

APPENDIX 12.3: ILLUSTRATIVE EXAMPLES USING R: COMPLETE ANNOTATED SYNTAX

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# R Code for Krasikova & LeBreton
#####
#####STEP 1: Loading Packages & Data#####
#####

# Install the multilevel package
install.packages("multilevel")

# Load the multilevel package into the library of
  active resources
library(multilevel)

# Load the lq2002 dataframe
#### Note: This dataframe contains the data used in
  a special issue of Leadership Quarterly (Vol 13)
  published in 2002
data(lq2002, package="multilevel")

# List the names of the variables included in the
  lq2002 data frame
names(lq2002)

# Examine the structure of the dataframe
str(lq2002)

# Note: The COMPID variable is the grouping
  variable
#### This variable is a nominal variable that simply
  identifies the Army Company to which soldiers
  were assigned (i.e., nested)
#### COMPID should be treated as a nominal/
  categorical variable, but it is currently classified as
  an integer variable
class(lq2002$COMPID)

#### We will reclassify this variable by overwriting in
  the dataframe
lq2002$COMPID=as.factor(lq2002$COMPID)
class(lq2002$COMPID)

#####
#####STEP 2: Estimating Non-Independence#####
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# Estimation of Non-Independence via ICC(1)
#### We will treat HOSTILE as our dependent variable
#### Using the aov function: regress the DV
  (HOSTILE) onto the grouping variable (COMPID)
#### aov works best if you have a balanced design
  (same number of L1 units nested in each L2 unit)
model.1a<-aov(HOSTILE~COMPID,data=lq2002,
  na.action=na.omit)
summary(model.1a)
#### now simply apply the ICC1 function to the
  model.1a output
ICC1(model.1a)

#### With unbalanced designs, it is probably better
  to estimate a "Null" Model using the lme function
  from the nlme package
#### The nlme package is automatically loaded when
  using multilevel
#### Otherwise use: install.packages("nlme")
#### Followed by: library("nlme")
#### The data are unbalanced
counts=table(lq2002$COMPID)
barplot(counts, main="# of Soldiers Nested in Army
  Companies",
  xlab = "Army Company Identification Number",
  ylab = "# of Soldiers")
model.1b=(lme(HOSTILE~1,random=~1|COMPID,
  data=lq2002,na.action=na.omit))

#### Obtain the variance components from this
  model
VarCorr(model.1b)

#### Manually compute the ICC(1)
ICC1.model.1b=.0594961/(.0594961+1.0166930);
  ICC.model.1b

#####
#####STEP 3: Estimating Within-Group Agreement####
#####

# Estimation of Within-Group Agreement using rwg
  and rwgj functions
#### We are interested in whether soldiers nested
  in Army companies agree in their perceptions of
  leadership climate
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names(lq2002)
### We will estimate the single item rwg for the first
  leadership climate item
### We will estimate rwg using both a uniform null
  distribution and a slightly skewed distribution
rwg.lead01.un = rwg(lq2002$LEAD01,
  lq2002$COMPID,ranvar=2.00)
rwg.lead01.ss=rwg(lq2002$LEAD01,
  lq2002$COMPID, ranvar=1.34)
summary(rwg.lead01.un); summary(rwg.lead01.ss)
hist(rwg.lead01.un$rwg,
xlab = "Estimate of rwg",
ylab = "Frequency")

### We can test whether the observed rwg=.4234 is
  statistically significantly different from zero
### Need to specify a group size for the simulation;
  so we selected 42 (the mean group size)
rwg.lead01.sim = rwg.sim(gsize=42,
  nresp=5,nrep=10000)
quantile(rwg.lead01.sim,c(.90,.95,.99))

### We will estimate the multi-item rwgj across the
  11 leadership climate items
rwgj.lead.un=rwg.j(lq2002[,c(3:13)],
  lq2002$COMPID,ranvar=2.00)
rwgj.lead.ss=rwg.j(lq2002[,c(3:13)],
  lq2002$COMPID,ranvar=1.34)
summary(rwgj.lead.un); summary(rwgj.lead.ss)
rwgj.lead.sim=rwg.j.sim(gsize=42, nitems=11,nresp
  =5,itemcors=cor(lq2002[,3:13]),nrep=10000)
quantile(rwgj.lead.sim,c(.90,.95,.99))

# The multilevel package also contains functions that
  allow users to compute other measures of agreement
### ad.m can be used to compute the Average Devia-
  tion index (Burke, Finkelstein, & Dusig, 1999)
### awg can be used to estimate the agreement
  within group index (Brown & Hauenstein, 2005)
### rgr.agree can be used to compute agreement
  using a random group resampling procedure
  (Bliese & Halverson, 2002)
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### rwg.j.lindell can be used to compute agreement
  using the r*wgj statistic (Lindell, Brandt, &
  Whitney, 1999)

#####
###STEP 3: Estimating Reliability of Group Means###
#####

# Estimation of the ICC2; stability or reliability of
  group means
### We will treat LEAD (the scale score for the
  11 leadership climate items) as our L1 variable
### Using the aov function: regress the DV (LEAD)
  onto the grouping variable (COMPID)
### As noted above, aov works best if you have a
  balanced design (same number of L1 units nested
  in each L2 unit)
model.2a<-aov(LEAD~COMPID,data=lq2002,
  na.action=na.omit)
summary(model.2a)
### now simply apply the ICC1 & ICC2 functions
  to the model.2a output
ICC1(model.2a)
ICC2(model.2a)
### As noted above, with unbalanced designs it is
  probably better to estimate a "Null" Model using
  the lme function ### The data are unbalanced
model.2b=(lme(LEAD~1,random=~1|COMPID,
  data=lq2002,na.action=na.omit))

### Obtain the variance components from this model
VarCorr(model.2b)

### Manually compute the ICC(1)
ICC1.model.2b=0.07434663/
  (0.07434663+0.61513752); ICC.model.2b

### Manually compute the ICC(2)
### Note: Need to specify the number of raters/
  group to estimate the ICC(2); we will use the
  mean of 42 raters
ICC2.model.2b=0.07434663/
  (0.07434663+0.61513752/42); ICC2.model.2b
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