Instructional Online Supplement to

"Using Structural Equation Modeling to Reproduce and Extend ANOVA-based Generalizability Theory Analyses for Psychological Assessments"

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1. GT Analyses Using *GENOVA*

GENOVA (Crick & Brennan, 1983) is an ANSI FORTRAN computer program used for univariate generalizability analyses with complete, balanced designs. It has both G and D study capabilities. 'GENOVA' and its manual can be downloaded from the following website:
http://www.education.uiowa.edu/centers/casma/computer-programs.

Data used in this supplement represent responses to IPIP-BFM-100 Extraversion scale (20 items on a 5-point scale; see Goldberg, 1999) for two separate occasions.

1.1. Data Preparation for *GENOVA* Analyses

When using 'GENOVA' to perform G-theory analysis, data must be arranged in a wide format that has a column for each variable. Tables S1 and S2 depict this wide format.

Table S1. *Example Data Structure for GENOVA p × i design — Occasion 1*

ID	Time1_Item1	Time1_Item2	Time1_Item3	...	Time1_Item20
1	1	4	4	...	4
2	2	2	3	...	2
3	2	4	4	...	2
4	3	4	4	...	2
5	2	2	2	...	3

Corresponding input text file for this structure is as follows for the first 5 observations:

```
1 4 4 2 4 4 1 2 1 4 4 3 4 4 1 5 4 2 3 4      PERSON 1
2 2 3 2 3 3 2 2 2 1 3 2 3 3 3 3 3 2 3 2      PERSON 2
2 4 4 4 4 4 4 2 3 4 4 4 3 4 4 4 4 5 4 2      PERSON 3
3 4 4 4 4 4 4 3 4 3 4 3 2 4 4 4 4 5 4 2      PERSON 4
2 2 2 2 2 3 1 2 2 2 3 2 3 2 3 1 3 1 2 3      PERSON 5
```

Table S2. *Example Data Structure for GENOVA p × i × o design*

ID	Time1_Item1	Time1_Item2	...	Time1_Item20	Time2_Item1	Time2_Item2	...	Time2_Item20
1	1	4	...	4	1	4	...	4
2	2	2	...	2	2	2	...	2
3	2	4	...	2	3	4	...	4
4	3	4	...	2	4	4	...	4
5	2	2	...	3	3	3	...	3

Corresponding input text file for this structure is as follows for the first 5 observations:

```
 1 4 4 2 4 4 1 2 1 4 4 3 4 4 1 5 4 2 3 4 1 4 4 2 4 4 1 2 2 2 4 4 4 4 2 4 4 2 2 4      PERSON 1
 2 2 3 2 3 3 2 2 2 1 3 2 3 3 3 3 3 2 3 2 2 2 4 4 3 3 2 2 2 1 3 2 3 3 3 3 3 2 3 2      PERSON 2
 2 4 4 4 4 4 4 2 3 4 4 4 3 4 4 4 4 5 4 2 3 4 4 4 4 4 4 2 4 2 4 4 2 4 3 4 4 5 4 4      PERSON 3
 3 4 4 4 4 4 4 3 4 3 4 3 2 4 4 4 4 5 4 2 4 4 4 4 4 5 4 4 3 3 3 4 3 4 4 4 4 4 4 4      PERSON 4
 2 2 2 2 2 3 1 2 2 2 3 2 3 2 3 1 3 1 2 3 3 3 3 2 2 3 2 2 3 2 3 2 4 2 3 2 3 2 3 3      PERSON 5
```

1.2. *GENOVA* Sample Control Card for *p* × *i* Design

```
GSTUDY      IPIP-BFM-100 Extraversion - p x i Occasion 1
OPTIONS     RECORDS 10
EFFECT      * P 359 0
EFFECT      + I 20 0
FORMAT      (20F2.0)
PROCESS     7
DSTUDY      IPIP-BFM-100 Extraversion - p x i Occasion 1
DOPTIONS    NEGATIVE
DEFFECT     $ P
DEFFECT       I 20
ENDDSTUDY
FINISH
```

- First EFFECT card: Number of observations for ‘P’ = 359; The ‘0’ indicates ‘P’ is a random effect
- Second EFFECT card: Number of items = 5; The ‘0’ indicates ‘I’ is a random effect
- FORMAT card: Number of variables per row = 20
- PROCESS card: GENOVA would request an input data file associated with the integer parameter of 7
- DOPTIONS card: Do not replace negative variances with zero
- First DEFFECT card: The default sample size of ‘P’ (n = 359) from the G study is applied to the D study
- Second DEFFECT card: Number of items for the D study = 20

Output from the above control card is shown below:

```
     OBJECT OF MEASUREMENT :      P                        FACETS :      I
   G STUDY POPULATION SIZE : INFINITE     G STUDY UNIVERSE SIZES : INFINITE
   D STUDY POPULATION SIZE : INFINITE     D STUDY UNIVERSE SIZES : INFINITE
       D STUDY SAMPLE SIZE :   359          D STUDY SAMPLE SIZES :    20
------------------------------------------------------------------------------------------------------------------------------
                        VARIANCE COMPONENTS IN TERMS OF                            VARIANCE COMPONENTS IN TERMS OF
              G STUDY UNIVERSE (OF ADMISSIBLE OBSERVATIONS) SIZES         D STUDY UNIVERSE (OF GENERALIZATION) SIZES
            -------------------------------------------------------  -----------------------------------------------------
                                                VARIANCE COMPONENTS                                         VARIANCE COMPONENTS
              VARIANCE     FINITE   D STUDY      FOR MEAN SCORES        VARIANCE     FINITE   D STUDY      FOR MEAN SCORES
             COMPONENTS   UNIVERSE SAMPLING ------------------------- COMPONENTS   UNIVERSE SAMPLING -------------------------
              FOR SINGLE    COR-      FRE-                  STANDARD    FOR SINGLE    COR-      FRE-                  STANDARD
EFFECT      OBSERVATIONS  RECTIONS QUENCIES    ESTIMATES      ERRORS  OBSERVATIONS  RECTIONS QUENCIES    ESTIMATES      ERRORS
------------------------------------------------------------------------------------------------------------------------------
P              0.43496    1.0000         1    0.43496      0.03510     0.43496    1.0000         1    0.43496      0.03510
I              0.17115    1.0000        20    0.00856      0.00267     0.17115    1.0000        20    0.00856      0.00267
PI             0.71871    1.0000        20    0.03594      0.00062     0.71871    1.0000        20    0.03594      0.00062
------------------------------------------------------------------------------------------------------------------------------
          QFM = QUADRATIC FORM

------------------------------------------------------------------------------------------------------------------------------


                                                  STANDARD
                                        STANDARD  ERROR OF
                               VARIANCE DEVIATION VARIANCE

            UNIVERSE SCORE      0.43496   0.65951   0.03510
     EXPECTED OBSERVED SCORE    0.47089   0.68622   0.03510
           LOWER CASE DELTA     0.03594   0.18957   0.00062         GENERALIZABILITY COEFFICIENT =  0.92369  (12.10372)
           UPPER CASE DELTA     0.04449   0.21093   0.00274                                  PHI =  0.90720  ( 9.77579)
                       MEAN     0.00987   0.09934
```

1.3. *GENOVA* Sample Control Card for *p* × *i* × *o* Design

```
GSTUDY      IPIP-BFM-100 Extraversion - p x i x o
OPTIONS     RECORDS 10
EFFECT      * P 359 0
EFFECT        O 2 0
EFFECT        I 20 0
FORMAT      (40F2.0)
PROCESS     9
DSTUDY      IPIP-BFM-100 Extraversion - p x i x o
DOPTIONS    NEGATIVE
DEFFECT     $ P
DEFFECT       O 1
DEFFECT       I 20
ENDDSTUDY
FINISH
```

- First EFFECT card: Number of observations for ‘P’ = 359; The ‘0’ indicates ‘P’ is a random effect
- Second EFFECT card: Number of occasions = 5; The ‘0’ indicates ‘O’ is a random effect
- Third EFFECT card: Number of items = 5; The ‘0’ indicates ‘I’ is a random effect
- FORMAT card: Number of variables per row = 40
- PROCESS card: GENOVA would request an input data file associated with the integer parameter of 9
- DOPTIONS card: Do not replace negative variances with zero
- First DEFFECT card: The default sample size of ‘P’ (n = 359) from the G study is applied to the D study

- Second DEFFECT card: Number of occasions for the D study = 1
- Third DEFFECT card: Number of items for the D study = 20

Output from the above control card is shown below:

```
    OBJECT OF MEASUREMENT :      P                    FACETS :      O           I
  G STUDY POPULATION SIZE : INFINITE     G STUDY UNIVERSE SIZES : INFINITE    INFINITE
  D STUDY POPULATION SIZE : INFINITE     D STUDY UNIVERSE SIZES : INFINITE    INFINITE
      D STUDY SAMPLE SIZE :   359          D STUDY SAMPLE SIZES :     1          20
------------------------------------------------------------------------------------------------------------------------------------
                          VARIANCE COMPONENTS IN TERMS OF                                    VARIANCE COMPONENTS IN TERMS OF
               G STUDY UNIVERSE (OF ADMISSIBLE OBSERVATIONS) SIZES               D STUDY UNIVERSE (OF GENERALIZATION) SIZES
            ----------------------------------------------------------  ----------------------------------------------------------
                                                   VARIANCE COMPONENTS                                    VARIANCE COMPONENTS
              VARIANCE     FINITE   D STUDY          FOR MEAN SCORES         VARIANCE     FINITE   D STUDY         FOR MEAN SCORES
             COMPONENTS   UNIVERSE SAMPLING --------------------------   COMPONENTS   UNIVERSE SAMPLING --------------------------
              FOR SINGLE     COR-      FRE-                      STANDARD   FOR SINGLE     COR-      FRE-                      STANDARD
EFFECT      OBSERVATIONS RECTIONS QUENCIES    ESTIMATES         ERRORS  OBSERVATIONS RECTIONS QUENCIES    ESTIMATES         ERRORS
------------------------------------------------------------------------------------------------------------------------------------
P              0.42853    1.0000        1    0.42853        0.03471      0.42853    1.0000        1    0.42853        0.03471
O              0.00132    1.0000        1    0.00132        0.00122      0.00132    1.0000        1    0.00132        0.00122
I              0.15136    1.0000       20    0.00757        0.00237      0.15136    1.0000       20    0.00757        0.00237
PO             0.02070    1.0000        1    0.02070        0.00269      0.02070    1.0000        1    0.02070        0.00269
PI             0.37452    1.0000       20    0.01873        0.00047      0.37452    1.0000       20    0.01873        0.00047
OI             0.00147    1.0000       20    0.00007        0.00004      0.00147    1.0000       20    0.00007        0.00004
POI            0.30498    1.0000       20    0.01525        0.00026      0.30498    1.0000       20    0.01525        0.00026
------------------------------------------------------------------------------------------------------------------------------------
           QFM = QUADRATIC FORM

------------------------------------------------------------------------------------------------------------------------------------


                                                 STANDARD
                                       STANDARD  ERROR OF
                              VARIANCE DEVIATION  VARIANCE

              UNIVERSE SCORE   0.42853   0.65462   0.03471
    EXPECTED OBSERVED SCORE   0.48321   0.69513   0.03470
           LOWER CASE DELTA   0.05468   0.23383   0.00272          GENERALIZABILITY COEFFICIENT =  0.88684  ( 7.83728)
           UPPER CASE DELTA   0.06364   0.25228   0.00380                                   PHI =  0.87069  ( 6.73320)
                       MEAN   0.01031   0.10155
```

2. GT Analysis using the R *lavaan* Package

The *lavaan* package in R (Rosseel, 2012; Rosseel et al., 2023) is a free open-source package for latent variable modeling. Sample code is provided below for using the package for GT analyses, including estimation of variance components, G coefficients, and D coefficients as well as their respective Monte Carlo confidence intervals for the $p \times i$ and $p \times i \times o$ designs.

2.1. Data Preparation for *lavaan* GT analyses

Data again represent responses to IPIP-BFM-100 Extraversion scale (20 items on a 5-point scale; see Goldberg, 1999) for two separate occasions. Following essential data cleaning, the dataset as well as relevant R libraries are loaded. These libraries include: *lavaan* (Rosseel, 2012; Rosseel et al., 2023), *semTools* (Jorgensen et al., 2022), *psych* (Revelle, 2022), *dplyr* (Wickham er al., 2015), *lemon* (Edwards, 2019), and *knitr* (Xie, 2022). All item variables are renamed in the format of t1_1-t1_20 for Occasion 1 and t2_1-t2_20 for Occasion 2.

```
library(lavaan)
library(semTools)
```

```r
library(psych)
library(dplyr)
library(lemon)
library(knitr)
knit_print.data.frame <- lemon_print
options(scipen = 100)

ipip <- read.csv('IPIP_ext.csv')
names(ipip)<- c(paste0("t",1,"_",1:20),paste0("t",2,"_",1:20))
```

2.2. Descriptive Statistics and Reliabilities - Occasions 1 & 2

```r
rel <- data.frame("IPIP" = c(mean(rowSums(ipip[,1:20], na.rm = TRUE)),sd(rowS
ums(ipip[,1:20], na.rm = TRUE)),alpha(ipip[,1:20], na.rm = TRUE)$total$raw_al
pha, mean(rowSums(ipip[,21:40]), na.rm = TRUE),sd(rowSums(ipip[,21:40]), na.r
m = TRUE),alpha(ipip[,21:40], na.rm = TRUE)$total$raw_alpha, cor(rowSums(ipip
[,1:20], na.rm = TRUE), rowSums(ipip[,21:40], na.rm = TRUE))))
row.names(rel) <- c("Occasion 1 Mean", "Occasion 1 SD","Occasion 1 Alpha",
                    "Occasion 2 Mean", "Occasion 2 SD","Occasion 2 Alpha",
                    "Test-retest")
rel

##                        IPIP
## Occasion 1 Mean  64.2200557
## Occasion 1 SD    13.7243021
## Occasion 1 Alpha  0.9236858
## Occasion 2 Mean  65.3147632
## Occasion 2 SD    14.0787323
## Occasion 2 Alpha  0.9353930
## Test-retest       0.9258974
```

2.3. $p \times i$ design using *lavaan* - Occasion 1

R code for estimating ULS and WLSMV estimates for variance components and reliability-like coefficients for the $p \times i$ design (Occasion 1 only) using the *lavaan* package is shown below.

```r
## Specify the model

model_pi <-'
# Define person factor
Person =~ 1*t1_1 + 1*t1_2 + 1*t1_3 + 1*t1_4 + 1*t1_5 +
1*t1_6 + 1*t1_7 + 1*t1_8 + 1*t1_9 + 1*t1_10 +
1*t1_11 + 1*t1_12 + 1*t1_13 + 1*t1_14 + 1*t1_15 +
1*t1_16 + 1*t1_17 + 1*t1_18 + 1*t1_19 + 1*t1_20

# Specify person factor mean and variance
Person ~ mu_p*1
Person ~~ v_p*Person

# Specify item intercepts
```

```
t1_1 ~ mu1*1
t1_2 ~ mu2*1
t1_3 ~ mu3*1
t1_4 ~ mu4*1
t1_5 ~ mu5*1
t1_6 ~ mu6*1
t1_7 ~ mu7*1
t1_8 ~ mu8*1
t1_9 ~ mu9*1
t1_10 ~ mu10*1
t1_11 ~ mu11*1
t1_12 ~ mu12*1
t1_13 ~ mu13*1
t1_14 ~ mu14*1
t1_15 ~ mu15*1
t1_16 ~ mu16*1
t1_17 ~ mu17*1
t1_18 ~ mu18*1
t1_19 ~ mu19*1
t1_20 ~ mu20*1

# Apply effect-coding constraints
mu20 == -1*(mu1 + mu2 + mu3 + mu4 + mu5 +
            mu6 + mu7 + mu8 + mu9 + mu10 +
            mu11 + mu12 + mu13 + mu14 + mu15 +
            mu16 + mu17 + mu18 + mu19)

# Define item variance
v_i := (mu1^2 + mu2^2 + mu3^2 + mu4^2 + mu5^2 +
        mu6^2 + mu7^2 + mu8^2 + mu9^2 + mu10^2 +
        mu11^2 + mu12^2 + mu13^2 + mu14^2 + mu15^2 +
        mu16^2 + mu17^2 + mu18^2 + mu19^2 + mu20^2)/(20-1)

# Specify p x i interaction variance (+ error)
t1_1 ~~ v_pi*t1_1
t1_2 ~~ v_pi*t1_2
t1_3 ~~ v_pi*t1_3
t1_4 ~~ v_pi*t1_4
t1_5 ~~ v_pi*t1_5
t1_6 ~~ v_pi*t1_6
t1_7 ~~ v_pi*t1_7
t1_8 ~~ v_pi*t1_8
t1_9 ~~ v_pi*t1_9
t1_10 ~~ v_pi*t1_10
t1_11 ~~ v_pi*t1_11
t1_12 ~~ v_pi*t1_12
t1_13 ~~ v_pi*t1_13
t1_14 ~~ v_pi*t1_14
t1_15 ~~ v_pi*t1_15
t1_16 ~~ v_pi*t1_16
```

```
t1_17 ~~ v_pi*t1_17
t1_18 ~~ v_pi*t1_18
t1_19 ~~ v_pi*t1_19
t1_20 ~~ v_pi*t1_20

# Define variance components and G, global D, and cut-score specific D
# coefficients
## Number of items = 20; Number of people = 359
## Cut score = 2 standard deviations away from the mean
  vc_p := v_p
  vc_pi := v_pi
  vc_i := v_i
  G := v_p / (v_p + v_pi/20)
  D := v_p / (v_p + v_pi/20 + v_i/20)
  CS_D := (v_p + (4*v_p/G - v_p/359 - v_pi/(359*20) - v_i/20)) /
  (v_p + (4*v_p/G - v_p/359 - v_pi/(359*20) - v_i/20) + v_pi/20 + v_i/20)
  ## Correction for bias applied '

## Specify item thresholds for WLSMV estimation

thre_pi <-
't1_1 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_2 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_3 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_4 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_5 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_6 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_7 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_8 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_9 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_10 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_11 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_12 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_13 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_14 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_15 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_16 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_17 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_18 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_19 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_20 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4'

## Get estimates of variance components and reliability-like coefficient
## using ULS

pi_uls <- lavaan(model_pi, data = ipip,  estimator = "ULS")
uls_est <- select(data.frame(parameterEstimates(pi_uls)),label,est,se)
```

```
## Get Monte Carlo confidence intervals (90%) for the above ULS-based
## estimates

set.seed(1234)
uls_mc <- data.frame(monteCarloCI(pi_uls, level = 0.9))
uls_mc <- cbind(label= rownames(uls_mc),uls_mc) %>% subset(select=-est)

uls_all <- merge (uls_est, uls_mc, by = "label", sort=F) %>% filter(label %in
% c("vc_p","vc_pi","vc_i","G","D","CS_D")) %>% subset(select=-label)
colnames(uls_all) = c("Estimate","Standard Error","90% CI - LL", "90% CI - UL
")
rownames(uls_all) = c("Person","Person × item and other error","Item","G coef
ficient","Global D coefficient","Cut-score specific D coefficient")
```

Table S3. *Variance Components, G Coefficients, and D Coefficients for GT* pi *Observed Score Design*

	Estimate	Standard Error	90% CI - LL	90% CI - UL
Person	0.43496	0.00383	0.42860	0.44127
Person × item and other error	0.71871	0.01242	0.69815	0.73928
Item	0.17315	0.01009	0.15937	0.19274
G coefficient	0.92369	0.00153	0.92112	0.92622
Global D coefficient	0.90701	0.00184	0.90369	0.90976
Cut-score specific D coefficient	0.98105	0.00039	0.98034	0.98163

```
## Get estimates of variance components and reliability-like coefficients
## using WLSMV

pi_wlsmv <- lavaan(model = c(model_pi, thre_pi), data = ipip,  estimator = "W
LSMV", parameterization = "theta", ordered = names(ipip[,1:20]))
wlsmv_est <- select(data.frame(parameterEstimates(pi_wlsmv)),label,est,se)

## Get Monte Carlo confidence intervals (90%) for the above WLSMV-based
## estimates

wlsmv_mc <- data.frame(monteCarloCI(pi_wlsmv, level = 0.9))
wlsmv_mc <- cbind(label= rownames(wlsmv_mc),wlsmv_mc) %>% subset(select=-est)

wlsmv_all <- merge (wlsmv_est, wlsmv_mc, by = "label", sort=F) %>% filter(lab
el %in% c("vc_p","vc_pi","vc_i","G","D","CS_D")) %>% subset(select=-label)
colnames(wlsmv_all) = c("Estimate","Standard Error","90% CI - LL", "90% CI -
UL")
rownames(wlsmv_all) = c("Person","Person × item and other error","Item","G co
efficient","Global D coefficient","Cut-score specific D coefficient")
```

Table S4. *Variance Components, G Coefficients, and D Coefficients for GT* `pi` *CLRV Design*

	Estimate	Standard Error	90% CI - LL	90% CI - UL
Person	1.85390	0.12720	1.64739	2.06039
Person × item and other error	1.98439	0.03194	1.93214	2.03673
Item	0.60615	0.03828	0.55155	0.67745
G coefficient	0.94920	0.00334	0.94311	0.95409
Global D coefficient	0.93470	0.00425	0.92673	0.94083
Cut-score specific D coefficient	0.98673	0.00088	0.98508	0.98799

2.4. *p* × *i* × *o* design using *lavaan*

R code for estimating ULS and WLSMV estimates for variance components, reliability-like coefficients, and proportions of measurement error for the $p \times i \times o$ design using the *lavaan* package is shown below.

```
model_pio <-'
# Define the person factor
Person =~ 1*t1_1 + 1*t1_2 + 1*t1_3 + 1*t1_4 + 1*t1_5 +
1*t1_6 + 1*t1_7 + 1*t1_8 + 1*t1_9 + 1*t1_10 +
1*t1_11 + 1*t1_12 + 1*t1_13 + 1*t1_14 + 1*t1_15 +
1*t1_16 + 1*t1_17 + 1*t1_18 + 1*t1_19 + 1*t1_20 +
1*t2_1 + 1*t2_2 + 1*t2_3 + 1*t2_4 + 1*t2_5 +
1*t2_6 + 1*t2_7 + 1*t2_8 + 1*t2_9 + 1*t2_10 +
1*t2_11 + 1*t2_12 + 1*t2_13 + 1*t2_14 + 1*t2_15 +
1*t2_16 + 1*t2_17 + 1*t2_18 + 1*t2_19 + 1*t2_20

# Define the item factors
Item1 =~ 1*t1_1 + 1*t2_1
Item2 =~ 1*t1_2 + 1*t2_2
Item3 =~ 1*t1_3 + 1*t2_3
Item4 =~ 1*t1_4 + 1*t2_4
Item5 =~ 1*t1_5 + 1*t2_5
Item6 =~ 1*t1_6 + 1*t2_6
Item7 =~ 1*t1_7 + 1*t2_7
Item8 =~ 1*t1_8 + 1*t2_8
Item9 =~ 1*t1_9 + 1*t2_9
Item10 =~ 1*t1_10 + 1*t2_10
Item11 =~ 1*t1_11 + 1*t2_11
Item12 =~ 1*t1_12 + 1*t2_12
Item13 =~ 1*t1_13 + 1*t2_13
Item14 =~ 1*t1_14 + 1*t2_14
Item15 =~ 1*t1_15 + 1*t2_15
Item16 =~ 1*t1_16 + 1*t2_16
Item17 =~ 1*t1_17 + 1*t2_17
Item18 =~ 1*t1_18 + 1*t2_18
Item19 =~ 1*t1_19 + 1*t2_19
Item20 =~ 1*t1_20 + 1*t2_20
```

```
# Define the occasion factors
Occasion1 =~ 1*t1_1 + 1*t1_2 + 1*t1_3 + 1*t1_4 + 1*t1_5 +
1*t1_6 + 1*t1_7 + 1*t1_8 + 1*t1_9 + 1*t1_10 +
1*t1_11 + 1*t1_12 + 1*t1_13 + 1*t1_14 + 1*t1_15 +
1*t1_16 + 1*t1_17 + 1*t1_18 + 1*t1_19 + 1*t1_20

Occasion2 =~ 1*t2_1 + 1*t2_2 + 1*t2_3 + 1*t2_4 + 1*t2_5 +
1*t2_6 + 1*t2_7 + 1*t2_8 + 1*t2_9 + 1*t2_10 +
1*t2_11 + 1*t2_12 + 1*t2_13 + 1*t2_14 + 1*t2_15 +
1*t2_16 + 1*t2_17 + 1*t2_18 + 1*t2_19 + 1*t2_20

# Specify factor means
Person ~ mu_p*1
Occasion1 ~ mu_o1*1
Occasion2 ~ mu_o2*1
Item1 ~ mu_i1*1
Item2 ~ mu_i2*1
Item3 ~ mu_i3*1
Item4 ~ mu_i4*1
Item5 ~ mu_i5*1
Item6 ~ mu_i6*1
Item7 ~ mu_i7*1
Item8 ~ mu_i8*1
Item9 ~ mu_i9*1
Item10 ~ mu_i10*1
Item11 ~ mu_i11*1
Item12 ~ mu_i12*1
Item13 ~ mu_i13*1
Item14 ~ mu_i14*1
Item15 ~ mu_i15*1
Item16 ~ mu_i16*1
Item17 ~ mu_i17*1
Item18 ~ mu_i18*1
Item19 ~ mu_i19*1
Item20 ~ mu_i20*1

# Specify item intercepts
t1_1 ~ mu1_1*1
t1_2 ~ mu1_2*1
t1_3 ~ mu1_3*1
t1_4 ~ mu1_4*1
t1_5 ~ mu1_5*1
t1_6 ~ mu1_6*1
t1_7 ~ mu1_7*1
t1_8 ~ mu1_8*1
t1_9 ~ mu1_9*1
t1_10 ~ mu1_10*1
t1_11 ~ mu1_11*1
```

```
t1_12 ~ mu1_12*1
t1_13 ~ mu1_13*1
t1_14 ~ mu1_14*1
t1_15 ~ mu1_15*1
t1_16 ~ mu1_16*1
t1_17 ~ mu1_17*1
t1_18 ~ mu1_18*1
t1_19 ~ mu1_19*1
t1_20 ~ mu1_20*1
t2_1 ~ mu2_1*1
t2_2 ~ mu2_2*1
t2_3 ~ mu2_3*1
t2_4 ~ mu2_4*1
t2_5 ~ mu2_5*1
t2_6 ~ mu2_6*1
t2_7 ~ mu2_7*1
t2_8 ~ mu2_8*1
t2_9 ~ mu2_9*1
t2_10 ~ mu2_10*1
t2_11 ~ mu2_11*1
t2_12 ~ mu2_12*1
t2_13 ~ mu2_13*1
t2_14 ~ mu2_14*1
t2_15 ~ mu2_15*1
t2_16 ~ mu2_16*1
t2_17 ~ mu2_17*1
t2_18 ~ mu2_18*1
t2_19 ~ mu2_19*1
t2_20 ~ mu2_20*1

# Apply effect-coding constraints
## Item intercepts sum to 0 for the person factor
mu2_20 == -1*(mu1_1 + mu1_2 + mu1_3 + mu1_4 + mu1_5 +
            mu1_6 + mu1_7 + mu1_8 + mu1_9 + mu1_10 +
            mu1_11 + mu1_12 + mu1_13 + mu1_14 + mu1_15 +
            mu1_16 + mu1_17 + mu1_18 + mu1_19 + mu1_20 +
            mu2_1 + mu2_2 + mu2_3 + mu2_4 + mu2_5 +
            mu2_6 + mu2_7 + mu2_8 + mu2_9 + mu2_10 +
            mu2_11 + mu2_12 + mu2_13 + mu2_14 + mu2_15 +
            mu2_16 + mu2_17 + mu2_18 + mu2_19)

## Item intercepts sum to 0 for the item factors
mu2_1 == -1*mu1_1
mu2_2 == -1*mu1_2
mu2_3 == -1*mu1_3
mu2_4 == -1*mu1_4
mu2_5 == -1*mu1_5
mu2_6 == -1*mu1_6
mu2_7 == -1*mu1_7
mu2_8 == -1*mu1_8
```

```
mu2_9 == -1*mu1_9
mu2_10 == -1*mu1_10
mu2_11 == -1*mu1_11
mu2_12 == -1*mu1_12
mu2_13 == -1*mu1_13
mu2_14 == -1*mu1_14
mu2_15 == -1*mu1_15
mu2_16 == -1*mu1_16
mu2_17 == -1*mu1_17
mu2_18 == -1*mu1_18
mu2_19 == -1*mu1_19
mu2_20 == -1*mu1_20

## Item intercepts sum to 0 for the occasion factors
mu1_20 == -1*(mu1_1 + mu1_2 + mu1_3 + mu1_4 + mu1_5 +
            mu1_6 + mu1_7 + mu1_8 + mu1_9 + mu1_10 +
            mu1_11 + mu1_12 + mu1_13 + mu1_14 + mu1_15 +
            mu1_16 + mu1_17 + mu1_18 + mu1_19)
mu2_20 == -1*(mu2_1 + mu2_2 + mu2_3 + mu2_4 + mu2_5 +
            mu2_6 + mu2_7 + mu2_8 + mu2_9 + mu2_10 +
            mu2_11 + mu2_12 + mu2_13 + mu2_14 + mu2_15 +
            mu2_16 + mu2_17 + mu2_18 + mu2_19)

## Item factor means sum to 0
mu_i20 == -1*(mu_i1 + mu_i2 + mu_i3 + mu_i4 + mu_i5 +
            mu_i6 + mu_i7 + mu_i8 + mu_i9 + mu_i10 +
            mu_i11 + mu_i12 + mu_i13 + mu_i14 + mu_i15 +
            mu_i16 + mu_i17 + mu_i18 + mu_i19)

## Occasion factor means sum to 0
mu_o2 == -1 *(mu_o1)

# Specify person factor variance
Person ~~ v_p*Person

# Identify item factor variance
v_i := (mu_i1^2 + mu_i2^2 + mu_i3^2 + mu_i4^2 + mu_i5^2 +
        mu_i6^2 + mu_i7^2 + mu_i8^2 + mu_i9^2 + mu_i10^2 +
        mu_i11^2 + mu_i12^2 + mu_i13^2 + mu_i14^2 + mu_i15^2 +
        mu_i16^2 + mu_i17^2 + mu_i18^2 + mu_i19^2 + mu_i20^2)/19

# Identify occasion factor variance
v_o := (mu_o1^2 + mu_o2^2)/1

# Identify i x o interaction variance
v_io := (mu1_1^2 + mu1_2^2 + mu1_3^2 + mu1_4^2 + mu1_5^2 +
            mu1_6^2 + mu1_7^2 + mu1_8^2 + mu1_9^2 + mu1_10^2 +
            mu1_11^2 + mu1_12^2 + mu1_13^2 + mu1_14^2 + mu1_15^2 +
            mu1_16^2 + mu1_17^2 + mu1_18^2 + mu1_19^2 + mu1_20^2 +
```

```
            mu2_1^2 + mu2_2^2 + mu2_3^2 + mu2_4^2 + mu2_5^2 +
            mu2_6^2 + mu2_7^2 + mu2_8^2 + mu2_9^2 + mu2_10^2 +
            mu2_11^2 + mu2_12^2 + mu2_13^2 + mu2_14^2 + mu2_15^2 +
            mu2_16^2 + mu2_17^2 + mu2_18^2 + mu2_19^2 + mu2_20^2)/39

# Identify p x i interaction variance
  Item1 ~~ v_pi*Item1
  Item2 ~~ v_pi*Item2
  Item3 ~~ v_pi*Item3
  Item4 ~~ v_pi*Item4
  Item5 ~~ v_pi*Item5
  Item6 ~~ v_pi*Item6
  Item7 ~~ v_pi*Item7
  Item8 ~~ v_pi*Item8
  Item9 ~~ v_pi*Item9
  Item10 ~~ v_pi*Item10
  Item11 ~~ v_pi*Item11
  Item12 ~~ v_pi*Item12
  Item13 ~~ v_pi*Item13
  Item14 ~~ v_pi*Item14
  Item15 ~~ v_pi*Item15
  Item16 ~~ v_pi*Item16
  Item17 ~~ v_pi*Item17
  Item18 ~~ v_pi*Item18
  Item19 ~~ v_pi*Item19
  Item20 ~~ v_pi*Item20

# Identify p x o interaction variance
  Occasion1 ~~ v_po*Occasion1
  Occasion2 ~~ v_po*Occasion2

# Identify p x i x o interaction variance (+ error)
  t1_1 ~~ v_pio*t1_1
  t1_2 ~~ v_pio*t1_2
  t1_3 ~~ v_pio*t1_3
  t1_4 ~~ v_pio*t1_4
  t1_5 ~~ v_pio*t1_5
  t1_6 ~~ v_pio*t1_6
  t1_7 ~~ v_pio*t1_7
  t1_8 ~~ v_pio*t1_8
  t1_9 ~~ v_pio*t1_9
  t1_10 ~~ v_pio*t1_10
  t1_11 ~~ v_pio*t1_11
  t1_12 ~~ v_pio*t1_12
  t1_13 ~~ v_pio*t1_13
  t1_14 ~~ v_pio*t1_14
  t1_15 ~~ v_pio*t1_15
  t1_16 ~~ v_pio*t1_16
  t1_17 ~~ v_pio*t1_17
  t1_18 ~~ v_pio*t1_18
```

```
  t1_19 ~~ v_pio*t1_19
  t1_20 ~~ v_pio*t1_20
  t2_1 ~~ v_pio*t2_1
  t2_2 ~~ v_pio*t2_2
  t2_3 ~~ v_pio*t2_3
  t2_4 ~~ v_pio*t2_4
  t2_5 ~~ v_pio*t2_5
  t2_6 ~~ v_pio*t2_6
  t2_7 ~~ v_pio*t2_7
  t2_8 ~~ v_pio*t2_8
  t2_9 ~~ v_pio*t2_9
  t2_10 ~~ v_pio*t2_10
  t2_11 ~~ v_pio*t2_11
  t2_12 ~~ v_pio*t2_12
  t2_13 ~~ v_pio*t2_13
  t2_14 ~~ v_pio*t2_14
  t2_15 ~~ v_pio*t2_15
  t2_16 ~~ v_pio*t2_16
  t2_17 ~~ v_pio*t2_17
  t2_18 ~~ v_pio*t2_18
  t2_19 ~~ v_pio*t2_19
  t2_20 ~~ v_pio*t2_20

# Define variance components, and G, global D, and cut-score specific D
# coefficients
## Number of items = 20; Number of occasions = 1; Number of people = 359
## Cut score = 2 standard deviations away from the mean
  vc_p := v_p
  vc_pi := v_pi
  vc_po := v_po
  vc_pio := v_pio
  vc_i := v_i
  vc_o := v_o
  vc_io := v_io
  G := v_p / (v_p + v_pi/20 + v_po/1 + v_pio/(20*1))
  SFE := (v_pi/20)/ (v_p + v_pi/20 + v_po/1 + v_pio/(20*1))
  TE :=  (v_po/1)/ (v_p + v_pi/20 + v_po/1 + v_pio/(20*1))
  RRE := (v_pio/20)/ (v_p + v_pi/20 + v_po/1 + v_pio/(20*1))
  D := v_p / (v_p + v_pi/20 + v_po/1 + v_pio/(20*1) + v_i/20 + v_o/1 + v_io/(
20*1))
  CS_D := (v_p + (4*v_p/G-v_p/359-v_pi/(359*20)-v_po/(359*1)-v_pio/(359*20*1)
-v_i/20-v_o/1-v_io/(20*1))) /
  (v_p + (4*v_p/G-v_p/359-v_pi/(359*20)-v_po/(359*1)-v_pio/(359*20*1)-v_i/20-
v_o/1-v_io/(20*1)) +
  v_pi/20 + v_po/1 + v_pio/(20*1) + v_i/20 + v_o/1 + v_io/(20*1))
  ## Correction for bias applied '

## Specify item thresholds for WLSMV estimation
thre_pio <- 't1_1 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_2 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
```

```
t1_3 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_4 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_5 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_6 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_7 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_8 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_9 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_10 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_11 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_12 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_13 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_14 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_15 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_16 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_17 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_18 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_19 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t1_20 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_1 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_2 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_3 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_4 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_5 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_6 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_7 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_8 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_9 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_10 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_11 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_12 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_13 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_14 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_15 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_16 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_17 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_18 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_19 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4
t2_20 |thr_1*t1 + thr_2*t2 + thr_3*t3 + thr_4*t4'

## Get estimates of variance components and reliability-like coefficient
## using ULS

pio_uls <- lavaan(model_pio, data = ipip,  estimator = "ULS")
uls_est <- select(data.frame(parameterEstimates(pio_uls)),label,est,se)

## Get Monte Carlo confidence intervals (90%) for the above ULS-based
## estimates

set.seed(1234)
```

```
uls_mc <- data.frame(monteCarloCI(pio_uls, level = 0.9))
uls_mc <- cbind(label= rownames(uls_mc),uls_mc) %>% subset(select=-est)

uls_all <- merge (uls_est, uls_mc, by = "label", sort=F) %>% filter(label %in
% c("vc_p","vc_pi","vc_po","vc_pio","vc_i","vc_o","vc_io","SFE","TE","RRE","G
","D","CS_D")) %>% subset(select=-label)
colnames(uls_all) = c("Estimate","Standard Error","90% CI - LL", "90% CI - UL
")
rownames(uls_all) = c("Person","Person × item","Person × occasion","Person ×
item × occasion and other error","Item","Occasion","Item × occasion","G coeff
icient","Specific-factor error","Transient error","random-response error","Gl
obal D coefficient","Cut-score specific D coefficient")
```

Table S5. *G Coefficients, D Coefficients, and Partitioning of Variance for GT* pio *Observed Score Design*

	Estimate	Standard Error	90% CI - LL	90% CI - UL
Person	0.42853	0.00271	0.42408	0.43293
Person × item	0.37452	0.01212	0.35445	0.39437
Person × occasion	0.02070	0.00383	0.01447	0.02704
Person × item × occasion and other error	0.30498	0.01497	0.28018	0.32943
Item	0.15357	0.00672	0.14398	0.16621
Occasion	0.00150	0.00091	0.00037	0.00342
Item × occasion	0.00113	0.00057	0.00141	0.00377
G coefficient	0.88684	0.00738	0.87470	0.89891
Specific-factor error	0.03875	0.00127	0.03666	0.04084
Transient error	0.04285	0.00778	0.03013	0.05564
Random-response error	0.03156	0.00157	0.02897	0.03414
Global D coefficient	0.87022	0.00739	0.85754	0.88173
Cut-score specific D coefficient	0.97353	0.00152	0.97092	0.97588

```
## Get estimates of variance components and reliability-like coefficient
## using WLSMV

pio_wlsmv <- lavaan(model = c(model_pio, thre_pio), data = ipip,  estimator =
"WLSMV", parameterization = "theta", ordered = names(ipip))
wlsmv_est <- select(data.frame(parameterEstimates(pio_wlsmv)),label,est,se)

## Get Monte Carlo confidence intervals (90%) for the above WLSMV-based
## estimates

set.seed(1234)
wlsmv_mc <- data.frame(monteCarloCI(pio_wlsmv, level = 0.9))
wlsmv_mc <- cbind(label= rownames(wlsmv_mc),wlsmv_mc) %>% subset(select=-est)

wlsmv_all <- merge (wlsmv_est, wlsmv_mc, by = "label", sort=F) %>% filter(lab
```

```
el %in% c("vc_p","vc_pi","vc_po","vc_pio","vc_i","vc_o","vc_io","SFE","TE","R
RE","G","D","CS_D")) %>% subset(select=-label)
colnames(wlsmv_all) = c("Estimate","Standard Error","90% CI - LL", "90% CI -
UL")
rownames(wlsmv_all) = c("Person","Person × item","Person × occasion","Person
× item × occasion and other error","Item","Occasion","Item × occasion","G coe
fficient","Specific-factor error","Transient error","Random-response error","
Global D coefficient","Cut-score specific D coefficient")
```

Table S6. *G Coefficients, D Coefficients, and Partitioning of Variance for GT `pio` CLRV Design*

	Estimate	Standard Error	90% CI - LL	90% CI - UL
Person	1.00098	0.07373	0.87892	1.12206
Person × item	0.67676	0.02528	0.63524	0.71879
Person × occasion	0.07604	0.00805	0.06283	0.08917
Person × item × occasion and other error	0.37255	0.00978	0.35658	0.38863
Item	0.30682	0.01914	0.27905	0.34205
Occasion	0.00270	0.00158	0.00074	0.00599
Item × occasion	0.00217	0.00071	0.00190	0.00444
G coefficient	0.88622	0.00964	0.86918	0.90092
Specific-factor error	0.02996	0.00198	0.02696	0.03356
Transient error	0.06733	0.00783	0.05502	0.08095
Random-response error	0.01649	0.00116	0.01476	0.01863
Global D coefficient	0.87220	0.01017	0.85381	0.88739
Cut-score specific D coefficient	0.97402	0.00209	0.97021	0.97713

3. Tables with Key Formulas for Illustrated Generalizability Theory Designs

Table S7. Formulas for Persons by Items Generalizability Theory Designs

Paritioning of variance	Individual score level	$\hat{\sigma}^2_{Y_{pi}} = \hat{\sigma}^2_p + \hat{\sigma}^2_{pi,e} + \hat{\sigma}^2_i$
	Item mean score level	$\hat{\sigma}^2_{Y_{pI}} = \hat{\sigma}^2_p + \frac{\hat{\sigma}^2_{pi,e}}{n'_i}$
Absolute error variance component	Item variance	$\hat{\sigma}^2_i = \frac{1}{n_i - 1}\sum_{1}^{n_i}(Intercept_i)^2$
G and D coefficients	Ĝ coefficient	$\frac{\hat{\sigma}^2_p}{\hat{\sigma}^2_p + \left(\frac{\hat{\sigma}^2_{pi,e}}{n'_i}\right)}$
	Global D̂ coefficient	$\frac{\hat{\sigma}^2_p}{\hat{\sigma}^2_p + \left(\frac{\hat{\sigma}^2_{pi,e}}{n'_i} + \frac{\hat{\sigma}^2_i}{n'_i}\right)}$
	Cut - score specific D̂ coefficient	$\frac{\hat{\sigma}^2_p + \left[(\bar{Y}\text{- Cut-score})^2 - \hat{\sigma}^2_{\bar{Y}}\right]}{\hat{\sigma}^2_p + \left[(\bar{Y}\text{- Cut-score})^2 - \hat{\sigma}^2_{\bar{Y}}\right] + \left(\frac{\hat{\sigma}^2_{pi,e}}{n'_i} + \frac{\hat{\sigma}^2_i}{n'_i}\right)}$ where $\hat{\sigma}^2_{\bar{Y}} = \frac{\hat{\sigma}^2_p}{n'_p} + \frac{\hat{\sigma}^2_{pi,e}}{n'_p n'_i} + \frac{\hat{\sigma}^2_i}{n'_i}$ and corrects for bias (see Brennan & Kane, 1977)

Note. $\hat{\sigma}^2$ = estimated variance component, Y_{pi} = score for a particular person on a given item, Y_{pI} = mean across all items for a particular person, n_i = number of items for generalizability study, and n'_i = number of items for decision study.

Table S8. Formulas for Persons by Items by Occasions Generalizability Theory Designs

Paritioning of variance	Individual score level	$\hat{\sigma}^2_{Y_{pio}} = \hat{\sigma}^2_p + \hat{\sigma}^2_{pi} + \hat{\sigma}^2_{po} + \hat{\sigma}^2_{pio,e} + \hat{\sigma}^2_i + \hat{\sigma}^2_o + \hat{\sigma}^2_{io}$
	Item mean score level	$\hat{\sigma}^2_{Y_{pIO}} = \hat{\sigma}^2_p + \frac{\hat{\sigma}^2_{pi}}{n'_i} + \frac{\hat{\sigma}^2_{po}}{n'_o} + \frac{\hat{\sigma}^2_{pio,e}}{n'_i n'_o}$
Absolute error variance component	Item variance	$\hat{\sigma}^2_i = \frac{1}{\mathrm{n_i} - 1} \sum_{1}^{n_i} (Item\ factor\ mean_i)^2$
	Occasion variance	$\hat{\sigma}^2_{\mathrm{o}} = \frac{1}{\mathrm{n_o} - 1} \sum_{1}^{\mathrm{n_o}} (\mathrm{Occasion\ factor\ mean_o})^2$
	Item × Occasion variance	$\hat{\sigma}^2_{io} = \frac{1}{(\mathrm{n_i} \times \mathrm{n_o}) - 1} \sum_{1}^{n_i \times n_o} (Intercept_{io})^2$
G and D coefficients	**$\hat{\mathrm{G}}$ coefficient**	$\frac{\hat{\sigma}^2_p}{\hat{\sigma}^2_p + \left(\frac{\hat{\sigma}^2_{pi}}{n'_i} + \frac{\hat{\sigma}^2_{po}}{n'_o} + \frac{\hat{\sigma}^2_{pio,e}}{n'_i n'_o}\right)}$
	Global $\hat{\mathrm{D}}$ coefficient	$\frac{\hat{\sigma}^2_p}{\hat{\sigma}^2_p + \left(\frac{\hat{\sigma}^2_{pi}}{n'_i} + \frac{\hat{\sigma}^2_{po}}{n'_o} + \frac{\hat{\sigma}^2_{pio,e}}{n'_i n'_o} + \frac{\hat{\sigma}^2_i}{n'_i} + \frac{\hat{\sigma}^2_o}{n'_o} + \frac{\hat{\sigma}^2_{io}}{n'_i n'_o}\right)}$
	Cut - score specific $\hat{\mathrm{D}}$ coefficient	$\frac{\hat{\sigma}^2_p + [(\bar{Y} \text{- Cut-score})^2 - \hat{\sigma}^2_{\bar{Y}}]}{\hat{\sigma}^2_p + [(\bar{Y} \text{- Cut-score})^2 - \hat{\sigma}^2_{\bar{Y}}] + \left(\frac{\hat{\sigma}^2_{pi}}{n'_i} + \frac{\hat{\sigma}^2_{po}}{n'_o} + \frac{\hat{\sigma}^2_{pio,e}}{n'_i n'_o} + \frac{\hat{\sigma}^2_i}{n'_i} + \frac{\hat{\sigma}^2_o}{n'_o} + \frac{\hat{\sigma}^2_{io}}{n'_i n'_o}\right)}$ where $\hat{\sigma}^2_{\bar{Y}} = \frac{\hat{\sigma}^2_p}{n'_p} + \frac{\hat{\sigma}^2_{pi}}{n'_p n'_i} + \frac{\hat{\sigma}^2_{po}}{n'_p n'_o} + \frac{\hat{\sigma}^2_{pio,e}}{n'_p n'_i n'_o} + \frac{\hat{\sigma}^2_i}{n'_i} + \frac{\hat{\sigma}^2_o}{n'_o} + \frac{\hat{\sigma}^2_{io}}{n'_i n'_o}$ and corrects for bias (see Brennan & Kane, 1977)

Note. $\hat{\sigma}^2$ = estimated variance component, Y_{pio} = score for a particular person on a given combination of item and occasion, Y_{pIO} = mean across all items and occasions for a particular person, n_i = number of items for generalizability study, n_o = number of occasions for generalizability study, n'_i = number of items for decision study, and n'_o = number of occasions for decision study.

4. Abbreviations Used Throughout the Supplement

CI - LL: Confidence Interval - Lower Limit

CI - UL: Confidence Interval - Upper Limit

GT: Generalizability Theory

ULS: Unweighted Least Squares

WLSMV: Diagonally Weighted Least Squares in R

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