects. I this chapter, the autoregressive mediation approach is used.

14.3 METHODS FOR THE ANALYSIS OF TRAINING INTERVENTION WITH MEDIATION EFFECTS

Before introducing the methods for analyzing training intervention witl mediation effects, let us consider a typical training intervention scenaric Suppose we have $T (T \geq 4)$ occasions of measures on mediation and outpu variables and one training intervention (a single measure). The trainin intervention happens between the first measurement occasion (baselin occasion) and the second measurement occasion. The research question are whether there is a training intervention effect on the output variable

whether the training effect is mediated by the mediation variable, and how long the training effect would last.

For this training intervention example, the training interventions could be modeled as the X variable in Figure 14.2. However, there are no repeated measures on the training intervention itself. Instead, the training intervention can be considered as a shock to the mediation and output variable system. Therefore, the longitudinal mediation models described in Figure 14.2 may not fit the data structure of training intervention exactly. Furthermore, there are multiple occasions of data on mediation and output variables which could make the cross-sectional mediation method less sufficient to analyze the data. Therefore, it is necessary to develop a model to accommodate the data structure of the training intervention with mediation effects.

A prospective model for the analysis of training intervention with mediation effects is portrayed in Figure 14.3. M_t and Y_t represent the mediation variable and the outcome variable, respectively, for occasion t, $t = 1, 2, \ldots, T$. I represents the training intervention variable. The lowercase letters in the path diagram represent the unknown path coefficients. Certainly, there are different alternatives to this model. For instance, there could be a concurrent relationship between the mediation variable and the output variable instead of the lagged relationship described in Figure 14.3. Here we use this model [a similar idea has been discussed in MacKinnon (1994)], which can also be viewed as a variation of the longitudinal mediation model (Cole & Maxwell, 2003), as an example to illustrate the general idea of training intervention data analysis with mediation effects.

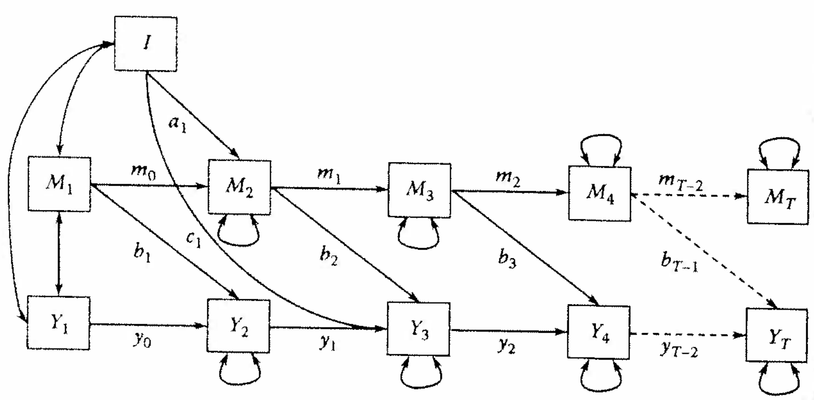

FIGURE 14.3 A model for analyzing training intervention with mediation effects.

In this model, training intervention has both direct effect and indirec effect through the mediator variable on the output variable. The direc effect of training intervention on Y_3 is c_1 and the indirect effect is a_1b_2 The total effect of training intervention on Y_3 is $c_1 + a_1b_2$. We can alsc calculate the total effect of training intervention on Y_4 by summarizing al paths from the training variable I to Y_4, $(c_1 + a_1b_2)y_2 + a_1m_1b_3$. Similarly the training effect on Y_T can also be calculated. An underlying assumptior of this model is that those who receive training change over time in the same way as those who do not receive training. However, this assumption can be relaxed by either adding an interaction term into the model or analyzing the data in the multiple group analysis framework.

14.3.1 Evaluating Training Effects

The whole sample of an intervention study can usually be divided into multiple groups based on the study design. For instance, there could be two groups in the study: a control group and a training group. To analyze the training effect, we need to estimate the unknown path coefficients. The model in Figure 14.3 implies that for the control group ($I = 0$), we have $Y_3 = b_2M_2 + y_1Y_2 + e_{Y_3}$. For the group receiving the training intervention ($I = 1$), we have $Y_3 = b_2M_2 + c_1 + y_1Y_2 + e_{Y_3}$. Thus, b_2 and y_1 are the same for both groups. Therefore, it is important to notice the underlying assumption that the coefficients, especially for ms, bs, and ys, are the same for both the control group and the training group. However, it could be also reasonable to believe that b_2 may be different for the two groups.

From a developmental perspective, the purpose of training intervention can be viewed as improving the performance/skills and/or preventing the decline of a targeted ability so that the targeted ability can maintain a high level of performance over time. There are different ways to achieve this goal. First, training may increase the level of performance of a targeted ability immediately after training. Thus, the level of performance will be at a higher level than otherwise without training in the future (see Figure 14.4a). Second, training may reduce the rate of decline of performance. Thus, the level of performance after training will also be at a higher level than otherwise without training as shown in Figure 14.4b. Third, the ideal outcome of training is an increased level of performance and a reduced rate of decline as portrayed in Figure 14.4c. These three patterns of training effects can be related to the following models.

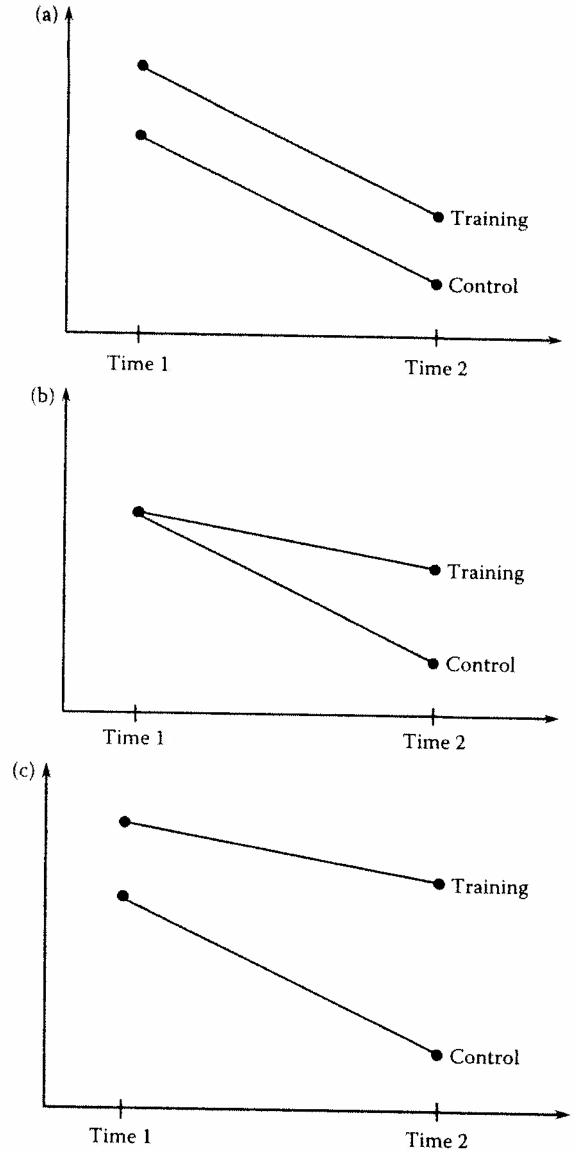

FIGURE 14.4 Three possible outcomes of training effects, (a) level only, (b) slope only, and (c) both level and slope.

In terms of the training intervention study, we may expect $Y_3 = b_2^* M_2 + c_1 + y_1^* Y_2 + e_{Y_3}$ with $b_2^* > b_2$ for the training group, which means that training could also influence the path coefficients. There are two methods for analyzing the influences of training effects on the path coefficients,

which we dub the "interaction method" and the "multiple group metho
For the interaction method, we can analyze the data from both the cont
group and the training group together by fitting a model with interacti
to the raw data as

$$Y_3 = i + b_2 M_2 + c_1 I + y_1 Y_2 + d_1 M_2 I + d_2 Y_2 I + e_{Y_3}, \qquad (14$$

where i represents the intercept of the control group and d_1 and d_2 coefficients for the interaction terms. Thus, for the control group ($I =$ $Y_3 = i + b_2 M_2 + y_1 Y_2 + e_{Y_3}$ and for the training group, $Y_3 = i + c_1$ $(b_2 + d_1)M_2 + (y_1 + d_2)Y_2 + e_{Y_3}$.

For the multiple group method, we can fit separate models to the cont and training groups,

$$Y_3 = i^{(j)} + b_2^{(j)} M_2 + y_1^{(j)} Y_2 + e_{Y_3}, \quad j = 0, 1, \qquad (14$$

where $j = 0$ for the control group and $j = 1$ for the training group. represents the intercept for the jth group. It can be shown that $b_2^{(0)} =$ $y_1^{(0)} = y_1$, $b_2^{(1)} = b_2 + d_1$, $y_1^{(1)} = y_1 + d_2$, and $i^{(1)} - i^{(0)} = c_1$ with t parameters on the left side from the multiple group method and t parameters on the right side from the interaction method.

We can relate the models with the three patterns of training effects Figure 14.4. If c_1 is significant and neither d_1 nor d_2 is significant, t pattern in Figure 14.4a is plausible. If only d_1 or d_2 or both are significa but c_1 is not significant, we could have the pattern in Figure 14.4b. If both and at least one of d_1 and d_2 are significant, the last pattern in Figure 14. could be detected.

Similarly, a_1 in Figure 14.3 can be estimated using either method. F example, with the multiple group method, we can first fit a model,

$$M_2 = i_M^{(j)} + m_0^{(j)} M_1 + e_{M_1}, \quad j = 0, 1, \qquad (14.$$

to the control group ($j = 0$) and the training group ($j = 1$), separate Then, $a_1 = i_M^{(1)} - i_M^{(0)}$. The training effect on Y_3 is $c_1 + a_1(b_2 + d_1)$ fro the interaction method and $i^{(1)} - i^{(0)} + (i_M^{(1)} - i_M^{(0)})b_2^{(1)}$ from the mul ple group method. Furthermore, we have $c_1 + a_1(b_2 + d_1) = i^{(1)} - i^{(0)}$ $(i_M^{(1)} - i_M^{(0)})b_2^{(1)}$ for the total effect.

There are advantages and disadvantages to either method. The interaction method is able to estimate all parameters in one step, but this procedure will become complex and difficult to interpret and implement as the number of parameters grows. The multiple group method is easier to implement, interpret, and is more flexible, which has the ability to deal with different variances due to treatment. In the current research, the multiple group method will be used for the data analysis. To summarize, the following steps can be applied to obtain the model parameter estimates. In the first step, the model described as below can be fit to each group separately,

$$M_t = i_{M_t}^{(j)} + m_{t-2}^{(j)} M_{t-1} + e_{M_t},$$
$$Y_t = i_{Y_t}^{(j)} + b_{t-1}^{(j)} M_{t-1} + y_{t-1}^{(j)} Y_{t-1} + e_{Y_t}, \tag{14.6}$$

where $i_{M_t}^{(j)}$ denotes the intercept of M_t for jth group, the superscript $^{(j)}$ denotes the jth group, $j = 0, 1$ represent the control group and the training group, respectively. In the second step, we can calculate a_1 by $a_1 = i_{M_2}^{(1)} - i_{M_2}^{(0)}$. In addition, we can calculate c_1 by $c_1 = i_{Y_3}^{(1)} - i_{Y_3}^{(0)}$. In the third step, we can calculate the training effects based on the estimated parameters. For example, the training effect on Y_3 is $c_1 + a_1 b_2^{(1)}$.

14.3.2 Evaluating Training Effects over Time

Predicting training effects beyond the observed occasions is of interest to researchers from both methodological and substantive perspectives. Methodologically, Cole and Maxwell (2003) have shown that the time interval was important for evaluating the indirect effects and the time interval may affect the estimated effects. By evaluating the training effects over time, the evolvement of the training effects could be captured and the training effects may be portrayed in a more accurate way. For example, training may only demonstrate its effects after a certain amount of time. Without estimating the training effects after this amount of time, one may not be able to observe the significance of training effects.

There are also many substantive studies on the long-term effects of training in different study areas. For example, Willis and Nesselroade (1990) examined the effects of multiple phases of cognitive training on older adults' intellectual performance over a 7-year period. Willis et al. (2006) found that cognitive training resulted in improved cognitive abilities specific to the abilities trained even 5 years after the initiation of the intervention. Schlaug, Norton, Overy, and Winner (2005) demonstrated that music training in children results in long-term enhancement of visual spatial, verbal, and mathematical performance.

To predict the training effects beyond the observed occasions stationarity needs to be tested and/or assumed. Stationarity has many different definitions under different contexts. For instance, in mathematical statistics, stationarity is observed when the probability distribution of a process at a fixed time is the same for all times. Kenny (1979, p. 287) defined stationarity as "an unchanging causal structure." Cole and Maxwell (2003, p. 560) interpreted Kenny's definition as "the degree to which one set of variables produces change in another set that remains the same over time." In the current research, Kenny's definition is used. We acknowledge that this is a rather weak adaption of the stationarity concept because only the regression coefficients are required to be invariant over time. And we do not require the residual variances to be invariant over time.

For the model portrayed in Figure 14.3, if it is stationary for the control group, one would expect that $m_0^{(0)} = m_1^{(0)} = m_2^{(0)} = \cdots = m_{T-2}^{(0)} \equiv m^{(0)}$, $b_1^{(0)} = b_2^{(0)} = b_3^{(0)} = \cdots = b_{T-1}^{(0)} \equiv b^{(0)}$, and $y_0^{(0)} = y_1^{(0)} = y_2^{(0)} = \cdots = y_{T-2}^{(0)} \equiv y^{(0)}$. For the training group, one would expect that $m_1^{(1)} = m_2^{(1)} = \cdots = m_{T-2}^{(1)} \equiv m^{(1)}$, $b_2^{(1)} = b_3^{(1)} = \cdots = b_{T-1}^{(1)} \equiv b^{(1)}$, and $y_2^{(1)} = \cdots = y_{T-2}^{(1)} \equiv y^{(1)}$. Here, the model parameters are invariant over time after the intervention treatment time-point.

To test the stationarity of the model, the chi-square difference test (likelihood ratio test) can be used. For example, to test $m_0^{(0)} = m_1^{(0)} = m_2^{(0)} = \cdots = m_{T-2}^{(0)}$, a model with freely estimated parameters can be first estimated to obtain the chi-square fit value χ_1^2 with degrees of freedom df_1. Then, we can constrain the parameters to be equal and estimate the model again and get χ_2^2 with df_2. Finally, we compare the chi-square difference $\Delta\chi^2 = \chi_2^2 - \chi_1^2$ with the critical value c_α from the chi-square distribution with degree of freedom $df_2 - df_1$. If $\Delta\chi^2 < c_\alpha$, we cannot reject the stationarity of the model. More tests, such as $m_0^{(0)} = m_1^{(0)} = m_2^{(0)} = \cdots = m_{T-2}^{(0)}$ versus $m_0^{(0)} = m_1^{(0)} = \ldots = m_{T-3}^{(0)} \neq m_{T-2}^{(0)}$ can be performed to test stationarity for all possible comparisons.

Note that we cannot test stationarity beyond the observed data. For example, although we can conclude that $m_0^{(0)} = m_1^{(0)} = \cdots = m_{T-2}^{(0)}$, we cannot say that $m_0^{(0)} = m_1^{(0)} = \cdots = m_{T-2}^{(0)} = m_{T-1}^{(0)}$ without collecting more data. However, if we assume that $m_0^{(0)} = m_1^{(0)} = \cdots = m_{T-2}^{(0)} = m_{t-1}^{(0)}$ for $t \geq T - 1$, we can make inference beyond observed data, such as inference on the training effects beyond the Tth occasion.

After obtaining the model parameters and satisfying the stationarity test, we can predict the training effects over time in a more parsimonious model. Because the training intervention happens between the first occasion and the second occasion and there is a lagged relationship between the mediation variable and the output variable, there are no training effects on the first occasion and the second occasion such as $I(1) = I(2) = 0$ with $I(t)$ representing the training effect at time t. At occasion 3, $I(3) = c_1 + a_1 b^{(1)}$. At occasion T, we have $I(T) = I(T-1)y^{(1)} + a_1[m^{(1)}]^{T-3}b^{(1)}$. With the stationarity, although we did not observe data from the occasion $T+1$ and above, we can predict the training effect by using $I(t) = I(t-1)y^{(1)} + a_1[m^{(1)}]^{t-3}b^{(1)}, t > T$.

14.3.3 Multiple Training Interventions

In some studies, there could be more than one training intervention. For example, besides the training intervention between the first and the second measurement occasions, there could be another training intervention (we can call it "booster training intervention") for some of the participants between the second measurement occasion and the third measurement occasion (see Figure 14.5). In this case, the overall sample can be divided into three groups: a control group, an initial training group with only the first training intervention, and a booster training group with both the first training intervention and the second training intervention. The second training intervention has also both a direct effect and an indirect effect through the mediator variable on the output variable for the booster training group. The direct effect of the second training intervention on Y_4 is c_2 and the indirect effect is $a_2 b_3$. The total effect of the second training intervention on Y_4 is $c_2 + a_2 b_3$. Similarly, we can evaluate the second training effect over time, $B(1) = B(2) = B(3) = 0, B(4) = c_2 + a_2 b^{(2)}$, and $B(t) = B(t-1)y^{(2)} + a_2[m^{(2)}]^{t-4}b^{(2)}, t = 5, 6, \ldots$ with $B(t)$ representing the second training effect at time t and the superscript $^{(2)}$ denoting the

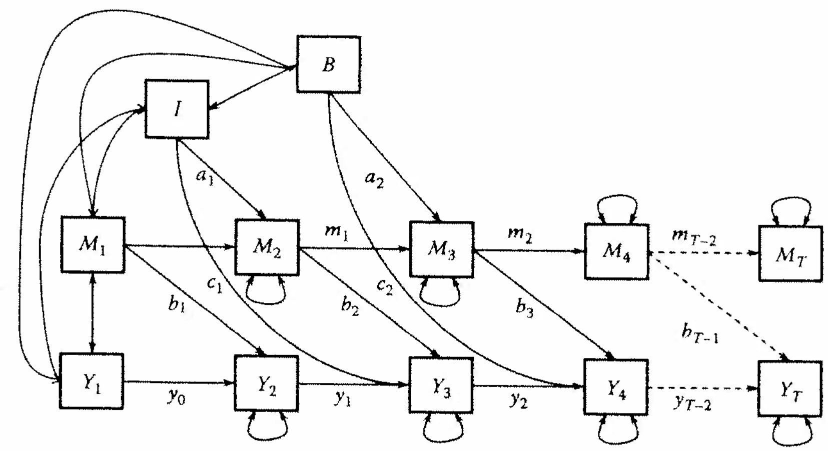

FIGURE 14.5 A model for analyzing two training interventions with mediation effects.

parameters from the booster training group. The overall training effects of the first training effect and the second training effect $O(t)$ at time t can then be calculated by $O(t) = I(t) + B(t)$.

14.3.4 Model Estimation and Confidence Intervals

For a mediation model, such as the one in Figure 14.5, different methods can be used to estimate the unknown parameters. The popular structural equation modeling (SEM) methods can usually be used to estimate the parameters for both the training effects parameters and other parameters simultaneously in SEM software. Furthermore, some SEM software, such as Mplus (Muthén & Muthén, 1998–2007), can also produce the standard errors for the training effects. In the current study, we program the estimation procedure in R (R Development Core Team, 2005), a free statistical program, based on the multiple group method outlined in a previous subsection. The procedure is based on the least squares method and cannot directly produce the standard error estimates for the unknown parameters. To estimate the standard errors, an additional bootstrap step can be used. The technical details of bootstrap methods can be found elsewhere (e.g., Efron, 1979, 1987; Efron & Tibshirani, 1993). Here, we focus only on the bootstrap procedure for the current study.

In the first step, we sample data from the original data set with replacement. For the training intervention data, there could be multiple groups, for example, the control group ($N = n_1$), the initial training group ($N = n_2$), and the booster training group ($N = n_3$). To keep the data structure, we first sample data from each group and then combine the sampled data together. More specifically, we first sample a data set with $N = n_1$ from the control group with replacement, sample a data set with $N = n_2$ with replacement from the initial training group, and then sample a data set with $N = n_3$ with replacement from the booster training group. After obtaining a sampled data set for each group, we can combine the three data sets together into one sample with $N = n_1 + n_2 + n_3$.

In the second step, we estimate the unknown parameters θ^* (denoting all the unknown parameters) and the training effects $I(t)^*$, $B(t)^*$, and $O(t)^*$ with $*$ denoting the results from the bootstrap sampling data. By repeating steps 1 and 2 for a number of times, denoting B, we can obtain a series of results for the unknown parameters θ_b^* and the training effects, $I(t)_b^*$, $B(t)_b^*$, and $O(t)_b^*$ with $b = 1, \ldots, B$. The confidence intervals for the unknown parameters and the training effects are then constructed using the quantiles of the bootstrap estimates of the unknown parameters and the training effects. For example, the $100(1 - \alpha)\%$ confidence interval can be constructed using the $\alpha/2$ and $1 - \alpha/2$ quantiles. An example of the R codes for the parameter estimation and confidence interval construction is provided in the CD.

14.4 EMPIRICAL DATA ANALYSIS

In the previous section, methods for analyzing training interventions with mediation effects have been introduced and discussed. In this section, the methods will be applied to an empirical study to illustrate the data analysis procedure.

The empirical data examined in this study is from the ACTIVE study (Jobe et al. 2001; Tennstedt, 2001). The ACTIVE study is a randomized and controlled study designed to determine whether cognitive training interventions can affect cognitively based measures of daily functioning. The cognitive training interventions included training in reasoning, memory, and speed. In the current study, we will investigate whether and how the training in reasoning ability affects the cognitively demanding everyday functioning.

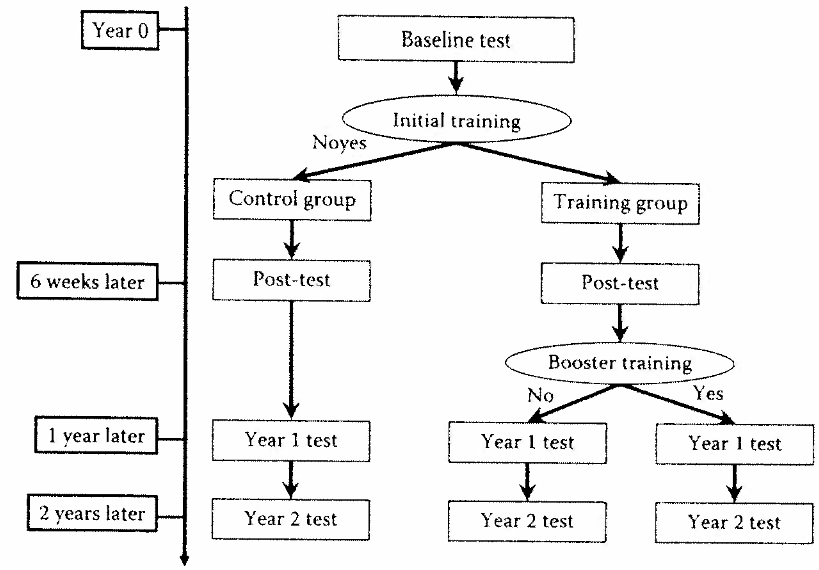

FIGURE 14.6 The ACTIVE reasoning training study design.

14.4.1 ACTIVE Study Design

The overall design of the ACTIVE study is given in Figure 14.6.* The procedure outlined below applies to training in each of three cognitive abilities: only the data from the reasoning ability training and control groups will be used in this study. All the participants ($N = 828$) examined in the current study were first given the baseline test. Participants were then randomly divided into the control group ($N = 414$) and the reasoning training group ($N = 414$). The reasoning training group was given the initial training on reasoning ability during a period of less than 6 weeks. Right after the initial training, participants in both the control and reasoning training groups were administered the post-test. Then the reasoning training group was divided into two groups randomly. One group ($N = 245$) was given a second or "booster" training course, mirroring the first training, about 11 months after the post-test. All participants were tested at the first and second years following the post-test.

* For a complete account of the research design of the ACTIVE study, refer to Jobe et al. (2001). The public data can be downloaded from http://www.icpsr.umich.edu/cocoon/ICPSR/STUDY/04248.xml.

14.4.2 Training Interventions

14.4.2.1 *Initial Training Intervention*

Initial training interventions were provided to participants in ten 60- to 75-min sessions through small groups with three to five participants. The training involved teaching strategies for finding the pattern in a letter or word series (e.g., a c e g i . . .) and identifying the next item in the series (Willis, 1987). Training sessions focused on applying these strategies to solve everyday problems (e.g., mnemonic strategies to remember a grocery list and reasoning strategies to understand the pattern in a bus schedule). Most participants received all 10 training sessions in a specified order within a 6-week interval with a small number of participants finishing training in less than 6 weeks. Participants who attended at least 80% of the training sessions (8 out of 10) were used in the current study. The initial training was conducted between May 1998 and December 1999 (Jobe et al. 2001).

14.4.2.2 *Booster Training Intervention*

The booster training was provided to a subset of participants who had received the initial training approximately 11 months after the end of the initial training. The booster training was delivered in four 75-min sessions over a 3-week period. The structure and content of the sessions were similar to those used in the initial training. The goal was to help participants maintain the gains made from the initial training. The booster training was conducted from May 1999 through December 2000 (Jobe et al., 2001).

14.4.3 Assessments

Both proximal and primary outcomes were measured. Proximal outcomes refer to the direct outcome measures of training interventions and primary outcomes refer to the outcome measures of cognitively demanding daily activities related to living independently (Jobe et al., 2001).

Three direct proximal outcomes were assessed: Word Series, Letter Series, and Letter Sets. These measures were standardized, timed, paper-and-pencil assessments, and were administered at each testing occasion. The Word Series (Gonda & Schaie, 1985) test consisted of 30 items. For each item, participants were presented a series of words and were required to choose the next word from five possible answers. The Letter Series

(Thurstone & Thurstone, 1949) test also consisted of 30 items. Instead of words, for each item, participants were presented a series of letters and were required to choose the next possible letter. The Letter Sets (Ekstrom, French, Harman, & Derman, 1976) test consisted of 14 items and participants were asked to select the set of letters that did not belong with the others. For each test, scores represented the total number of correct answers.

The primary outcome, the everyday problem-solving ability, was measured by the Everyday Problems Test (Willis & Marsiske, 1993). Participants were presented with 14 everyday stimuli, such as medication labels, transportation schedules, telephone rate charts, and Medicare benefit charts, and were asked to answer two questions about each stimulus. Scores represented the number of correct answers generated (Jobe et al., 2001).

14.4.4 Research Questions

Previous studies have shown that reasoning ability and everyday problem-solving ability are strongly related constructs, and that the reasoning ability can predict subsequent performance on cognitively demanding tasks of daily living, such as comprehension of medication labels, utilization of emergency telephone information, and understanding of transportation schedules (Diehl, Willis, & Schaie, 1995; Willis, 1996; Willis, Jay, Diehl, & Marsiske, 1992). In this study, we have two empirical research questions. The first research question is whether training interventions improve the proximal outcomes, which in turn improve the primary outcome. More specifically, we hypothesize that training interventions, both the initial and booster training, on reasoning improve reasoning ability, which in turn improves everyday problem-solving ability. The second question is how long the training effects would last.

14.4.5 Descriptive Statistics

To measure reasoning ability, a composite score was formed from the three measures—Word Series, Letter Series, and Letter Sets in the data analysis. First, the z scores for each test by pooling data from all four occasions were obtained and then the average of the z scores of the three tests, as the measure of reasoning ability, was calculated. The everyday problem test was also converted to z score in the analysis.

TABLE 14.1

Descriptive Statistics of the ACTIVE Sample

	Control		Initial		Booster		Overall	
	M	sd	*M*	sd	*M*	sd	*M*	sd
N	414		169		245		818	
Age	73.65	5.74	73.18	5.47	72.77	5.34	73.30	5.58
Gender	0.72	0.45	0.79	0.41	0.76	0.43	0.74	0.44
Education	13.57	2.59	13.69	2.54	13.58	2.71	13.60	2.61
R1	−0.31	0.83	−0.22	0.81	−0.28	0.82	−0.28	0.83
R2	−0.07	0.87	0.44	0.90	0.40	0.90	0.17	0.92
R3	−0.14	0.87	0.17	0.87	0.35	0.90	0.07	0.90
R4	−0.11	0.87	0.13	0.91	0.22	0.91	0.04	0.90
E1	−0.03	0.98	−0.03	0.96	−0.02	1.03	−0.03	0.99
E2	0.05	0.96	0.11	0.97	0.07	1.01	0.07	0.98
E3	0.01	1.00	0.00	1.02	0.00	1.01	0.00	1.01
E4	−0.03	1.00	−0.04	0.98	−0.08	1.10	−0.04	1.03

Note: *M*: mean; sd: standard deviation. R_t and E_t represent the reasoning ability and everyday problem test score at occasion *t*.

The descriptive statistics are summarized in Table 14.1 and the trajectories for both reasoning ability and everyday problem test are displayed in Figure 14.7. The average age of the whole sample was 73.3 (sd = 5.58) and the average education level was about 13.60 (sd = 2.61) years. Seventy-four

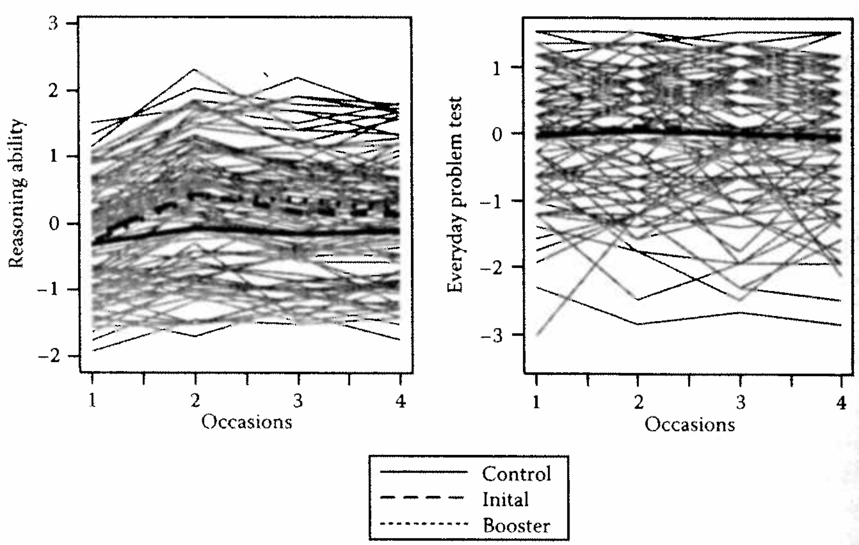

FIGURE 14.7 The trajectory plots of a subset of the ACTIVE data for the reasoning ability and the everyday problem-solving ability. The thick lines represent the mean trajectories from the three groups.

percent of the sample was female. There was no significant difference ($F = 2.22, p = 0.11$) in these demographic features (age, education level and gender) among the three groups based on a multivariate analysis of variance (MANOVA) analysis. From both the trajectory plot and the descriptive statistics, reasoning ability and everyday problem-solving ability seemed to increase right after the training interventions. The deviations due to the initial training and booster training are reflected at time 2 and time 3, respectively, in Figure 14.7. However, we would like to emphasize that modeling the shape of the trajectories is not the focus of this study.

14.4.6 Model Selection

Before conducting the mediation analysis, an appropriate model needs to be selected to describe the relationship between the mediation variable and the output variable. In this section, we sought to first validate the nature of the mediation relationship between reasoning and everyday problem solving before the intervention effects are incorporated into the models as are shown in Figures 14.3 and 14.5.

Three possible models (see Figure 14.8) are considered for the ACTIVE data. Model 1 (Figure 14.8a) hypothesizes that there is a lag relationship between reasoning ability and everyday problem-solving ability (paths from R_t to E_{t+1}), and there is no concurrent relationship from R_t to E_t. This model implies that training first improves the reasoning ability and the reasoning ability at current occasion, and then in turn improves everyday problem solving ability at a later occasion. In other words, the influence of reasoning ability on everyday problem solving is conditional on the passage of time. This model directly reflects the ideas of longitudinal mediation analysis as in Figure 14.2.

Model 2 (Figure 14.8b) hypothesizes that there is a concurrent relationship between reasoning ability and everyday problem-solving ability from R_t to E_t, and there is no lag relationship between the two variables (paths from R_t to E_{t+1}). This model implies that the improvement in reasoning ability can immediately reflect on the improvement of everyday problem-solving ability. The time required for the conversion of reasoning-ability improvement to everyday problem-solving-ability improvement can be neglected or is much shorter than the time interval between measurement occasions.

Model 3 (Figure 14.8c) combines the ideas from both Model 1 and Model 2. The reasoning ability has both instantaneous and lag influences

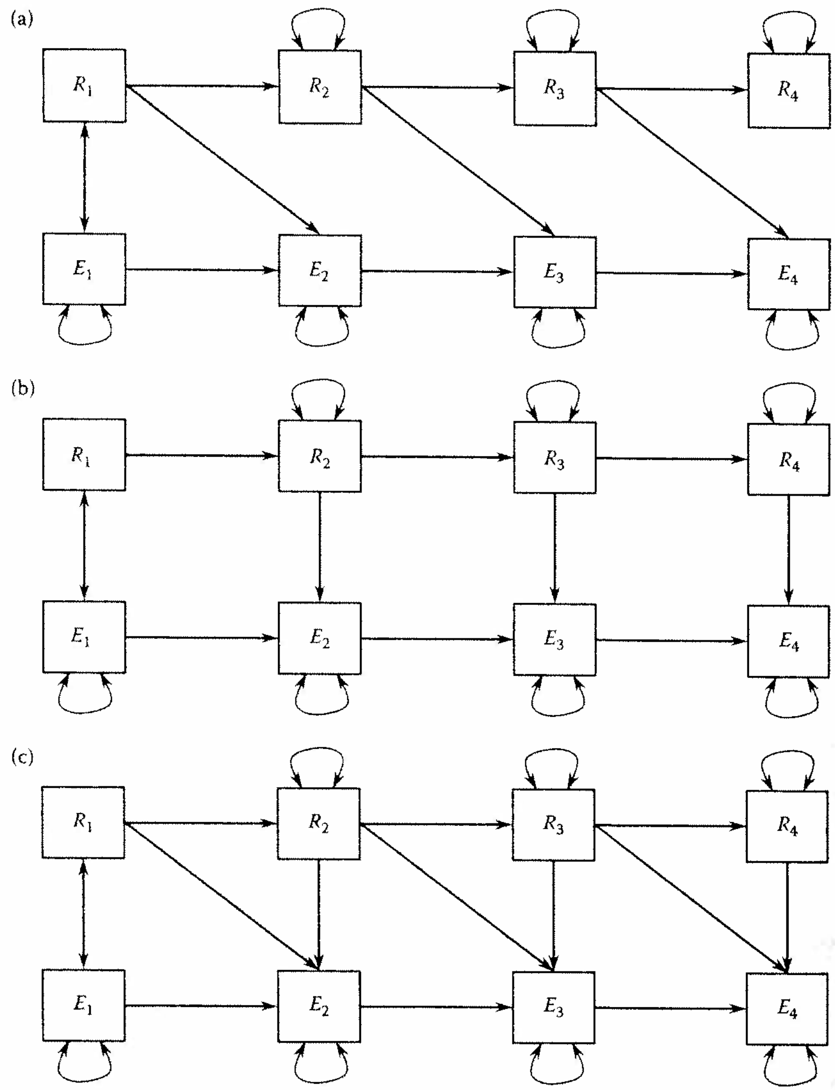

FIGURE 14.8 Possible models for the analysis of ACTIVE data (R_t and E_t represent the reasoning ability and everyday problem test score at occasion t); (a) Model 1, (b) Model 2, and (c) Model 3.

on the everyday problem-solving ability. This model implies that an improvement in reasoning ability may not convert to an improvement in everyday problem-solving ability all at once or just in a short time. The whole conversion process may spread over multiple measurement occasions.

TABLE 14.2

Model Fit Statistics for the Models in Figure 14.8

	Chi-Square/df	AIC	BIC	RMSEA
Model 1	110/36	8958	9298	0.085
Model 2	84/36	8932	9272	0.069
Model 3	71/27	8938	9320	0.077

Note: df: degrees of freedom; AIC: Akaike information criterion; BIC: Bayesian information criterion; RMSEA: root mean square error of approximation.

To determine which model fits the data best, each model was fitted to the ACTIVE data. Goodness of fit indexes such as chi-square value, AIC, and BIC were used to compare the model fit. The three fit statistics are provided in Table 14.2. Based on the fit statistics, we can see that Model 2 fits the current data better than the other proposed models. This could indicate that an improvement in reasoning ability can immediately convert to an improvement in everyday problem-solving ability or the conversion time from improvement in reasoning ability to improvement in everyday problem-solving ability, is much shorter than the one year time interval between occasions.

Note that although the regression path from reasoning to everyday problem solving links two concurrent variables, an inherent time lag has been built into the design of the ACTIVE study; for example, the participants were trained before the test was administered. Thus, Model 2 in Figure 14.8 still reflects the main ideas of longitudinal mediation shown in Model 1. In the following data analysis, Model 2 is used.

14.4.7 Mediation Analysis

After determining that Model 2 in Figure 14.8b represents the data relatively better, we further investigate how training improves the everyday problem-solving ability. The mediation model for the ACTIVE data is portrayed in Figure 14.9. In this model, initial training has a direct influence on everyday problem-solving ability at the second occasion. It also has an indirect influence through the mediation of R_2. The initial training effects on E_3 and E_4 are both indirect. Both the direct and indirect effects can be tested to check whether they are significant or not. For evaluating the booster training effects, we can use similar procedures.

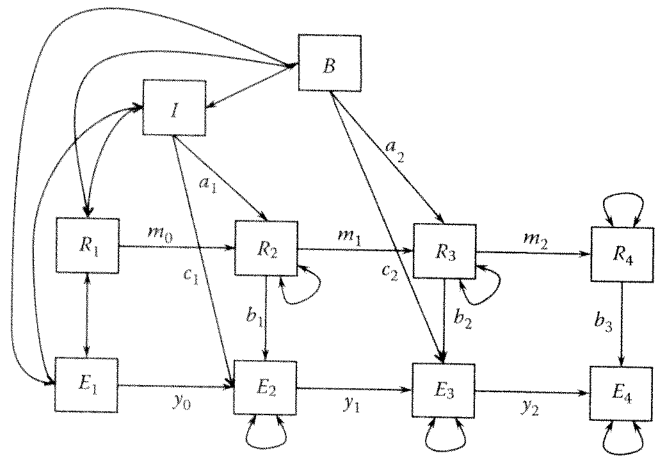

FIGURE 14.9 The mediation model for the ACTIVE data (R_t and E_t represent the reasoning ability and everyday problem test score at occasion t).

The estimated direct and indirect effects of initial training on E_2 and of booster training on E_3 are given in Table 14.3. Based on the confidence intervals, the direct effects of both initial c_1 and booster c_2 training were not significantly different from 0. However, the indirect effects were both significantly positive. Thus, the training effects on everyday problem-solving ability were totally mediated by reasoning ability. In the upcoming analysis, we fixed $c_1 = c_2 = 0$.

Based on the model with constraints ($c_1 = c_2 = 0$), the initial and booster training effects at different observed occasions were estimated and summarized in Table 14.4. It can be seen that training showed increased effects over time within the observed occasions. The initial training effect on

TABLE 14.3

Estimated Direct and Indirect Training Effects

		Estimate	Lower	Upper
		Initial		
Direct	c_1	−0.058	−0.167	0.038
Indirect	a_1b_1	0.103	0.055	0.157
		Booster		
Direct	c_2	−0.016	−0.137	0.081
Indirect	a_2b_2	0.049	0.025	0.082

Note: Lower and upper denotes the lower and upper bounds of confidence intervals.

TABLE 14.4

Estimated Training Effects at Different Observed Occasions and Confidence Intervals

	Initial Training Effect Only			Booster Training Effects Only			Overall		
	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
E2	0.103	0.055	0.157				0.103	0.055	0.157
E3	0.155	0.097	0.216	0.049	0.025	0.082	0.204	0.139	0.274
E4	0.182	0.128	0.241	0.093	0.054	0.143	0.275	0.206	0.358

Note: Lower and upper denotes the lower and upper bounds of confidence intervals.

E_4 was larger than that on E_3, which, in turn, was larger than that on E_2. Furthermore, the booster training effect on E_4 was also larger than that on E_3.

14.4.8 Stationarity and Prediction

In the previous section, we have discussed that one can calculate or predict training effects beyond observed occasions if a model is stationary. From Table 14.4, we found that training effects actually increased with time. Thus, it will be interesting to investigate how the training effects change over time after the fourth measurement occasion. To predict the training effects, we first test the stationarity of the model in Figure 14.9 for each group.

14.4.8.1 Stationarity of the Control Group

For the control group, here, testing stationarity is to test H_0: $m_1 = m_2$, $b_1 = b_2 = b_3$, and $y_1 = y_2$. Note that we did not test whether $m_0 = m_1$ because the time interval between the first and second occasions was not the same as the later time intervals. To implement the test, we first fitted the model in Figure 14.9 without any constraints and obtained the $\chi^2 = 409.13$ with degrees of freedom df $= 18$. Then, we fitted the model again with the constraints $m_1 = m_2, b_1 = b_2 = b_3$, and $y_1 = y_2$ and obtained the $\chi^2 = 416.04$ with df $= 22$. The difference between the models is $\Delta\chi^2 = 6.91$ with Δdf $= 4$.The p-value is 0.14. The possible individual tests, such as $m_1 = m_2$, $b_1 = b_2 = b_3, y_1 = y_2$ versus $m_1 \neq m_2$, $b_1 = b_2 = b_3, y_1 = y_2$, were also conducted and found no significant results. Thus, we can conclude that the model for the control group is stationary given the current data. The estimated path coefficients are given in Table 14.5.

TABLE 14.5

Estimated Path Coefficients for the Three Groups

	Control		Initial		Booster	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
$R_1 \to E_1$	0.773	0.043	0.799	0.069	0.909	0.054
$R_1 \to R_2$	0.952	0.021	0.995	0.039	0.959	0.034
$R_2 \to R_3$	0.916	0.014	0.913	0.022	0.914	0.025
$R_3 \to R_4$	0.916	0.014	0.913	0.022	0.937	0.025
$E_1 \to E_2$	0.701	0.026	0.731	0.042	0.716	0.040
$E_2 \to E_3$	0.731	0.021	0.741	0.031	0.677	0.036
$E_3 \to E_4$	0.731	0.021	0.741	0.031	0.733	0.040
$R_2 \to E_2$	0.228	0.020	0.211	0.029	0.216	0.046
$R_3 \to E_3$	0.228	0.020	0.211	0.029	0.290	0.033
$R_4 \to E_4$	0.228	0.020	0.211	0.029	0.290	0.033

Note: s.e.: standard error. $X \to Y$ represents the path from X to Y. R_t and E_t represent the reasoning ability and everyday problem test score at occasion t.

14.4.8.2 *Stationarity of the Initial Training Group*

For the initial training group, testing stationarity is also to test H_0: $m_1 = m_2$, $b_1 = b_2 = b_3$, and $y_1 = y_2$. We first fitted the model without any constraints and obtained $\chi^2 = 117.99$ with degrees of freedom df $= 18$. Then, we fitted the model again with the constraints $m_1 = m_2$, $b_1 = b_2 = b_3$, and $y_1 = y_2$ and obtained $\chi^2 = 123.07$ with df $= 22$. The difference between the models is $\Delta\chi^2 = 5.08$ with Δdf $= 4$. The p-value is 0.28. Individual tests were also conducted and no significant results were found. Thus, we can also conclude that the model for the initial group is stationary. The estimated path coefficients are given in Table 14.5.

14.4.8.3 *Stationarity of the Booster Training Group*

For the booster training group, there is no reason to test $m_1 = m_2$ and $y_1 = y_2$ because the coefficients before and after the booster training can vary. Here we can only test H_0: $b_2 = b_3$. We obtained $\Delta\chi^2 = 0.98$ with Δdf $= 1$. The p-value is 0.32. The estimated path coefficients are also given in Table 14.5.

14.4.9 Predicting Training Effects over Time

Given the current observed data in the ACTIVE study, there is no way to test whether $m_2 = m_t, t \geq 3, b_3 = b_t, t \geq 4$, and $y_2 = y_t, t \geq 3$. Thus, we have

to assume that the model was stationary beyond the fourth occasion, if w want to extrapolate beyond the observed occasions. With this assumptior we can calculate or predict the training effects beyond the observed dat occasions.

Let $I(t)$ and $B(t)$ represent the initial and booster training effects o everyday problem-solving ability at occasion t. Clearly, $I(1) = 0$ an $B(1) = B(2) = 0$. With the parameter estimates in Table 14.5, we have

$$I(2) = a_1 b_1^{(1)} = 0.091,$$

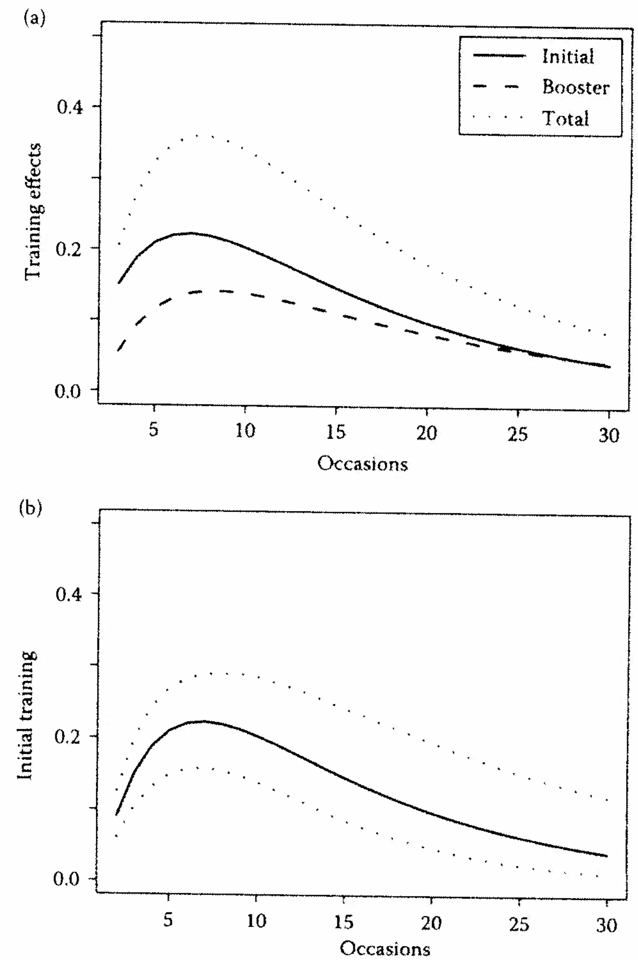

FIGURE 14.10 Plot of estimated training effects and 95% confidence intervals; (a) training effects, (b) CI for initial training, (c) CI for booster training, and (d) CI for total training.

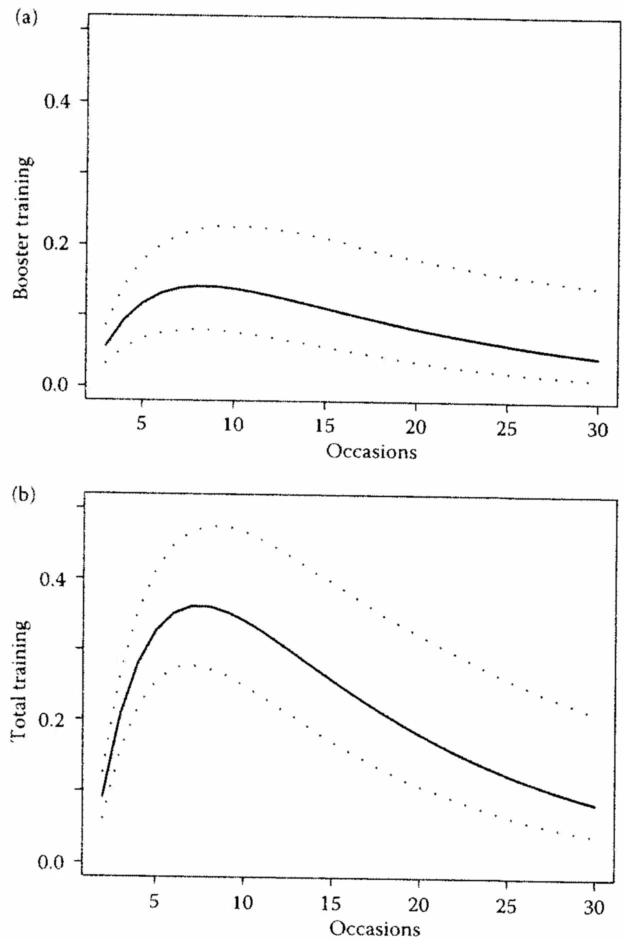

FIGURE 14.10 continued

and

$$I(3) = I(2)y_1^{(1)} + a_1 m_1^{(1)} b_1^{(1)} = 0.151,$$

where $^{(1)}$ denotes that the parameters were from the initial training group. In general, we have

$$I(t) = I(t-1)y_1^{(1)} + a_1[m_1^{(1)}]^{t-2}b_1^{(1)}, \quad t \geq 3.$$
$$= 0.741I(t-1) + 0.091(0.913)^{t-2},$$

Similarly, we can calculate the booster training effects as

$$B(3) = a_2 b_2^{(2)} = 0.056$$

and

$$B(t) = B(t-1)y_2^{(2)} + a_2[m_2^{(2)}]^{t-2}b_2^{(2)}, \quad t \geq 4,$$
$$= 0.733B(t-1) + 0.056(0.937)^{t-2},$$

where $^{(2)}$ denotes that the parameters were from the booster training group. Note that the training effects here are slightly different from those in Table 14.4 because the estimated parameters used here were under equality constraints. The overall training effects $O(t)$ can be calculated as

$$O(t) = I(t) + B(t).$$

The predicted initial, booster, and total training effects from time $t = 5$ to $t = 30$ are plotted in Figure 14.10a. The maximum initial training effect will be demonstrated at time $t = 7, I(7) = 0.222(0.033)$, about 6 years after the initial training. The maximum booster training effect will be demonstrated at time $t = 8, B(8) = 0.141(0.037)$, also about 6 years after the booster training. The total training effect peaked at time $t = 7, O(7) = 0.361(0.049)$.

Figure 14.10 also plots the 95% confidence intervals for the initial (Figure 14.10b), booster (Figure 14.10c), and total training effects (Figure 14.10d). The R codes for obtaining the confidence intervals can be found in the CD that comes with the book. Based on the confidence intervals, we can see that the initial training improved the everyday problem-solving ability and the booster training had significant effect above and beyond the initial training.

14.5 CONCLUSION AND DISCUSSION

We have outlined a variation on the longitudinal mediation model (Cole & Maxwell, 2003) adapted for application to intervention research. This model allows for the evaluation of not only the direct effects of an intervention, but also evaluation of mediation and changes to path coefficients themselves. The model was then applied to data from the ACTIVE study, to test the effects and longevity of the effects of reasoning training on everyday tasks. The results showed that the training effects on everyday problem-solving ability were totally mediated by reasoning ability and an improvement in reasoning ability can immediately convert to an improvement in everyday problem-solving ability. Based on the assumption that the model was stationary, the training effects over time were predicted and investigated through difference equations. The prediction showed that total training effects reached a peak after 6 years of the initial training or 5 years of the booster training.

While evaluating training, interventions may be studied more simply by adding group information into the model directly as covariates, and there could be practical difficulties in implementing this. Training may not only influence the level of the mediation variable and the output variable, but also the longitudinal relationship between the mediation variable and the output variable and the longitudinal structure of the mediation variable and the output variable. To simultaneously estimate the change in the level of the mediation variable and the longitudinal structure in one model, many interaction terms must be added to the model. Of course, when the intervention variable only influences the level of the mediation variable, the interaction method can be implemented with greater ease in commonly used SEM software. In this study, a multiple group method was discussed and applied to analyze the data.

Among the features of the proposed approach is its ability to predict training effects over time. Once stationarity is established or assumed, researchers can extrapolate what the process would look like beyond collected data. There are of course many concerns with such a process. In the analysis presented here, this assumption of stationarity may not be true in reality due to the nature of the ACTIVE sample. The average age of participants is 73.30, and the current model makes no adjustments to longitudinal prediction based on age. Participants may face sudden decline or terminal decline in the cognitive ability (Wilson, Beckett, Bienias, Evans, & Bennett, 2003; Wilson, Beck, Bienias, & Bennett, 2007). Thus, the predicted training effects can only be viewed as the maximum effects in ideal conditions.

The analysis of training intervention effects in the current study can also be interpreted from a dynamic systems analysis perspective. One may view the phenomenon to be investigated as a system developing in a certain way

before training or intervention; for instance, the system may be in its stationary status. The training can be viewed as a shock to an element (e.g., the mediator variable) of the system at a time-point. And the training or intervention may not only result in a change in the element (the mediator) on which the training directly influences, but also a change in the structure of the whole system. Using the ACTIVE study as an example, training not only increased the level of reasoning ability, but also changed the relationship between reasoning ability and everyday problem-solving ability. To study the training effects over time is equivalent to investigating how the effect of the shock evolves over time. With the methods we proposed, one can separate the training effects (shock) from the other confounding variables and study how the pure training effects change over time. Thus, even when the observed trajectories of the outcome variables decline or remain flat over time, the training effects, by themselves, may still be increasing over time. The reason why people observe declining trajectories of the outcome variable may be that the positive training effects cannot balance off the overall decline in the outcome variables.

While the longitudinal mediation model in this study was developed with psychological and medical intervention research in mind, it is applicable to many types of longitudinal studies with similar research designs. The intervention variables presented here can be replaced by a grouping variable at any number of time-points, provided the intervention variables are nominal (i.e., dummy coded). For instance, this model could be used in lifespan developmental research, where the intervention variables are replaced by a set of variables indicating presence or absence of dementia at some time-point. This model would closely resemble Cole & Maxwell's original model as shown in Figure 14.2 (Cole & Maxwell, 2003), with the added benefit that the relationships between the mediator and output variables could take any of the forms shown in Figure 14.8. The longitudinal mediation model is not inherently limited to a set number of intervention variables (or alternatively, a set number of groups), and thus can be applied to a number of situations that mirror these research designs.

Several perspectives of the current study can be improved in the future. First, longitudinal mediation analysis is useful for studying lag relationship in the data. It will be useful to investigate how to design a longitudinal mediation study that can best utilize the merits of longitudinal mediation analysis. Second, longitudinal mediation models (e.g., Collins et al., 1998; Cole & Maxwell, 2003) and their ancestor (Baron & Kenny, 1986) seem to be able to analyze the intrinsic temporal relationship, or causal relationship, among input, mediator, and output variables. However, how to scientifically relate these models with causal inference still needs much investigation. Third, a very weak definition of stationarity—the invariance of autoregressive coefficients—was adopted in this chapter. Even so, because of the limitation of only four measurement occasions, weak stationarity cannot be fully tested in the long-term prediction. Additional research is desired on how the stationarity influences the longitudinal mediation model performance.

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15

Exploring Intraindividual, Interindividual, and Intervariable Dynamics in Dyadic Interactions

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15.1 INTRODUCTION: DYADIC INTERACTIONS

A fundamental goal in the study of dyadic interactions is to understand the dynamics underlying the interrelations between two units in a dyad. In psychological research, most of the work on dyadic interactions concerns interactions between two individuals (i.e., parent–child, husband–wife, teacher–student). Psychological theories pertaining to dyadic interactions postulate such interactions in dynamic terms (e.g., attachment theory; Bowlby, 1982; Mikulincer & Shaver, 2007). In spite of this theoretical description, there is not much empirical work showing evidence for such dyadic interactions in dynamic terms, with attention to processes over time. One possibility for this mismatch between theory and empirical work is the lack of adequate methodology for uncovering the dynamics between two individuals from multiple time series. In this chapter, we propose a set of exploratory techniques designed to extract patterns of dynamics from dyadic interactions.

The chapter is organized as follows. We first describe common techniques used to analyze dyadic interactions and identify some limitations. We then