The EffectLiteR Approach for Analyzing Average and Conditional Effects – Supplementary Materials

Axel Mayer^a, Lisa Dietzfelbinger^b, Yves Rosseel^a, Rolf Steyer^b

^a Department of Data Analysis, Faculty of Psychology and Educational Sciences, Ghent University

^b Department of Methodology and Evaluation Research, Institute of Psychology, University of Jena

Supplement A: The EffectLiteR Software Package

A.1 Basic Commands

EffectLiteR is an R package (R Core Team, 2013) that can be used to estimate average and conditional effects of a treatment variable on an outcome variable, taking into account multiple continuous and categorical covariates. EffectLiteR also includes a graphical user interface based on the shiny package (RStudio and Inc., 2014). The R package is available from CRAN and can be installed as usual provided that a recent version of R is installed:

```
## Basic commands to install and run EffectLiteR ##  
  
install.packages("EffectLiteR") ## install package  
  
library(EffectLiteR) ## load package  
?effectLite ## get help for main function  
effectLiteGUI() ## opens the graphical user interface
```

Users who wish to try out EffectLiteR without installing any software can use the online version of the graphical user interface at <https://amayer.shinyapps.io/elrshiny/>. The development version of the package along with descriptions of how to install this version is available from <https://github.com/amayer2010>.

A.2 Screenshot of the Graphical User Interface

EffectLiteR

EffectLiteR

Data Manifest Variables

Latent Variables Options Interactions

Propensity Scores Complex Survey

☒ Latent dependent variable

Indicators of Latent Dependent Variable

y12 y22 y32

☒ Add latent covariates

Number of Latent Covariates 1

Indicators of Latent Covariate 1

y11 y21 y31

Latent covariates will be added to the list of continuous manifest covariates (if specified).

EffectLiteR

Data EffectLiteR lavaan Syntax lavaan Results Conditional Effects

Plot 1 Plot 2 Plot 3

----- Variables -----

Outcome variable Y: eta

Treatment variable X: x (Reference group: 0)

Categorical covariates K: k

Continuous covariates Z: xi1

Levels of Unfolded Categorical Covariate K

K	k
0	0
1	1

----- Regression Model -----

$E(Y|X,K,Z) = g_0(K,Z) + g_1(K,Z)*I_{X=1} + g_2(K,Z)*I_{X=2}$

$g_0(K,Z) = g_{000} + g_{001} * Z1 + g_{010} * I_{K=1} + g_{011} * I_{K=1} * Z1$

$g_1(K,Z) = g_{100} + g_{101} * Z1 + g_{110} * I_{K=1} + g_{111} * I_{K=1} * Z1$

$g_2(K,Z) = g_{200} + g_{201} * Z1 + g_{210} * I_{K=1} + g_{211} * I_{K=1} * Z1$

Intercept Function $g_0(K,Z)$

A.3 EffectLiteR Input Syntax

```
## Using EffectLiteR via the command line ##

library(EffectLiteR)

## measurement model
mm <- '
eta =~ 1*y12 + 1*y22 + 1*y32
xi =~ 1*y11 + 1*y21 + 1*y31
y11 + y21 + y31 + y12 + y22 + y32 ~ 0*1
,

## call effectLite()
## data generation for this example is described in Supplement C.1
m1 <- effectLite(y="eta", x="x", k="k", z="xi", control="0",
                 measurement=mm, data=d, fixed.cell=FALSE,
                 missing="fiml", syntax.only=FALSE)

print(m1)
```

A.4 Excerpts from EffectLiteR Output

```

# ----- Regression Model -----
#
#   E(Y|X,K,Z) = g0(K,Z) + g1(K,Z)*I_X=1 + g2(K,Z)*I_X=2
#   g0(K,Z) = g000 + g001 * Z1 + g010 * I_K=1 + g011 * I_K=1 * Z1
#   g1(K,Z) = g100 + g101 * Z1 + g110 * I_K=1 + g111 * I_K=1 * Z1
#   g2(K,Z) = g200 + g201 * Z1 + g210 * I_K=1 + g211 * I_K=1 * Z1
#
#
# ----- Main Hypotheses -----
#
#                               Wald Chi-Square   df   p-value
# No average effects                266      2         0
# No covariate effects in control group    835      3         0
# No treatment*covariate interaction      214      6         0
# No treatment effects                557      8         0
#
#
# ----- Average Effects -----
#
#           Estimate      SE   Est./SE   p-value   Effect Size
# E[g1(K,Z)]      0.729   0.0925     7.88   3.11e-15     0.410
# E[g2(K,Z)]      1.327   0.0814    16.30   0.00e+00     0.746
#
#
# ----- Effects given K=k -----
#
#           Estimate      SE   Est./SE   p-value   Effect Size
# E[g1(K,Z)|K=0]    0.476   0.144     3.30   9.57e-04     0.268
# E[g2(K,Z)|K=0]    0.694   0.116     6.01   1.91e-09     0.390
# E[g1(K,Z)|K=1]    0.953   0.118     8.07   6.66e-16     0.536
# E[g2(K,Z)|K=1]    1.885   0.109    17.35   0.00e+00     1.061

```

Supplement B: Complete Computations for the Motivating Example

B.1 Multigroup SEM with Stochastic Group Sizes for the Simulated Data Example

Group-invariant τ -equivalent measurement model

$$\begin{pmatrix} Y_{12} \\ Y_{22} \\ Y_{32} \\ Y_{11} \\ Y_{21} \\ Y_{31} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \eta \\ \xi \end{pmatrix} + \begin{pmatrix} \varepsilon_{12} \\ \varepsilon_{22} \\ \varepsilon_{32} \\ \varepsilon_{11} \\ \varepsilon_{21} \\ \varepsilon_{31} \end{pmatrix}$$

Group-specific structural model in each of the six groups (3 x 2)

$$\begin{pmatrix} \eta \\ \xi \end{pmatrix} = \begin{pmatrix} \alpha_{xk0} \\ \mu_{xk1} \end{pmatrix} + \begin{pmatrix} 0 & \alpha_{xk1} \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \eta \\ \xi \end{pmatrix} + \begin{pmatrix} \zeta_0 \\ \zeta_1 \end{pmatrix}$$

Group sizes for each of the six groups (3 x 2)

$$\log(n_{xk}) = \kappa_{xk}$$

B.2 Effect Functions

Based on the parameters α_{xkz} , μ_{xk1} , and κ_{xk} of the multigroup structural equation model, we can identify average and conditional effects. The parameterization of the regression $E(\eta | X, K, \xi)$ is given by:

$$E(\eta | X, K, \xi) = g_0(K, \xi) + g_1(K, \xi) \cdot I_{X=1} + g_2(K, \xi) \cdot I_{X=2}$$

$$g_0(K, \xi) = \gamma_{000} + \gamma_{010} \cdot K + \gamma_{001} \cdot \xi + \gamma_{011} \cdot K \cdot \xi$$

$$g_1(K, \xi) = \gamma_{100} + \gamma_{110} \cdot K + \gamma_{101} \cdot \xi + \gamma_{111} \cdot K \cdot \xi$$

$$g_2(K, \xi) = \gamma_{200} + \gamma_{210} \cdot K + \gamma_{201} \cdot \xi + \gamma_{211} \cdot K \cdot \xi$$

First, we compute the regression coefficients of the effect functions $g_1(K, \xi)$ and $g_2(K, \xi)$ following Equations 17 and 18:

$$\gamma_{100} = \alpha_{100} - \alpha_{000}$$

$$\gamma_{101} = \alpha_{101} - \alpha_{001}$$

$$\gamma_{110} = (\alpha_{110} - \alpha_{100}) - (\alpha_{010} - \alpha_{000})$$

$$\gamma_{111} = (\alpha_{111} - \alpha_{101}) - (\alpha_{011} - \alpha_{001})$$

$$\gamma_{200} = \alpha_{200} - \alpha_{000}$$

$$\gamma_{201} = \alpha_{201} - \alpha_{001}$$

$$\gamma_{210} = (\alpha_{210} - \alpha_{200}) - (\alpha_{010} - \alpha_{000})$$

$$\gamma_{211} = (\alpha_{211} - \alpha_{201}) - (\alpha_{011} - \alpha_{001})$$

B.3 Average and Conditional Effects

Average Effects AE_{i0} : In our example, there are two average effects, AE_{10} , the average effect of treatment $X = 1$ vs. $X = 0$, and AE_{20} , the average effect of treatment $X = 2$ vs. $X = 0$. Following Table 3, these are identified as:

$$\begin{aligned} E[g_1(K, \xi)] &= \gamma_{100} + \gamma_{110} \cdot E(K) + \gamma_{101} \cdot E(\xi) + \gamma_{111} \cdot E(K \cdot \xi) \\ E[g_2(K, \xi)] &= \gamma_{200} + \gamma_{210} \cdot E(K) + \gamma_{201} \cdot E(\xi) + \gamma_{211} \cdot E(K \cdot \xi) \end{aligned}$$

In order to compute the average effects based on model parameters, we need to compute the unconditional expectations of covariates and product terms (cf. Table 2):

$$\begin{aligned} P(X = x, K = k) &= \exp(\kappa_{xk}) / [\exp(\kappa_{00}) + \exp(\kappa_{01}) + \exp(\kappa_{10}) + \exp(\kappa_{11}) + \exp(\kappa_{20}) + \exp(\kappa_{21})] \\ E(\xi) &= \mu_{001} \cdot P(X = 0, K = 0) + \mu_{011} \cdot P(X = 0, K = 1) + \mu_{101} \cdot P(X = 1, K = 0) + \\ &\quad + \mu_{111} \cdot P(X = 1, K = 1) + \mu_{201} \cdot P(X = 2, K = 0) + \mu_{211} \cdot P(X = 2, K = 1) \\ P(K = 0) &= P(X = 0, K = 0) + P(X = 1, K = 0) + P(X = 2, K = 0) \\ P(K = 1) &= P(X = 0, K = 1) + P(X = 1, K = 1) + P(X = 2, K = 1) \\ E(\xi I_{K=1}) &= \mu_{011} \cdot P(X = 0, K = 1) + \mu_{111} \cdot P(X = 1, K = 1) + \mu_{211} \cdot P(X = 2, K = 1) \end{aligned}$$

Then, the average effects are identified as functions of the regression coefficients of the effect functions and the unconditional expectations of covariates and product terms.

Conditional Effects $CE_{i0;K=k}$: In our example, there are four $(K = k)$ -conditional effects, the two conditional effects of treatment $X = 1$ vs. $X = 0$ for males $CE_{10;K=0}$ and females $CE_{10;K=1}$, and the two conditional effects of treatment $X = 2$ vs. $X = 0$ for males $CE_{20;K=0}$ and females $CE_{20;K=1}$. Following Table 3, these are identified as:

$$\begin{aligned} E[g_1(K, \xi) | K = 0] &= \gamma_{100} + \gamma_{101} \cdot E(\xi | K = 0) \\ E[g_1(K, \xi) | K = 1] &= \gamma_{100} + \gamma_{110} + \gamma_{101} \cdot E(\xi | K = 1) + \gamma_{111} \cdot E(\xi | K = 1) \\ E[g_2(K, \xi) | K = 0] &= \gamma_{200} + \gamma_{201} \cdot E(\xi | K = 0) \\ E[g_2(K, \xi) | K = 1] &= \gamma_{200} + \gamma_{210} + \gamma_{201} \cdot E(\xi | K = 1) + \gamma_{211} \cdot E(\xi | K = 1) \end{aligned}$$

For the identification of the four $(K = k)$ -conditional effects, we need the regression coefficients of the effect functions (see above) and the $(K = k)$ -conditional expectations of ξ :

$$\begin{aligned} P(X = x | K = k) &= P(X = x, K = k) / P(K = k) \\ E(\xi | K = 0) &= \mu_{001} \cdot P(X = 0 | K = 0) + \mu_{101} \cdot P(X = 1 | K = 0) + \mu_{201} \cdot P(X = 2 | K = 0) \\ E(\xi | K = 1) &= \mu_{011} \cdot P(X = 0 | K = 1) + \mu_{111} \cdot P(X = 1 | K = 1) + \mu_{211} \cdot P(X = 2 | K = 1), \end{aligned}$$

where $P(K = k)$ and $P(X = x, K = k)$ have already been computed in the section about the identification of average effects.

Conditional Effects $CE_{t0;X=x}$: There are six different kinds of $(X = x)$ -conditional effects in our example, i.e., the three conditional effects of treatment $X = 1$ vs. $X = 0$ given values x of X , and the three conditional effects of treatment $X = 2$ vs. $X = 0$ given values x of X :

$$\begin{aligned}
E[g_1(K, \xi) | X = 0] &= \gamma_{100} + \gamma_{110} \cdot E(I_{K=1} | X = 0) + \gamma_{101} \cdot E(\xi | X = 0) + \gamma_{111} \cdot E(\xi I_{K=1} | X = 0) \\
E[g_1(K, \xi) | X = 1] &= \gamma_{100} + \gamma_{110} \cdot E(I_{K=1} | X = 1) + \gamma_{101} \cdot E(\xi | X = 1) + \gamma_{111} \cdot E(\xi I_{K=1} | X = 1) \\
E[g_1(K, \xi) | X = 2] &= \gamma_{100} + \gamma_{110} \cdot E(I_{K=1} | X = 2) + \gamma_{101} \cdot E(\xi | X = 2) + \gamma_{111} \cdot E(\xi I_{K=1} | X = 2) \\
E[g_2(K, \xi) | X = 0] &= \gamma_{200} + \gamma_{210} \cdot E(I_{K=1} | X = 0) + \gamma_{201} \cdot E(\xi | X = 0) + \gamma_{211} \cdot E(\xi I_{K=1} | X = 0) \\
E[g_2(K, \xi) | X = 1] &= \gamma_{200} + \gamma_{210} \cdot E(I_{K=1} | X = 1) + \gamma_{201} \cdot E(\xi | X = 1) + \gamma_{211} \cdot E(\xi I_{K=1} | X = 1) \\
E[g_2(K, \xi) | X = 2] &= \gamma_{200} + \gamma_{210} \cdot E(I_{K=1} | X = 2) + \gamma_{201} \cdot E(\xi | X = 2) + \gamma_{211} \cdot E(\xi I_{K=1} | X = 2)
\end{aligned}$$

In order to compute the $(X = x)$ -conditional effects, we also need the $(X = x)$ -conditional expectations of covariates and product terms:

$$\begin{aligned}
E(I_{K=k} | X = x) &= P(K = k | X = x) = P(X = x, K = k) / P(X = x) \\
E(\xi | X = 0) &= \mu_{001} \cdot P(K = 0 | X = 0) + \mu_{011} \cdot P(K = 1 | X = 0) \\
E(\xi | X = 1) &= \mu_{101} \cdot P(K = 0 | X = 1) + \mu_{111} \cdot P(K = 1 | X = 1) \\
E(\xi | X = 2) &= \mu_{201} \cdot P(K = 0 | X = 2) + \mu_{211} \cdot P(K = 1 | X = 2) \\
E(\xi I_{K=1} | X = 0) &= \mu_{011} \cdot P(K = 1 | X = 0) \\
E(\xi I_{K=1} | X = 1) &= \mu_{111} \cdot P(K = 1 | X = 1) \\
E(\xi I_{K=1} | X = 2) &= \mu_{211} \cdot P(K = 1 | X = 2)
\end{aligned}$$

Conditional Effects $CE_{t0;X=x,K=k}$: Finally, we consider $(X = x, K = k)$ -conditional effects. In our simulated example, there are twelve different such effects, i.e.,

$$\begin{aligned}
&E[g_1(K, \xi) | X = 0, K = 0], \quad E[g_1(K, \xi) | X = 0, K = 1], \quad E[g_1(K, \xi) | X = 1, K = 0], \\
&E[g_1(K, \xi) | X = 1, K = 1], \quad E[g_1(K, \xi) | X = 2, K = 0], \quad E[g_1(K, \xi) | X = 2, K = 1], \\
&E[g_2(K, \xi) | X = 0, K = 0], \quad E[g_2(K, \xi) | X = 0, K = 1], \quad E[g_2(K, \xi) | X = 1, K = 0], \\
&E[g_2(K, \xi) | X = 1, K = 1], \quad E[g_2(K, \xi) | X = 2, K = 0], \quad E[g_2(K, \xi) | X = 2, K = 1].
\end{aligned}$$

These effects can directly be computed based on regression coefficients of the effect functions and the model parameters for $(X = x, K = k)$ -conditional expectations of the continuous latent covariate:

$$\begin{aligned}
E[g_1(K, \xi) | X = x, K = 0] &= \gamma_{100} + \gamma_{101} \cdot \mu_{x01} \\
E[g_1(K, \xi) | X = x, K = 1] &= \gamma_{100} + \gamma_{110} + \gamma_{101} \cdot \mu_{x11} + \gamma_{111} \cdot \mu_{x11} \\
E[g_2(K, \xi) | X = x, K = 0] &= \gamma_{200} + \gamma_{201} \cdot \mu_{x01} \\
E[g_2(K, \xi) | X = x, K = 1] &= \gamma_{200} + \gamma_{210} + \gamma_{201} \cdot \mu_{x11} + \gamma_{211} \cdot \mu_{x11}
\end{aligned}$$

Supplement C: Data Generation

C.1 R Syntax to Generate Data

```
set.seed(33882)
N <- 1000

design <- expand.grid(k=0:1, x=0:2)
prob <- c(0.1, 0.2, 0.1, 0.1, 0.3, 0.2)
ind <- sample(1:6, size=N, replace=TRUE, prob=prob)

d <- design[ind,]

d <- within(d,{
  Ix1 <- as.numeric(x==1)
  Ix2 <- as.numeric(x==2)
  xi <- 1 + 0.5*k + 0.3*Ix1 + 0.4*Ix2 + rnorm(N,0,2)
  y11 <- xi + rnorm(N,0,sqrt(0.7))
  y21 <- xi + rnorm(N,0,sqrt(0.7))
  y31 <- xi + rnorm(N,0,sqrt(0.7))
  eta <- (0.1+0.8*xi) + (0.3+0.5*k+0.2*xi)*Ix1 +
    (0.3+0.5*k+0.2*xi+0.4*k*xi)*Ix2 + rnorm(N,0,0.7)
  y12 <- eta + rnorm(N,0,sqrt(0.8))
  y22 <- eta + rnorm(N,0,sqrt(0.8))
  y32 <- eta + rnorm(N,0,sqrt(0.8))
  x <- as.factor(x)
})

d <- subset(d, select = -c(eta,xi))
```

C.2 True Population Parameters for Data Generation

Cell and marginal probabilities:

	$K = 0$	$K = 1$	All
$X = 0$	0.1	0.2	0.3
$X = 1$	0.1	0.1	0.2
$X = 2$	0.3	0.2	0.5
All	0.5	0.5	1.0

Manifest variables:

$$\begin{aligned}
 Y_{11} &= \xi + \varepsilon_{11} & Y_{12} &= \eta + \varepsilon_{12} \\
 Y_{21} &= \xi + \varepsilon_{21} & Y_{22} &= \eta + \varepsilon_{22} \\
 Y_{31} &= \xi + \varepsilon_{31} & Y_{32} &= \eta + \varepsilon_{32}
 \end{aligned}$$

where $\text{Var}(\varepsilon_{11}) = \text{Var}(\varepsilon_{21}) = \text{Var}(\varepsilon_{31}) = 0.7$ and $\text{Var}(\varepsilon_{12}) = \text{Var}(\varepsilon_{22}) = \text{Var}(\varepsilon_{32}) = 0.8$.

Latent variables:

$$\begin{aligned}
 \xi &= 1 + 0.5 \cdot K + 0.3 \cdot I_{X=1} + 0.4 \cdot I_{X=2} + \zeta_1 \\
 \eta &= (0.1 + 0.8 \cdot \xi) + (0.3 + 0.5 \cdot K + 0.2 \cdot \xi) \cdot I_{X=1} \\
 &\quad + (0.3 + 0.5 \cdot K + 0.2 \cdot \xi + 0.4 \cdot K \cdot \xi) \cdot I_{X=2} + \zeta_0
 \end{aligned}$$

where $\text{Var}(\zeta_1) = 4$ and $\text{Var}(\zeta_0) = 0.49$.

C.3 True Average and Conditional Effects

True average and conditional effects of conventional therapy ($X = 1$ vs. $X = 0$) and of innovative therapy ($X = 2$ vs. $X = 0$) compared to the control group in the simulated data example.

Effect	True value	Effect	True value
True Average and Conditional Effects of Conventional Therapy			
Average Effect AE_{10}		Conditional Effects $CE_{10;X=x}$	
AE_{10}	0.852	$CE_{10;X=0}$	0.9
Effect Function $g_1(K, \xi)$		$CE_{10;X=1}$	0.86
γ_{100}	0.3	$CE_{10;X=2}$	0.82
γ_{101}	0.2	Conditional Effects $CE_{10;X=x,K=k}$	
γ_{110}	0.5	$CE_{10;X=0,K=0}$	0.5
γ_{111}	0	$CE_{10;X=1,K=0}$	0.56
Conditional Effects $CE_{10;K=k}$		$CE_{10;X=2,K=0}$	0.58
$CE_{10;K=0}$	0.56	$CE_{10;X=0,K=1}$	1.1
$CE_{10;K=1}$	1.144	$CE_{10;X=1,K=1}$	1.16
		$CE_{10;X=2,K=1}$	1.18
True Average and Conditional Effects of Innovative Therapy			
Average Effect AE_{20}		Conditional Effects $CE_{20;X=x}$	
AE_{20}	1.196	$CE_{20;X=0}$	1.3
Effect Function $g_2(K, \xi)$		$CE_{20;X=1}$	1.22
γ_{200}	0.3	$CE_{20;X=2}$	1.24
γ_{201}	0.2	Conditional Effects $CE_{20;X=x,K=k}$	
γ_{210}	0.5	$CE_{20;X=0,K=0}$	0.5
γ_{211}	0.4	$CE_{20;X=1,K=0}$	0.56
Conditional Effects $CE_{20;K=k}$		$CE_{20;X=2,K=0}$	0.58
$CE_{20;K=0}$	0.56	$CE_{20;X=0,K=1}$	1.7
$CE_{20;K=1}$	1.832	$CE_{20;X=1,K=1}$	1.88
		$CE_{20;X=2,K=1}$	1.94

The true effect functions are given by $g_t(K, \xi) = \gamma_{t00} + \gamma_{t10} \cdot K + \gamma_{t01} \cdot \xi + \gamma_{t11} \cdot K \cdot \xi$ for $t = 1, 2$. The reported effects are true average effects $AE_{t0} = E[g_t(K, \xi)]$, conditional effects given gender $CE_{t0;K=k} = E[g_t(K, \xi) | K = k]$, conditional effects given a treatment condition $CE_{t0;X=x} = E[g_t(K, \xi) | X = x]$ and conditional effects given gender and a treatment condition $CE_{t0;X=x,K=k} = E[g_t(K, \xi) | X = x, K = k]$.

Supplement D: Monte Carlo Study for Sample Size Considerations

```

library(EffectLiteR)
library(simsem)

set.seed(623523)
nrep <- 5000
dataList <- list(length=nrep)

for(i in 1:nrep){

  N <- 150
  design <- expand.grid(k=0:1, x=0:2)
  prob <- c(0.1, 0.2, 0.1, 0.1, 0.3, 0.2)
  ind <- sample(1:6, size=N, replace=TRUE, prob=prob)
  dpop <- design[ind,]

  dpop <- within(dpop,{
    Ix1 <- as.numeric(x==1)
    Ix2 <- as.numeric(x==2)
    eta1 <- 1 + 0.5*k + 0.3*Ix1 + 0.4*Ix2 + rnorm(N,0,2)
    y11 <- eta1 + rnorm(N,0,sqrt(0.7))
    y21 <- eta1 + rnorm(N,0,sqrt(0.7))
    y31 <- eta1 + rnorm(N,0,sqrt(0.7))
    eta2 <- (0.1+0.8*eta1) + (0.3+0.5*k+0.2*eta1)*Ix1 +
      (0.3+0.5*k+0.2*eta1+0.4*k*eta1)*Ix2 + rnorm(N,0,0.7)
    y12 <- eta2 + rnorm(N,0,sqrt(0.8))
    y22 <- eta2 + rnorm(N,0,sqrt(0.8))
    y32 <- eta2 + rnorm(N,0,sqrt(0.8))
    x <- as.factor(x)
    cell <- as.factor(paste0(x,k))
  })

  dpop <- subset(dpop, select=-c(eta2,eta1,Ix1,Ix2))
  dataList[[i]] <- dpop
}

## m1 is the fitted EffectLiteR model from Supplement A.3
analysisModel <- m1@lavaansyntax@model

Output <- sim(model=analysisModel, rawData=dataList, lavaanfun="sem", group="cell",
  group.label=c("00","01","10","11","20","21"), fixed.x=FALSE,
  group.w.free=TRUE)
summary(Output)

```

References

- R Core Team. (2013). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from <http://www.R-project.org/>
- RStudio and Inc. (2014). shiny: Web application framework for R [Computer software manual]. Retrieved from <http://CRAN.R-project.org/package=shiny> (R package version 0.10.1)