

# Instructional Online Supplement to “Extending Applications of Generalizability Theory- Based Bifactor Model Designs”

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## 1. Data Preparation

Examples used in this supplement represent two-occasion results for Open-mindedness domain (composite) and facet (subscale) scores from the updated Big Five Inventory (BFI-2; Soto & John, 2017). Following essential data cleaning, the dataset as well as relevant R libraries are loaded. All item variables are renamed with the labels 'T1\_' for Occasion 1 and 'T2\_' for Occasion 2. When using the *lavaan* (Rosseel, 2012) and *semTools* (Jorgensen et al., 2022) packages in R to perform Generalizability theory (GT; Cronbach et al., 1963) analyses, data must be arranged in a wide format that has a column for each variable. Sample code is provided below for using these packages for GT analyses, including estimation of G and D coefficients, proportions of measurement error, and respective Monte Carlo confidence intervals. The original dataset ([bfi2\\_open\\_389.csv](#)) was analyzed using the code provided in this supplement. A smaller set of 200 randomly selected cases ([BFI2\\_Openmindedness\\_Random\\_200.csv](#)) from the original dataset is available as additional Supplemental Material to enable readers to apply the illustrated code to a different dataset.

```
library(lavaan)
library(semTools)

bfi2_open <- read.csv("bfi2_open_389.csv", header = T)
```

## 2. Bifactor Model

The following code specifies the  $p \times i \times o$  bifactor model, which is used to obtain variance partitioning and scale viability indices.

```
model<- '

# General factor
general =~ NA*T1_5+lmd1*T1_5+lmd1*T1_20+lmd1*T1_35+lmd1*T1_50
          +lmd1*T2_5+lmd1*T2_20+lmd1*T2_35+lmd1*T2_50+
          lmd2*T1_15+lmd2*T1_30+lmd2*T1_45+lmd2*T1_60
          +lmd2*T2_15+lmd2*T2_30+lmd2*T2_45+lmd2*T2_60+
          lmd3*T1_10+lmd3*T1_25+lmd3*T1_40+lmd3*T1_55
          +lmd3*T2_10+lmd3*T2_25+lmd3*T2_40+lmd3*T2_55

# Group factors
F1 =~ NA*T1_5+dlt1*T1_5+dlt1*T1_20+dlt1*T1_35+dlt1*T1_50
      +dlt1*T2_5+dlt1*T2_20+dlt1*T2_35+dlt1*T2_50
F2 =~ NA*T1_15+dlt2*T1_15+dlt2*T1_30+dlt2*T1_45+dlt2*T1_60
      +dlt2*T2_15+dlt2*T2_30+dlt2*T2_45+dlt2*T2_60
F3 =~ NA*T1_10+dlt3*T1_10+dlt3*T1_25+dlt3*T1_40+dlt3*T1_55
      +dlt3*T2_10+dlt3*T2_25+dlt3*T2_40+dlt3*T2_55

# Occasion factors
OCC1 =~ NA*T1_5+sgm1*T1_5+sgm1*T1_20+sgm1*T1_35+sgm1*T1_50
        +sgm2*T1_15+sgm2*T1_30+sgm2*T1_45+sgm2*T1_60
```

```

+sgm3*T1_10+sgm3*T1_25+sgm3*T1_40+sgm3*T1_55
OCC2 =~ NA*T2_5+sgm1*T2_5+sgm1*T2_20+sgm1*T2_35+sgm1*T2_50
+sgm2*T2_15+sgm2*T2_30+sgm2*T2_45+sgm2*T2_60
+sgm3*T2_10+sgm3*T2_25+sgm3*T2_40+sgm3*T2_55
# Item factors
ITEM1 =~ 1*T1_5 + 1*T2_5
ITEM2 =~ 1*T1_20 + 1*T2_20
ITEM3 =~ 1*T1_35 + 1*T2_35
ITEM4 =~ 1*T1_50 + 1*T2_50
ITEM5 =~ 1*T1_10 + 1*T2_10
ITEM6 =~ 1*T1_25 + 1*T2_25
ITEM7 =~ 1*T1_40 + 1*T2_40
ITEM8 =~ 1*T1_55 + 1*T2_55
ITEM9 =~ 1*T1_15 + 1*T2_15
ITEM10 =~ 1*T1_30 + 1*T2_30
ITEM11 =~ 1*T1_45 + 1*T2_45
ITEM12 =~ 1*T1_60 + 1*T2_60

# General, group, and occasion variances
general~~1*general
F1~~1*F1
F2~~1*F2
F3~~1*F3
OCC1~~1*OCC1
OCC2~~1*OCC2

## p x i interaction variance
ITEM1 ~~ S_pi1*ITEM1
ITEM2 ~~ S_pi1*ITEM2
ITEM3 ~~ S_pi1*ITEM3
ITEM4 ~~ S_pi1*ITEM4
ITEM5 ~~ S_pi3*ITEM5
ITEM6 ~~ S_pi3*ITEM6
ITEM7 ~~ S_pi3*ITEM7
ITEM8 ~~ S_pi3*ITEM8
ITEM9 ~~ S_pi2*ITEM9
ITEM10 ~~ S_pi2*ITEM10
ITEM11 ~~ S_pi2*ITEM11
ITEM12 ~~ S_pi2*ITEM12

## p x i x o interaction variance (+ error)
T1_5~~e_var1*T1_5
T1_20~~e_var1*T1_20
T1_35~~e_var1*T1_35
T1_50~~e_var1*T1_50
T1_10~~e_var3*T1_10
T1_25~~e_var3*T1_25
T1_40~~e_var3*T1_40
T1_55~~e_var3*T1_55
T1_15~~e_var2*T1_15

```

```

T1_30~~e_var2*T1_30
T1_45~~e_var2*T1_45
T1_60~~e_var2*T1_60
T2_5~~e_var1*T2_5
T2_20~~e_var1*T2_20
T2_35~~e_var1*T2_35
T2_50~~e_var1*T2_50
T2_10~~e_var3*T2_10
T2_25~~e_var3*T2_25
T2_40~~e_var3*T2_40
T2_55~~e_var3*T2_55
T2_15~~e_var2*T2_15
T2_30~~e_var2*T2_30
T2_45~~e_var2*T2_45
T2_60~~e_var2*T2_60

```

```

## Factor mean
general ~ Mu*1
F1 ~ Mu1*1
F2 ~ Mu2*1
F3 ~ Mu3*1
OCC1 ~ mu_o1*1
OCC2 ~ 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

```

```

## Residual
T1_5 ~ mu11*1
T1_20 ~ mu12*1
T1_35 ~ mu13*1
T1_50 ~ mu14*1
T1_10 ~ mu15*1
T1_25 ~ mu16*1
T1_40 ~ mu17*1
T1_55 ~ mu18*1
T1_15 ~ mu19*1
T1_30 ~ mu110*1
T1_45 ~ mu111*1
T1_60 ~ mu112*1

```

```

T2_5 ~ mu21*1
T2_20 ~ mu22*1
T2_35 ~ mu23*1
T2_50 ~ mu24*1
T2_10 ~ mu25*1
T2_25 ~ mu26*1
T2_40 ~ mu27*1
T2_55 ~ mu28*1
T2_15 ~ mu29*1
T2_30 ~ mu210*1
T2_45 ~ mu211*1
T2_60 ~ mu212*1

## Effects coding identification constraints for model mean structure
mu212 == -1*(mu11 + mu12 + mu13 + mu14 +mu21 + mu22 + mu23 +mu24+
            mu15 + mu16 + mu17 + mu18 +mu25 + mu26 + mu27 + mu28 +
            mu19 + mu110 + mu111 + mu112+ mu29 + mu210 + mu211)

mu24 == -1*(mu11 + mu12 + mu13 + mu14 +mu21 + mu22 + mu23)
mu28 == -1*(mu15 + mu16 + mu17 + mu18 +mu25 + mu26 + mu27)
mu212 == -1*(mu19 + mu110 + mu111 + mu112+ mu29 + mu210 + mu211)

mu14 == -1*(mu11 + mu12 + mu13)
mu18 == -1*(mu15 + mu16 + mu17)
mu112 == -1*(mu19 + mu110 + mu111)
mu24 == -1*(mu21 + mu22 + mu23)
mu28 == -1*(mu25 + mu26 + mu27)
mu212 == -1*(mu29 + mu210 + mu211)

mu112 == -1*(mu11 + mu12 + mu13+mu14+ mu15 +
mu16 + mu17+mu18 +mu19 + mu110 + mu111)
mu212 == -1*(mu21 + mu22 + mu23+mu24+ mu25 +
mu26 + mu27+mu28 +mu29 + mu210 + mu211)

mu21 == -1*mu11
mu22 == -1*mu12
mu23 == -1*mu13
mu24 == -1*mu14
mu25 == -1*mu15
mu26 == -1*mu16
mu27 == -1*mu17
mu28 == -1*mu18
mu29 == -1*mu19
mu210 == -1*mu110
mu211 == -1*mu111
mu212 == -1*mu112
mu_i4 == -1*(mu_i1 + mu_i2 + mu_i3)
mu_i8 == -1*(mu_i5 + mu_i6 + mu_i7)
mu_i12 == -1*(mu_i9 + mu_i10 + mu_i11)

```

```

mu_o2 == -1*(mu_o1)

## Item (i) variance
S_i1 := (mu_i1^2 + mu_i2^2 + mu_i3^2 + mu_i4^2) / 3
S_i2 := (mu_i9^2 + mu_i10^2 + mu_i11^2 + mu_i12^2) / 3
S_i3 := (mu_i5^2 + mu_i6^2 + mu_i7^2 + mu_i8^2) / 3

## i x o interaction variance
S_io1:= (mu11^2 + mu12^2 + mu13^2 + mu14^2 + mu21^2 + mu22^2 + mu23^2 + mu24^2)/7
S_io2:= (mu19^2 + mu110^2 + mu111^2 + mu112^2 + mu29^2 + mu210^2 + mu211^2 + mu212^2)/7
S_io3:= (mu15^2 + mu16^2+ mu17^2+ mu18^2+ mu25^2 + mu26^2+ mu27^2+ mu28^2)/7

## Occasion (o) variance
S_o:= (mu_o1^2 + mu_o2^2 ) / 1

```

### 3. Variance Partitioning and Scale Viability

To obtain the results of variance partitioning and scale viability indices for the preceding bifactor model, the following formula code should be used as a model argument for the *lavaan* function. Within the formula code for each design, the number of occasions and items can be adjusted for alternative designs.

#### 3.1 $p \times i \times o$ Design

```

cal<-'
## Specify the number of occasions and items per subscale
occ := 2
item := 4

## G Coefficients and Proportions of Measurement Error

# Composite level
total_var_g:= (lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) +
(S_pi1 + S_pi2 + S_pi3)/item + ((sgm1 + sgm2 + sgm3)^2)/occ + (e_var1 + e_var2 + e_var3)/(item*occ)
G_coef := ((lmd1 + lmd3 + lmd3)^2+ (dlt1^2 + dlt2^2 + dlt3^2))/total_var_g
gen := ((lmd1 + lmd3 + lmd3)^2)/total_var_g
grp := (dlt1^2 + dlt2^2 + dlt3^2)/total_var_g
sfe := ((S_pi1 + S_pi2 + S_pi3)/item)/total_var_g
te := ((sgm1 + sgm2 + sgm3)^2/occ)/total_var_g
rre := ((e_var1 + e_var2 + e_var3)/(item*occ))/total_var_g
toterror:= sfe + te + rre

# Subscale level: Aesthetic Sensitivity
total_var_g1 := dlt1^2 + lmd1^2 + S_pi1/item + sgm1^2/occ + e_var1/(item*occ)
g1 := (dlt1^2+lmd1^2)/total_var_g1

```

```

gen1 := lmd1^2/total_var_g1
grp1 := dlt1^2/total_var_g1
sfe1 := (S_pi1/item)/total_var_g1
te1 := (sgm1^2/occ)/total_var_g1
rre1 := (e_var1/(item*occ))/total_var_g1
totale1 := sfe1 + te1 + rre1

# Subscale level: Creative Imagination
total_var_g2 := dlt2^2 + lmd2^2 + S_pi2/item + sgm2^2/occ + e_var2/(item*occ)
g2 := (dlt2^2+lmd2^2)/total_var_g2
gen2 := lmd2^2/total_var_g2
grp2 := dlt2^2/total_var_g2
sfe2 := (S_pi2/item)/total_var_g2
te2 := (sgm2^2/occ)/total_var_g2
rre2 := (e_var2/(item*occ))/total_var_g2
totale2 := sfe2 + te2 + rre2

# Subscale level: Intellectual Curiosity
total_var_g3 := dlt3^2 + lmd3^2 + S_pi3/item + sgm3^2/occ + e_var3/(item*occ)
g3 := (dlt3^2+lmd3^2)/total_var_g3
gen3 := lmd3^2/total_var_g3
grp3 := dlt3^2/total_var_g3
sfe3 := (S_pi3/item)/total_var_g3
te3 := (sgm3^2/occ)/total_var_g3
rre3 := (e_var3/(item*occ))/total_var_g3
totale3 := sfe3 + te3 + rre3

## Global D Coefficients and Proportions of Measurement Error

# Composite level
total_var_d:= total_var_g + (S_i1 + S_i2 + S_i3)/item + 3*S_o/occ + (S_io1 + S_io2 + S_io3)/(item*occ)
D_coef := ((lmd1 + lmd2 + lmd3)^2+ (dlt1^2 + dlt2^2 + dlt3^2))/total_var_d
gen_d := ((lmd1 + lmd2 + lmd3)^2)/total_var_d
grp_d := (dlt1^2 + dlt2^2 + dlt3^2)/total_var_d
sfe_d := ((S_pi1 + S_pi2 + S_pi3)/item)/total_var_d
te_d := ((sgm1 + sgm2 + sgm3)^2/occ)/total_var_d
rre_d := ((e_var1 + e_var2 + e_var3)/(item*occ))/total_var_d
i_d := ((S_i1 + S_i2 + S_i3)/item)/total_var_d
o_d:= (3*S_o/occ)/total_var_d
io_d := ((S_io1 + S_io2 + S_io3)/(item*occ))/total_var_d

# Subscale level: Aesthetic Sensitivity
total_var_d1 := total_var_g1 + S_i1/item + S_o/occ + S_io1/(item*occ)
d1 := (dlt1^2+lmd1^2)/total_var_d1
gen1_d := lmd1^2/total_var_d1
grp1_d := dlt1^2/total_var_d1
sfe1_d := (S_pi1/item)/total_var_d1
te1_d := (sgm1^2/occ)/total_var_d1
rre1_d := (e_var1/(item*occ))/total_var_d1

```

```

i_1_d := (S_i1/item)/total_var_d1
o_1_d := (S_o/occ)/total_var_d1
io_1_d := (S_io1/(item*occ))/total_var_d1

# Subscale level: Creative Imagination
total_var_d2 := total_var_g2 + S_i2/item + S_o/occ + S_io2/(item*occ)
d2 := (dlt2^2+lmd2^2)/total_var_d2
gen2_d := lmd2^2/total_var_d2
grp2_d := dlt2^2/total_var_d2
sfe2_d := (S_pi2/item)/total_var_d2
te2_d := (sgm2^2/occ)/total_var_d2
rre2_d := (e_var2/(item*occ))/total_var_d2
i_2_d := (S_i2/item)/total_var_d2
o_2_d := (S_o/occ)/total_var_d2
io_2_d := (S_io2/(item*occ))/total_var_d2

# Subscale level: Intellectual Curiosity
total_var_d3 := total_var_g3 + S_i3/item + S_o/occ + S_io3/(item*occ)
d3 := (dlt3^2+lmd3^2)/total_var_d3
gen3_d := lmd3^2/total_var_d3
grp3_d := dlt3^2/total_var_d3
sfe3_d := (S_pi3/item)/total_var_d3
te3_d := (sgm3^2/occ)/total_var_d3
rre3_d := (e_var3/(item*occ))/total_var_d3
i_3_d := (S_i3/item)/total_var_d3
o_3_d := (S_o/occ)/total_var_d3
io_3_d := (S_io3/(item*occ))/total_var_d3

## Common and Unique Explained Variance Ratios

# Composite level
ECV:= (lmd1 + lmd2 + lmd3)^2/((lmd1 + lmd2 + lmd3)^2 +dlt1^2 +dlt2^2 +dlt3^2)
EUV:= (dlt1^2 + dlt2^2 + dlt3^2)/(dlt1^2 + dlt2^2 + dlt3^2+(lmd1 + lmd2 + lmd3)^2)
ECV_div_EUV := ECV/EUV

# Subscale level: Aesthetic Sensitivity
ECV1 :=lmd1^2/(dlt1^2+lmd1^2)
EUV1 := dlt1^2/(dlt1^2+lmd1^2)
ECV_div_EUV1 := ECV1/EUV1

# Subscale level: Creative Imagination
ECV2 :=lmd2^2/(dlt2^2+lmd2^2)
EUV2 := dlt2^2/(dlt2^2+lmd2^2)
ECV_div_EUV2 := ECV2/EUV2

# Subscale level: Intellectual Curiosity
ECV3 :=lmd3^2/(dlt3^2+lmd3^2)
EUV3 := dlt3^2/(dlt3^2+lmd3^2)

```



```

ECV_div_EUV3 := ECV3/EUV3

## Subscale Value-Added Ratios
Var.X1 :=(gen_var1*item^2 + grp_var1*item^2 + po_var1*item^2/occ+
pi_var1*item + pio_var1*item/occ)*g1
Var.X2 :=(gen_var2*item^2 + grp_var2*item^2 + po_var2*item^2/occ+
pi_var2*item + pio_var2*item/occ)*g2
Var.X3 :=(gen_var3*item^2 + grp_var3*item^2 + po_var3*item^2/occ+
pi_var3*item + pio_var3*item/occ)*g3
Var.Z :=(9*gen_var*item^2 + 9*grp_var*item^2 + 9*po_var*item^2/occ+
9*pi_var*item + 9*pio_var*item/occ)*G_coef
prmse1 := (G_coef*(Var.X1+(0.350824883+(0.022494348+0.025949365)/occ+0.316268
17)*item^2)^2)/(Var.X1*Var.Z)
prmse2 := (G_coef*(Var.X2+(0.31626817+(0.025949365+0.04450095)/occ+0.305734)*
item^2)^2)/(Var.X2*Var.Z)
prmse3 := (G_coef*(Var.X3+(0.350824883+(0.022494348+0.04450095)/occ+0.305734)
*item^2)^2)/(Var.X3*Var.Z)
var1 := g1/prmse1
var2 := g2/prmse2
var3 := g3/prmse3'
Results <- lavaan(model = c(model, cal), orthogonal = "TRUE",
data =bfi2_open, estimator= "ULS")

monte<-monteCarloCI(Results, level=0.95)
monte

## G Coefficients and Proportions of Measurement Error
##
##          est ci.lower ci.upper
## total_var_g    3.880    3.833    3.940
## G_coef         0.849    0.834    0.864
## gen            0.750    0.730    0.766
## grp            0.100    0.090    0.113
## sfe            0.073    0.067    0.079
## te             0.040    0.027    0.056
## rre            0.037    0.033    0.040
## toterror       0.151    0.136    0.166
## total_var_g1   0.785    0.769    0.803
## g1             0.779    0.758    0.796
## gen1           0.453    0.413    0.492
## grp1           0.326    0.288    0.363
## sfe1           0.139    0.121    0.156
## te1            0.013    0.003    0.031
## rre1           0.069    0.059    0.080
## totale1        0.221    0.204    0.242
## total_var_g2   0.546    0.530    0.565
## g2             0.716    0.677    0.751
## gen2           0.503    0.461    0.543
## grp2           0.213    0.166    0.263
## sfe2           0.150    0.124    0.176

```

```

## te2          0.051    0.024    0.086
## rre2          0.083    0.066    0.099
## totale2       0.284    0.249    0.323
## total_var_g3  0.511    0.499    0.541
## g3            0.701    0.667    0.735
## gen3          0.671    0.597    0.714
## grp3          0.030    0.000    0.115
## sfe3          0.182    0.152    0.208
## te3           0.032    0.011    0.063
## rre3          0.085    0.067    0.101
## totale3       0.299    0.265    0.333

## Global D Coefficients and Proportions of Measurement Error
##               est ci.lower ci.upper
## total_var_d    3.930    3.887    4.016
## D_coef         0.839    0.819    0.852
## gen_d          0.740    0.718    0.755
## grp_d          0.099    0.089    0.111
## sfe_d          0.072    0.066    0.078
## te_d           0.040    0.027    0.055
## rre_d          0.036    0.033    0.040
## i_d            0.012    0.010    0.014
## o_d            0.001    0.000    0.016
## io_d           0.000    0.000    0.000
## total_var_d1   0.805    0.789    0.832
## d1             0.759    0.731    0.776
## gen1_d         0.442    0.400    0.478
## grp1_d         0.318    0.279    0.353
## sfe1_d         0.135    0.117    0.152
## te1_d          0.013    0.003    0.030
## rre1_d         0.068    0.057    0.078
## i_1_d          0.023    0.017    0.030
## o_1_d          0.002    0.000    0.025
## io_1_d         0.000    0.000    0.001
## total_var_d2   0.551    0.536    0.578
## d2             0.710    0.663    0.742
## gen2_d         0.498    0.453    0.536
## grp2_d         0.211    0.163    0.260
## sfe2_d         0.149    0.122    0.174
## te2_d          0.050    0.024    0.085
## rre2_d         0.082    0.065    0.098
## i_2_d          0.006    0.003    0.012
## o_2_d          0.003    0.000    0.036
## io_2_d         0.000    0.000    0.001
## total_var_d3   0.536    0.524    0.574
## d3             0.668    0.628    0.701
## gen3_d         0.640    0.565    0.679
## grp3_d         0.029    0.000    0.109
## sfe3_d         0.174    0.144    0.197
## te3_d          0.030    0.010    0.060

```

```
## rre3_d      0.081    0.064    0.096
## i_3_d       0.044    0.033    0.055
## o_3_d       0.003    0.000    0.037
## io_3_d      0.000    0.000    0.001

## Common and Unique Explained Variance Ratios
##           est ci.lower ci.upper
## ECV       0.882    0.867    0.894
## EUV       0.118    0.106    0.133
## ECV_div_EUV 7.509    6.530    8.424
## ECV1      0.582    0.534    0.630
## EUV1      0.418    0.370    0.466
## ECV_div_EUV1 1.391    1.144    1.700
## ECV2      0.702    0.641    0.762
## EUV2      0.298    0.238    0.359
## ECV_div_EUV2 2.357    1.785    3.204
## ECV3      0.957    0.840    1.000
## EUV3      0.043    0.000    0.160
## ECV_div_EUV3 22.170    5.233 2105.898

## Subscale Value-Added Ratios
##           est ci.lower ci.upper
## prmse1     0.715    0.715    0.717
## prmse2     0.724    0.716    0.735
## prmse3     0.790    0.779    0.804
## var1       1.088    1.057    1.114
## var2       0.989    0.921    1.048
## var3       0.887    0.829    0.944
```

### 3.2 Restricted $p \times i$ Design

```
cal_res_pi <- '
## Specify the number of items per subscale
item := 4

## G Coefficients, Global D Coefficients, and Proportions of Measurement Error
# Composite level
total_var_gi := (lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) +
(S_pi1 + S_pi2 + S_pi3)/item + ((sgm1 + sgm2 + sgm3)^2) + (e_var1 + e_var2 +
e_var3)/item
gcoef_pi := ((lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) + ((sgm1 + s
gm2 + sgm3)^2))/total_var_gi
gen_pi := ((lmd1 + lmd2 + lmd3)^2 + ((sgm1 + sgm2 + sgm3)^2))/total_var_gi
grp_pi := (((sgm1 + sgm2 + sgm3)^2))/total_var_gi
err_pi := ((S_pi1 + S_pi2 + S_pi3)/item + (e_var1 + e_var2 + e_var3)/item)/total_var_gi
total_var_di := total_var_gi + (S_i1 + S_i2 + S_i3)/item + (S_io1 + S_io2 + S
```

```

_io3)/item
dcoef_pi := ((lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) + ((sgm1 + sgm2 + sgm3)^2))/total_var_di

# Subscale level: Aesthetic Sensitivity
gcoef_pi_s1 := (lmd1^2 + dlt1^2 + sgm1^2)/(lmd1^2 + dlt1^2 + sgm1^2 + S_pi1/item + e_var1/item)
gen_pi_s1 := lmd1^2 / (lmd1^2 + dlt1^2 + sgm1^2 + S_pi1/item + e_var1/item)
grp_pi_s1 := dlt1^2 / (lmd1^2 + dlt1^2 + sgm1^2 + S_pi1/item + e_var1/item)
err_pi_s1 := (S_pi1/item + e_var1/item)/(lmd1^2 + dlt1^2 + sgm1^2 + S_pi1/item + e_var1/item)
dcoef_pi_s1 := (lmd1^2 + dlt1^2 + sgm1^2)/(lmd1^2 + dlt1^2 + sgm1^2 + (S_pi1 + e_var1 + S_i1 + S_io1)/item)

# Subscale level: Creative Imagination
gcoef_pi_s2 := (lmd2^2 + dlt2^2 + sgm2^2)/(lmd2^2 + dlt2^2 + sgm2^2 + S_pi2/item + e_var2/item)
gen_pi_s2 := lmd2^2 / (lmd2^2 + dlt2^2 + sgm2^2 + S_pi2/item + e_var2/item)
grp_pi_s2 := dlt2^2 / (lmd2^2 + dlt2^2 + sgm2^2 + S_pi2/item + e_var2/item)
err_pi_s2 := (S_pi2/item + e_var2/item)/(lmd2^2 + dlt2^2 + sgm2^2 + S_pi2/item + e_var2/item)
dcoef_pi_s2 := (lmd2^2 + dlt2^2 + sgm2^2)/(lmd2^2 + dlt2^2 + sgm2^2 + (S_pi2 + e_var2 + S_i2 + S_io2)/item)

# Subscale level: Intellectual Curiosity
gcoef_pi_s3 := (lmd3^2 + dlt3^2 + sgm3^2)/(lmd3^2 + dlt3^2 + sgm3^2 + S_pi3/item + e_var3/item)
gen_pi_s3 := lmd3^2 / (lmd3^2 + dlt3^2 + sgm3^2 + S_pi3/item + e_var3/item)
grp_pi_s3 := dlt3^2 / (lmd3^2 + dlt3^2 + sgm3^2 + S_pi3/item + e_var3/item)
err_pi_s3 := (S_pi3/item + e_var3/item)/(lmd3^2 + dlt3^2 + sgm3^2 + S_pi3/item + e_var3/item)
dcoef_pi_s3 := (lmd3^2 + dlt3^2 + sgm3^2)/(lmd3^2 + dlt3^2 + sgm3^2 + (S_pi3 + e_var3 + S_i3 + S_io3)/item)

## Common and Unique Explained Variance Ratios
# Composite level
ECV_pi := (lmd1 + lmd2 + lmd3)^2/((lmd1 + lmd2 + lmd3)^2 + dlt1^2 + dlt2^2 + dlt3^2)
EUV_pi := (dlt1^2 + dlt2^2 + dlt3^2)/((lmd1 + lmd2 + lmd3)^2 + dlt1^2 + dlt2^2 + dlt3^2)
ECV_div_EUV_pi := ECV_pi/EUV_pi

# Subscale level: Aesthetic Sensitivity
ECV_pi_s1 := lmd1^2/(lmd1^2 + dlt1^2)
EUV_pi_s1 := dlt1^2/(lmd1^2 + dlt1^2)
ECV_div_EUV_pi_s1 := ECV_pi_s1/EUV_pi_s1

# Subscale level: Creative Imagination
ECV_pi_s2 := lmd2^2 / (lmd2^2 + dlt2^2)

```

```

EUV_pi_s2 := dlt2^2 / (lmd2^2+dlt2^2)
ECV_div_EUV_pi_s2 := ECV_pi_s2/EUV_pi_s2

# Subscale level: Intellectual Curiosity
ECV_pi_s3 := lmd3^2/(lmd3^2+dlt3^2)
EUV_pi_s3 := dlt3^2/(lmd3^2+dlt3^2)
ECV_div_EUV_pi_s3 := ECV_pi_s3/EUV_pi_s3

## Subscale value-added ratios
Var.X1 :=(lmd1^2*item^2 + dlt1^2*item^2 + (sgm1^2*item^2)/occ+
S_pi1*item + e_var1*item/occ)*gcoef_pi_s1
Var.X2 :=(lmd2^2*item^2 + dlt2^2*item^2 + (sgm2^2*item^2)/occ+
S_pi2*item + e_var2*item/occ)*gcoef_pi_s2
Var.X3 :=(lmd3^2*item^2 + dlt3^2*item^2 + (sgm3^2*item^2)/occ+
S_pi3*item + e_var3*item/occ)*gcoef_pi_s3
Var.Z :=(((lmd1 + lmd2 + lmd3)^2)*item^2 + (dlt1^2 + dlt2^2 + dlt3^2)*item^2
+(S_pi1 + S_pi2 + S_pi3)*item + (((sgm1 + sgm2 + sgm3)^2)*item^2)/occ + (e_va
r1 + e_var2 + e_var3)*item/occ)*gcoef_pi
prmse1 := (gcoef_pi*(Var.X1+(0.350824883+(0.022494348+0.025949365)/occ+0.3162
6817)*item^2)^2)/(Var.X1*Var.Z)
prmse2 := (gcoef_pi*(Var.X2+(0.31626817+(0.025949365+0.04450095)/occ+0.30573
4)*item^2)^2)/(Var.X2*Var.Z)
prmse3 := (gcoef_pi*(Var.X3+(0.350824883+(0.022494348+0.04450095)/occ+0.30573
4)*item^2)^2)/(Var.X3*Var.Z)
var1 := gcoef_pi_s1/prmse1
var2 := gcoef_pi_s2/prmse2
var3 := gcoef_pi_s3/prmse3'

Results <- lavaan(model = c(model, cal_res_pi), orthogonal = "TRUE",
data =bfi2_open, estimator= "ULS")

monte<-monteCarloCI(Results, level=0.95)
monte

## G Coefficients, Global D Coefficients, and Proportions of Measurement Error
###
##          est      ci.lower ci.upper
## total_var_gi      4.180      4.117      4.265
## total_var_di      4.226      4.164      4.313
## gcoef_pi          0.864      0.859      0.869
## gen_pi            0.771      0.759      0.781
## grp_pi            0.075      0.052      0.102
## err_pi            0.136      0.131      0.141
## dcoef_pi          0.854      0.849      0.860
## gcoef_pi_s1        0.744      0.730      0.759
## gen_pi_s1          0.418      0.379      0.456
## grp_pi_s1          0.301      0.266      0.335
## err_pi_s1          0.256      0.241      0.270
## dcoef_pi_s1        0.728      0.713      0.743
## gcoef_pi_s2        0.722      0.700      0.745

```

```

## gen_pi_s2      0.444    0.402    0.482
## grp_pi_s2      0.188    0.145    0.234
## err_pi_s2      0.278    0.255    0.300
## dcoef_pi_s2    0.717    0.695    0.740
## gcoef_pi_s3    0.685    0.665    0.713
## gen_pi_s3      0.601    0.531    0.646
## grp_pi_s3      0.027    0.000    0.104
## err_pi_s3      0.315    0.287    0.335
## dcoef_pi_s3    0.657    0.637    0.686

## Common and Unique Explained Variance Ratios
##               est ci.lower ci.upper
## ECV_pi        0.882    0.867    0.894
## EUV_pi        0.118    0.106    0.133
## ECV_div_EUV_pi 7.509    6.532    8.421
## ECV_pi_s1     0.582    0.533    0.630
## EUV_pi_s1     0.418    0.370    0.467
## ECV_div_EUV_pi_s1 1.391    1.143    1.701
## ECV_pi_s2     0.702    0.641    0.762
## EUV_pi_s2     0.298    0.238    0.359
## ECV_div_EUV_pi_s2 2.357    1.784    3.202
## ECV_pi_s3     0.957    0.839    1.000
## EUV_pi_s3     0.043    0.000    0.161
## ECV_div_EUV_pi_s3 22.170    5.218 2050.789

## Subscale Value-Added Ratios
## prmse1        0.687    0.673    0.699
## prmse2        0.695    0.676    0.711
## prmse3        0.760    0.731    0.778
## var1          1.082    1.052    1.119
## var2          1.038    0.991    1.095
## var3          0.901    0.859    0.971

```

### 3.3 Restricted $p \times o$ Design

```
cal_res_po<-'
## Specify the number of occasions per subscale
occ := 2

## G Coefficients, Global D Coefficients, and Proportions of Measurement Error
# Composite level
total_var_go:= (lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) +
(S_pi1 + S_pi2 + S_pi3)/item + ((sgm1 + sgm2 + sgm3)^2)/occ +
(e_var1 + e_var2 + e_var3)/(occ*item)
total_var_do:= total_var_go + 3*S_o/occ + (S_io1 + S_io2 + S_io3)/(occ*item)
gcoef_po := ((lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) +
(S_pi1 + S_pi2 + S_pi3)/item)/total_var_go
gen_po := ((lmd1 + lmd2 + lmd3)^2 + ((sgm1 + sgm2 + sgm3)^2))/total_var_go
grp_po := (((sgm1 + sgm2 + sgm3)^2))/total_var_go
err_po := (((sgm1 + sgm2 + sgm3)^2)/occ + (e_var1 + e_var2 + e_var3)/(occ*ite
m))/total_var_go
dcoef_po := ((lmd1 + lmd2 + lmd3)^2 + (dlt1^2 + dlt2^2 + dlt3^2) + ((sgm1 + s
gm2 + sgm3)^2))/total_var_do

# Subscale level: Aesthetic Sensitivity
gcoef_po_s1 := (lmd1^2 + dlt1^2 + S_pi1/item)/(lmd1^2 + dlt1^2 + (sgm1^2)/occ
+ S_pi1/item + e_var1/(item*occ))
gen_po_s1 := lmd1^2 /(lmd1^2 + dlt1^2 + (sgm1^2)/occ + S_pi1/item + e_var1/(i
tem*occ))
grp_po_s1 := dlt1^2 /(lmd1^2 + dlt1^2 + (sgm1^2)/occ + S_pi1/item + e_var1/(i
tem*occ))
err_po_s1 := ((sgm1^2)/occ + e_var1/(item*occ))/(lmd1^2 + dlt1^2 + (sgm1^2)/o
cc + S_pi1/item + e_var1/(item*occ))
dcoef_po_s1 := (lmd1^2 + dlt1^2 + (sgm1^2)/occ)/(lmd1^2 + dlt1^2 + (sgm1^2)/o
cc + S_pi1/item + e_var1/(item*occ) + S_o/occ + S_io1/(item*occ))

# Subscale level: Creative Imagination
gcoef_po_s2 := (lmd2^2 + dlt2^2 + S_pi2/item)/(lmd2^2 + dlt2^2 + (sgm2^2)/occ
+ S_pi2/item + e_var2/(item*occ))
gen_po_s2 := (lmd2^2) /(lmd2^2 + dlt2^2 + (sgm2^2)/occ + S_pi2/item + e_var2/
(item*occ))
grp_po_s2 := (dlt2^2) /(lmd2^2 + dlt2^2 + (sgm2^2)/occ + S_pi2/item + e_var2/
(item*occ))
err_po_s2 := ((sgm2^2)/occ + e_var2/(item*occ))/(lmd2^2 + dlt2^2 + (sgm2^2)/o
cc + S_pi2/item + e_var2/(item*occ))
dcoef_po_s2 := (lmd2^2 + dlt2^2 + (sgm2^2)/occ)/(lmd2^2 + dlt2^2 + (sgm2^2)/o
cc + S_pi2/item + e_var2/(item*occ) + S_o/occ + S_io2/(item*occ))

# Subscale level: Intellectual Curiosity
gcoef_po_s3 := (lmd3^2 + dlt3^2 + S_pi3/item)/(lmd3^2 + dlt3^2 + (sgm3^2)/occ
+ S_pi3/item + e_var3/(item*occ))
```

```

gen_po_s3 := (lmd3^2) / (lmd3^2 + dlt3^2 + (sgm3^2)/occ + S_pi3/item + e_var3/
(item*occ))
grp_po_s3 := (dlt3^2) / (lmd3^2 + dlt3^2 + (sgm3^2)/occ + S_pi3/item + e_var3/
(item*occ))
err_po_s3 := ((sgm3^2)/occ + e_var3/(item*occ)) / (lmd3^2 + dlt3^2 + (sgm3^2)/o
cc + S_pi3/item + e_var3/(item*occ))
dcoef_po_s3 := (lmd3^2 + dlt3^2 + (sgm3^2)/occ) / (lmd3^2 + dlt3^2 + (sgm3^2)/o
cc + S_pi3/item + e_var3/(item*occ) + S_o/occ + S_io3/(item*occ))

## Common and Unique Explained Variance Ratios
ECV_po := (lmd1 + lmd2 + lmd3)^2 / ((lmd1 + lmd2 + lmd3)^2 + dlt1^2 + dlt2^2 + dlt3^2)
EUV_po := (dlt1^2 + dlt2^2 + dlt3^2) / ((lmd1 + lmd2 + lmd3)^2 + dlt1^2 + dlt2^2 + dlt3^2)
ECV_div_EUV_po := ECV_po / EUV_po
ECV_po_s1 := lmd1^2 / (lmd1^2 + dlt1^2)
EUV_po_s1 := dlt1^2 / (lmd1^2 + dlt1^2)
ECV_div_EUV_po_s1 := ECV_po_s1 / EUV_po_s1
ECV_po_s2 := (lmd2^2) / (lmd2^2 + dlt2^2)
EUV_po_s2 := (dlt2^2) / (lmd2^2 + dlt2^2)
ECV_div_EUV_po_s2 := (ECV_po_s2) / (EUV_po_s2)
ECV_po_s3 := (lmd3^2) / (lmd3^2 + dlt3^2)
EUV_po_s3 := (dlt3^2) / (lmd3^2 + dlt3^2)
ECV_div_EUV_po_s3 := (ECV_po_s3) / (EUV_po_s3)

## Subscale Value-Added ratios
Var.X1 := (lmd1^2*item^2 + dlt1^2*item^2 + (sgm1^2*item^2)/occ +
S_pi1*item + e_var1*item/occ)*gcoef_po_s1
Var.X2 := (lmd2^2*item^2 + dlt2^2*item^2 + (sgm2^2*item^2)/occ +
S_pi2*item + e_var2*item/occ)*gcoef_po_s2
Var.X3 := (lmd3^2*item^2 + dlt3^2*item^2 + (sgm3^2*item^2)/occ +
S_pi3*item + e_var3*item/occ)*gcoef_po_s3
Var.Z := ((lmd1 + lmd2 + lmd3)^2*item^2 + (dlt1^2 + dlt2^2 + dlt3^2)*item^2
+(S_pi1 + S_pi2 + S_pi3)*item + (((sgm1 + sgm2 + sgm3)^2)*item^2)/occ +
(e_var1 + e_var2 + e_var3)*item/occ)*gcoef_po
prmse1 := (gcoef_po*((Var.X1+(0.350824883+(0.022494348+0.025949365)/
occ+0.31626817)*item^2)^2))/(Var.X1*Var.Z)
prmse2 := (gcoef_po*((Var.X2+(0.31626817+(0.025949365+0.04450095)/
occ+0.305734)*item^2)^2))/(Var.X2*Var.Z)
prmse3 := (gcoef_po*((Var.X3+(0.350824883+(0.022494348+0.04450095)/
occ+0.305734)*item^2)^2))/(Var.X3*Var.Z)
var1 := gcoef_po_s1/ prmse1
var2 := gcoef_po_s2/ prmse2
var3 := gcoef_po_s3/ prmse3
'

Results <- lavaan(model = c(model, cal_res_po), orthogonal = "TRUE",
data = bfi2_open, estimator = "ULS")

```



```
monte<-monteCarloCI(Results, level=0.95)
monte
```

### ## G Coefficients, Global D Coefficients, and Proportions of Measurement Error

##	est	ci.lower	ci.upper
## total_var_go	3.880	3.833	3.940
## total_var_do	3.885	3.841	3.969
## gcoef_po	0.923	0.908	0.935
## gen_po	0.831	0.813	0.848
## grp_po	0.081	0.055	0.112
## err_po	0.077	0.065	0.092
## dcoef_po	0.929	0.910	0.945
## gcoef_po_s1	0.917	0.901	0.930
## gen_po_s1	0.453	0.413	0.492
## grp_po_s1	0.326	0.288	0.363
## err_po_s1	0.083	0.070	0.099
## dcoef_po_s1	0.790	0.768	0.803
## gcoef_po_s2	0.866	0.835	0.891
## gen_po_s2	0.503	0.461	0.543
## grp_po_s2	0.213	0.166	0.263
## err_po_s2	0.134	0.109	0.165
## dcoef_po_s2	0.765	0.733	0.783
## gcoef_po_s3	0.883	0.855	0.906
## gen_po_s3	0.671	0.597	0.714
## grp_po_s3	0.030	0.000	0.115
## err_po_s3	0.117	0.094	0.145
## dcoef_po_s3	0.731	0.700	0.754

### ## Common and Unique Explained Variance Ratios

##	est	ci.lower	ci.upper
## ECV_po	0.882	0.867	0.894
## EUV_po	0.118	0.106	0.133
## ECV_div_EUV_po	7.509	6.536	8.422
## ECV_po_s1	0.582	0.534	0.629
## EUV_po_s1	0.418	0.371	0.466
## ECV_div_EUV_po_s1	1.391	1.144	1.701
## ECV_po_s2	0.702	0.641	0.762
## EUV_po_s2	0.298	0.238	0.359
## ECV_div_EUV_po_s2	2.357	1.786	3.203
## ECV_po_s3	0.957	0.840	1.000
## EUV_po_s3	0.043	0.000	0.160
## ECV_div_EUV_po_s3	22.170	5.265	2027.910

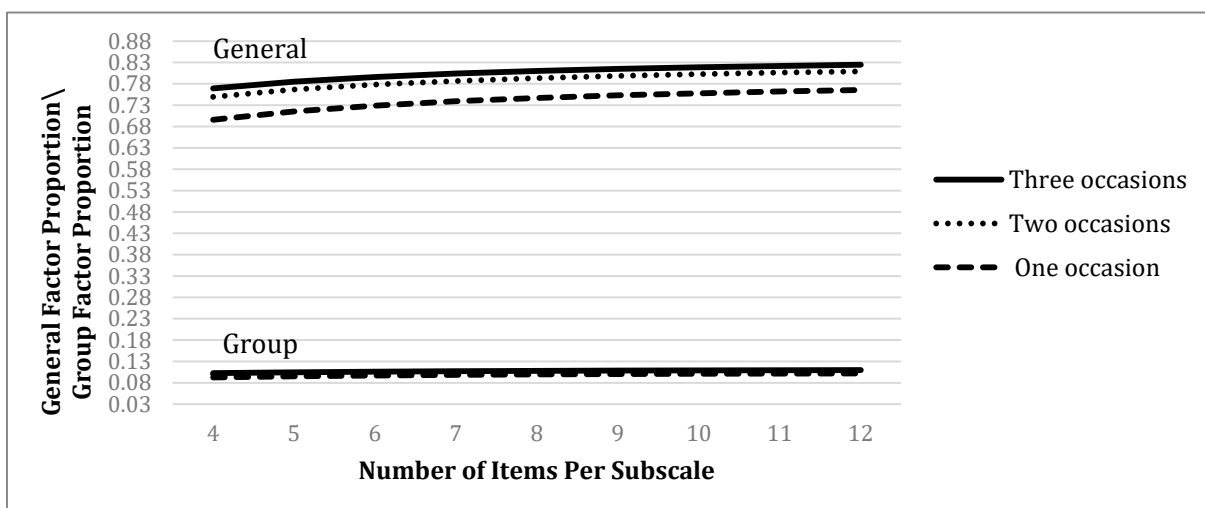
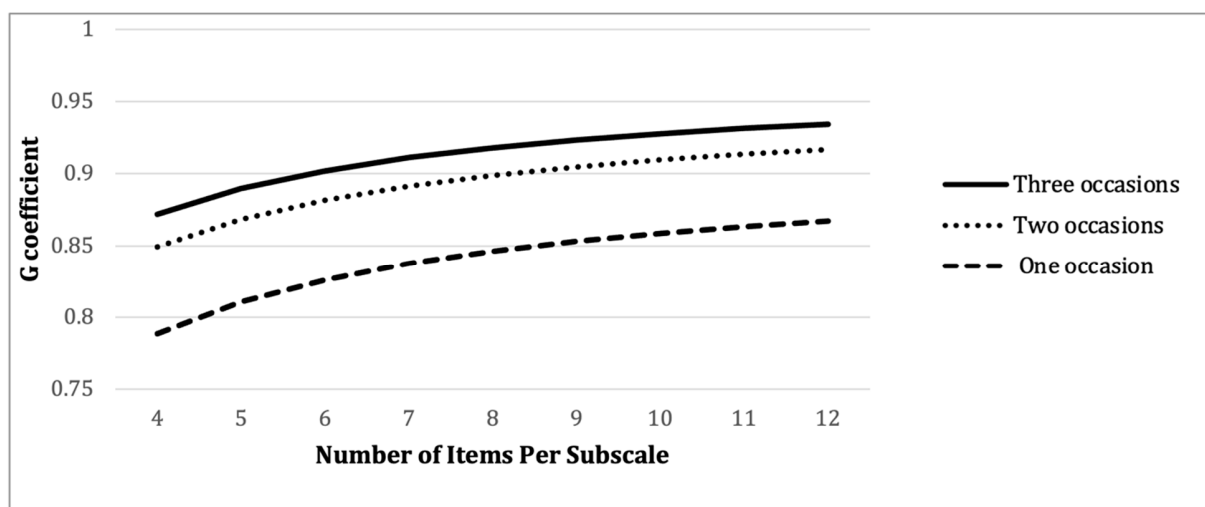
### ## Subscale Value-Added Ratios

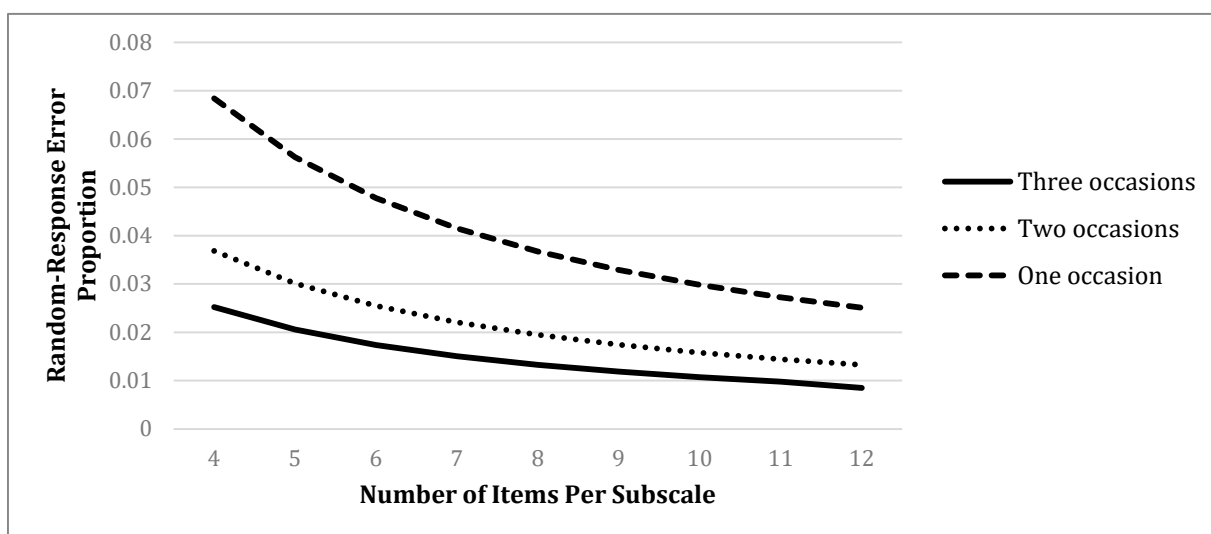
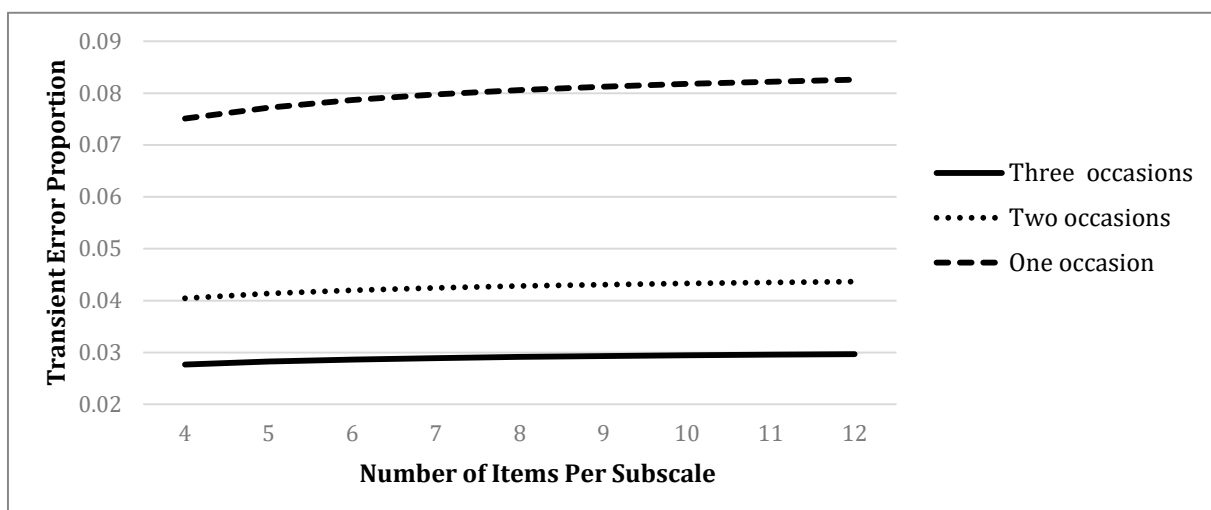
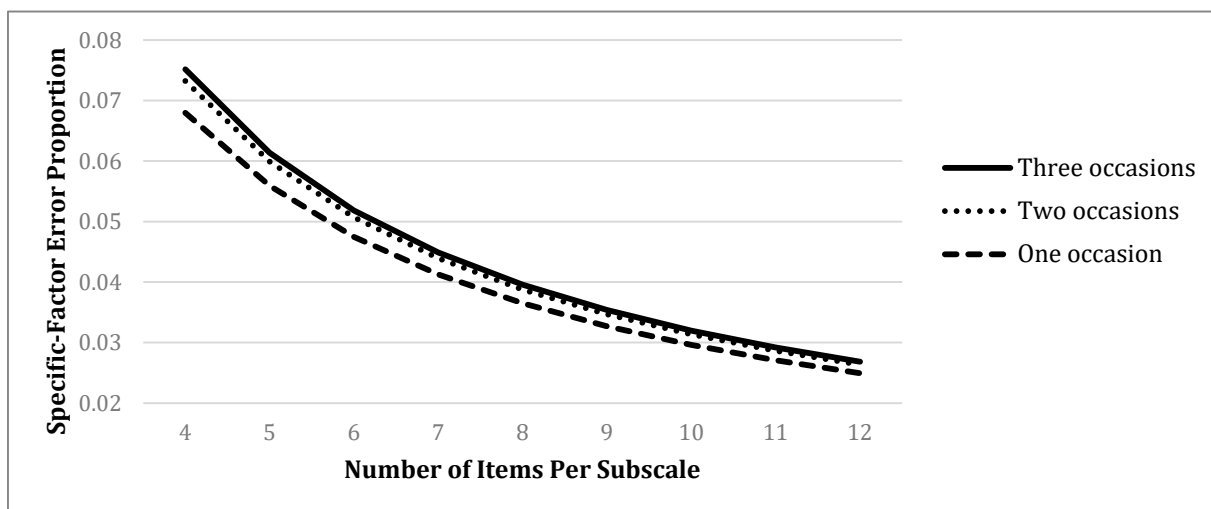
##	est	ci.lower	ci.upper
## prmse1	0.713	0.702	0.722
## prmse2	0.696	0.683	0.707
## prmse3	0.744	0.726	0.756

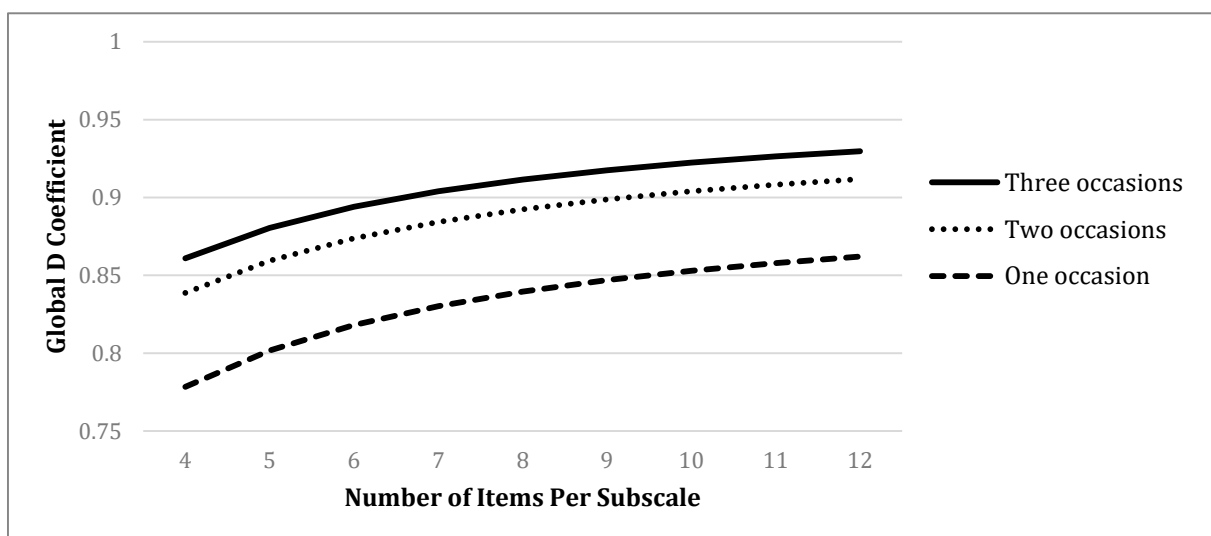
## var1	1.287	1.259	1.314
## var2	1.245	1.190	1.296
## var3	1.187	1.139	1.239

## 4. Prophecy Graphs for BFI-2 Open-mindedness Composite and Subscale Scores

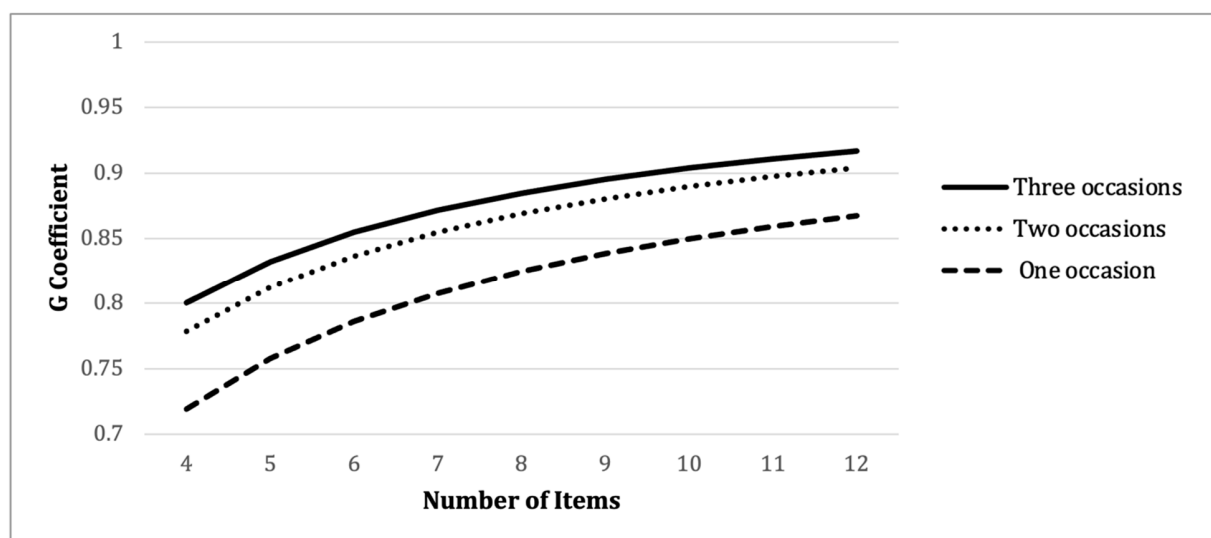
Figure S4.1 Prophecy graphs for Composite Score: Open-mindedness

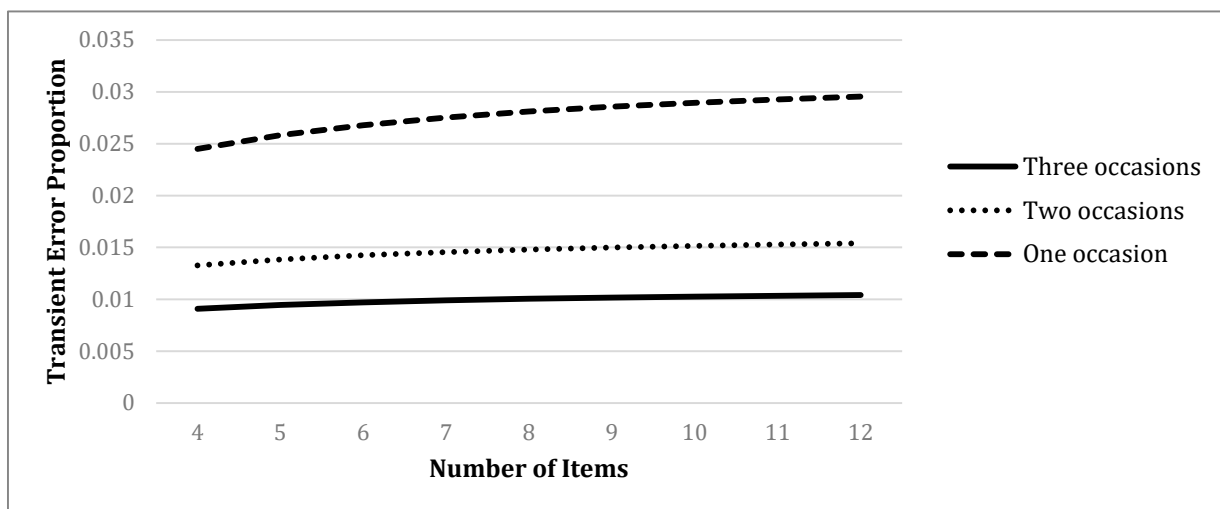
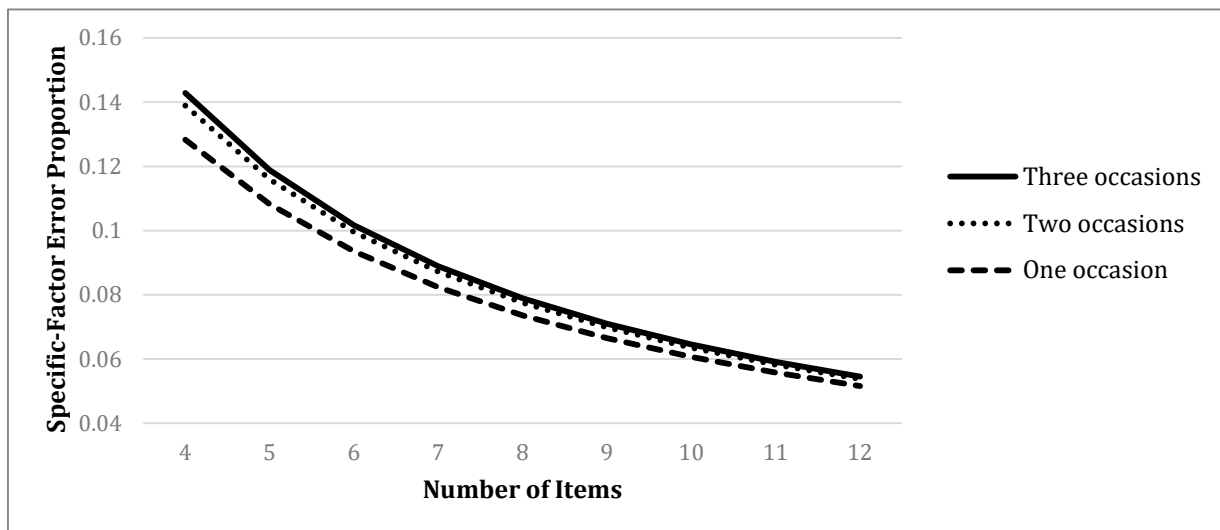
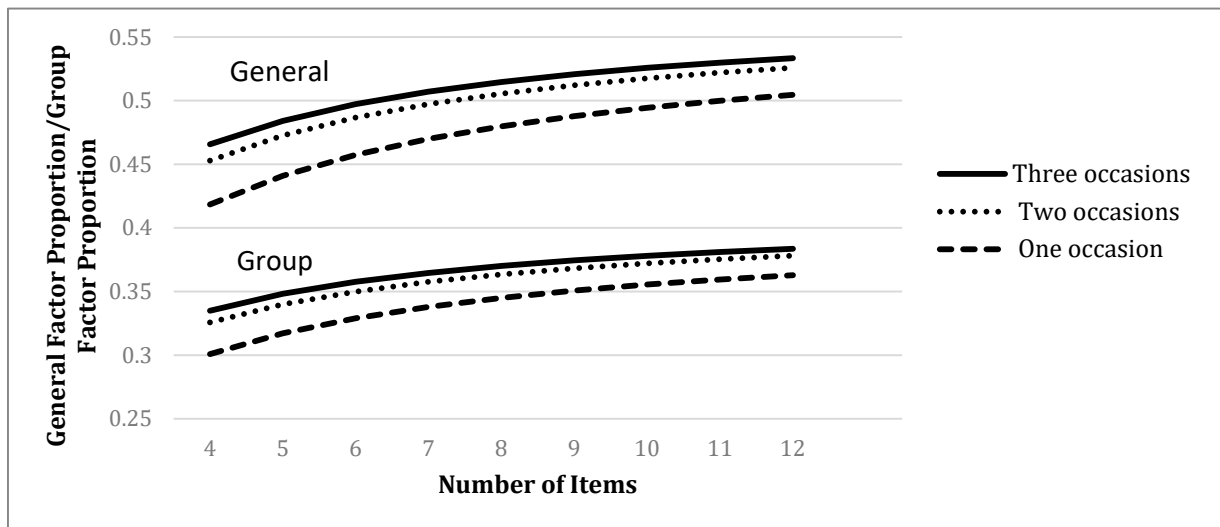


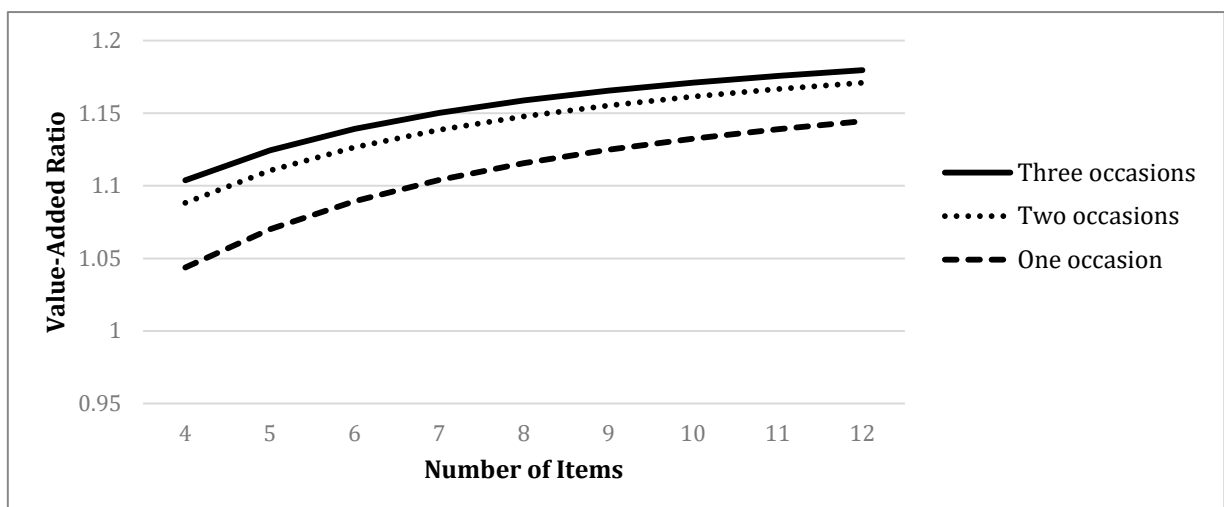
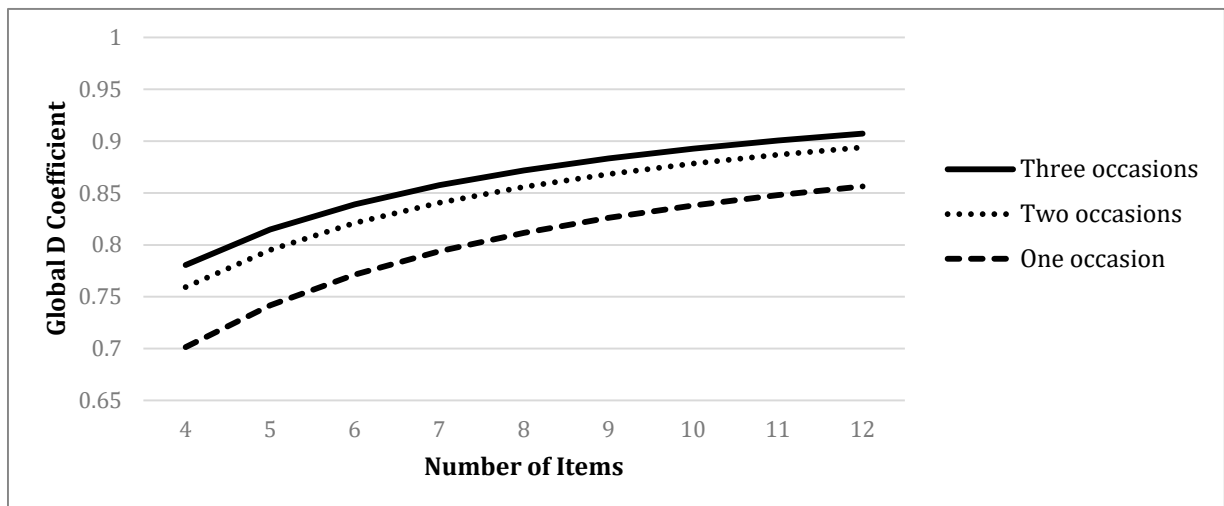
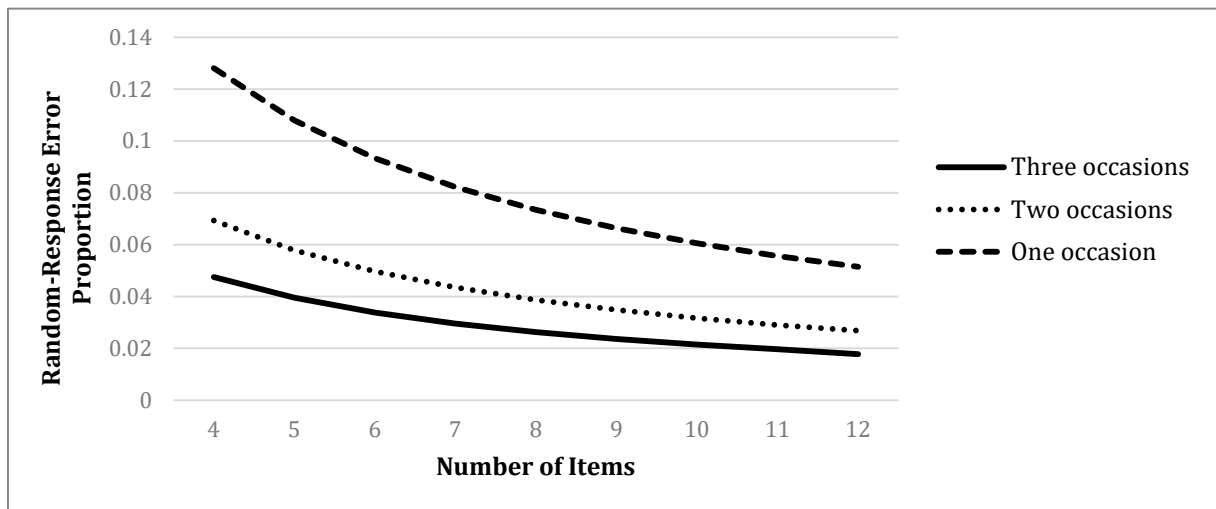




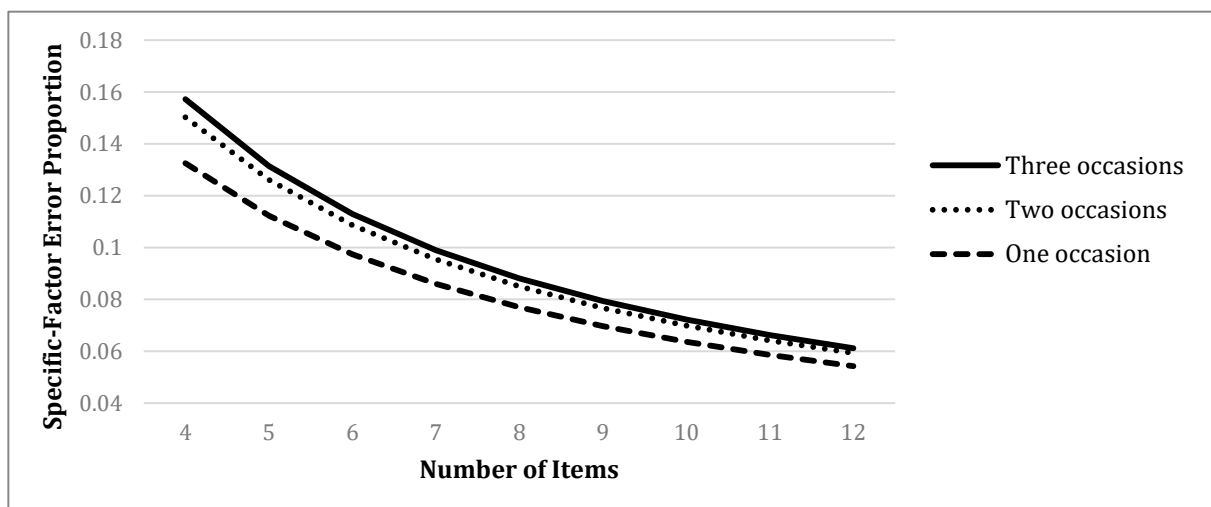
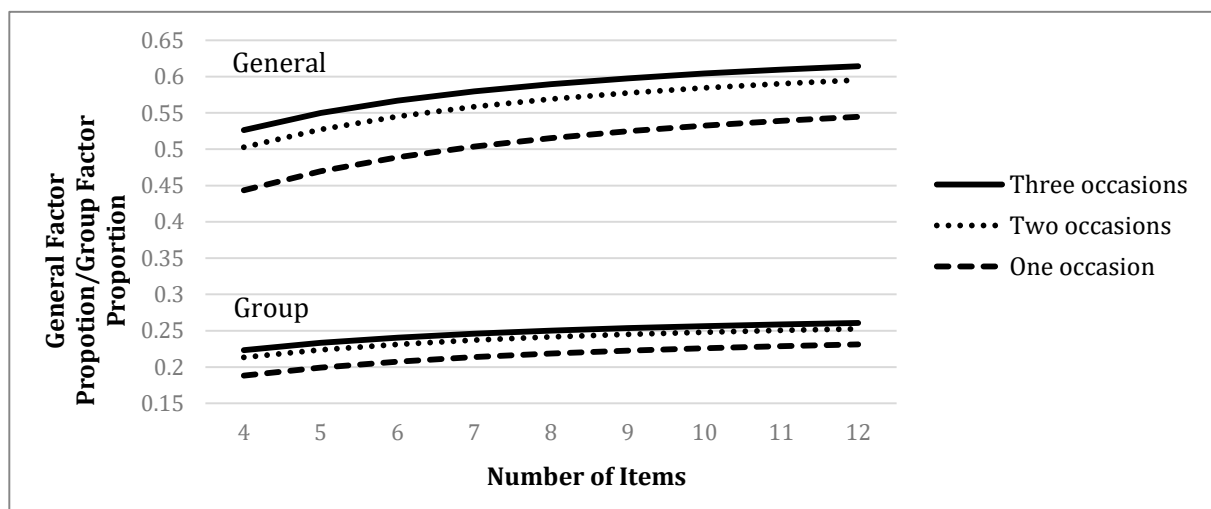
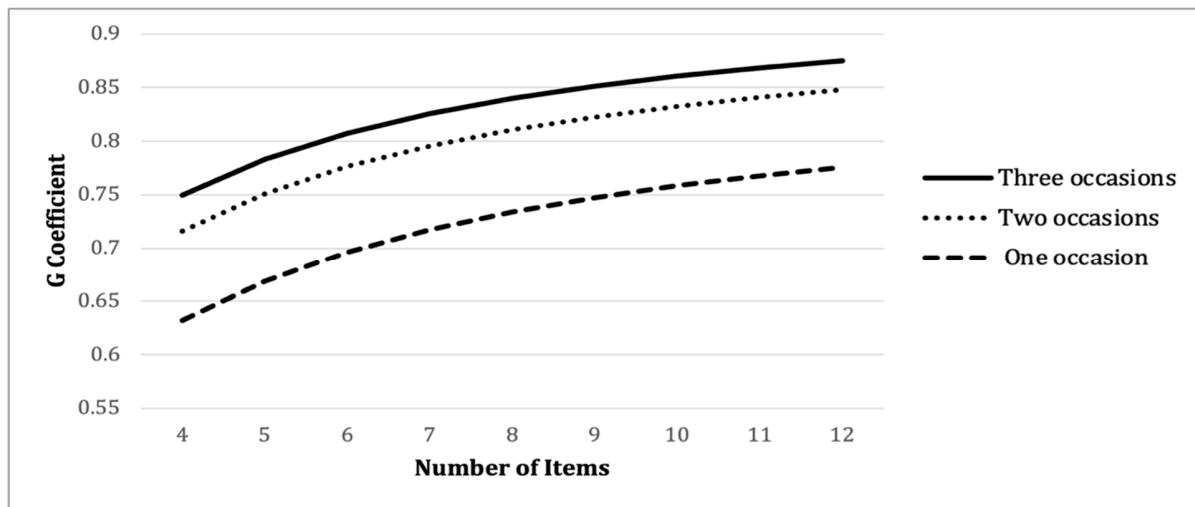
**Figure S4.2 Prophecy Graphs for Subscale Score: Aesthetic Sensitivity**

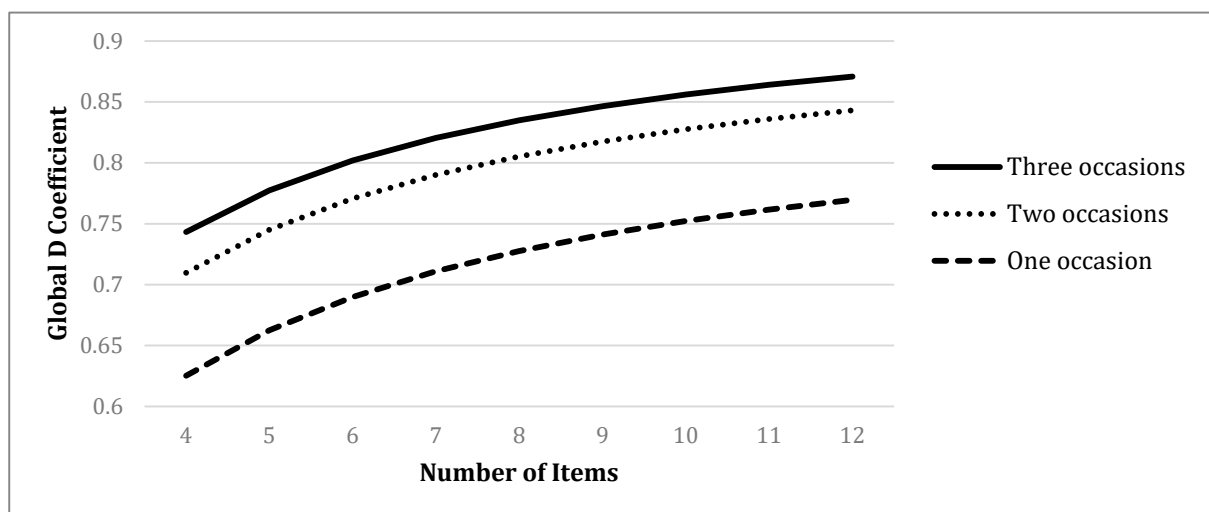
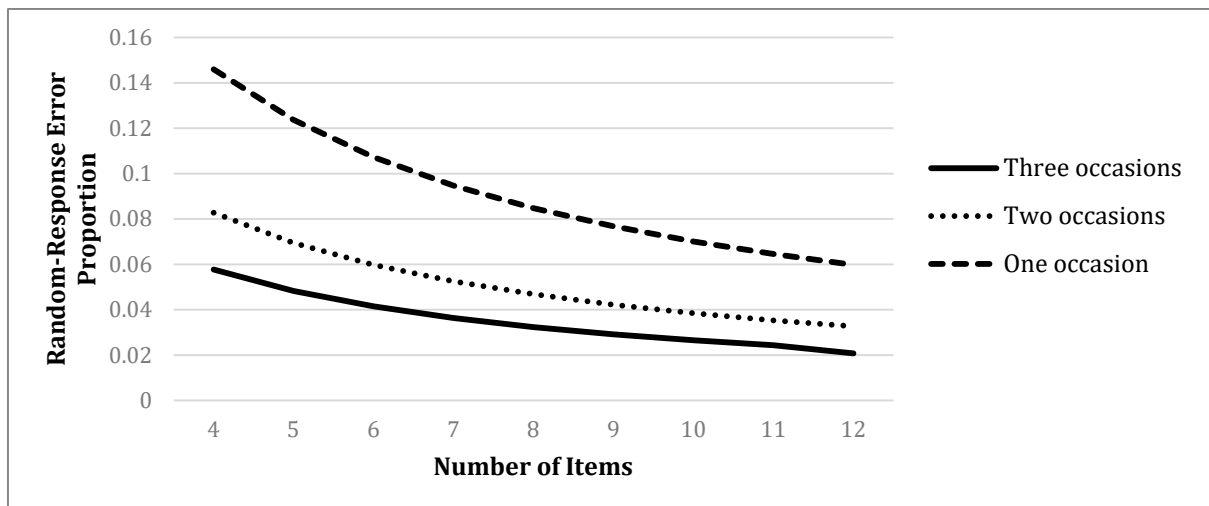
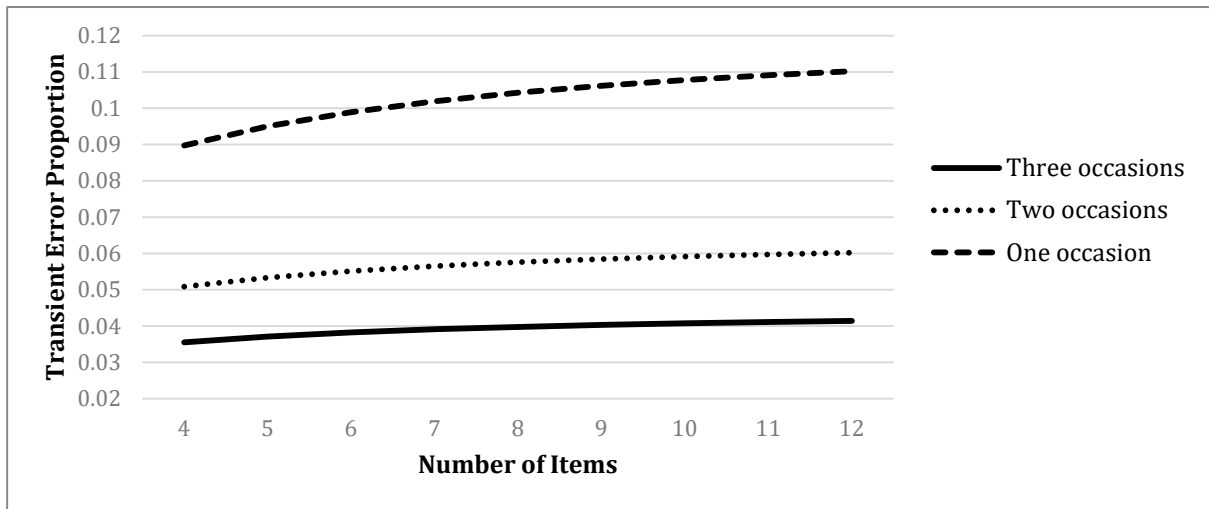




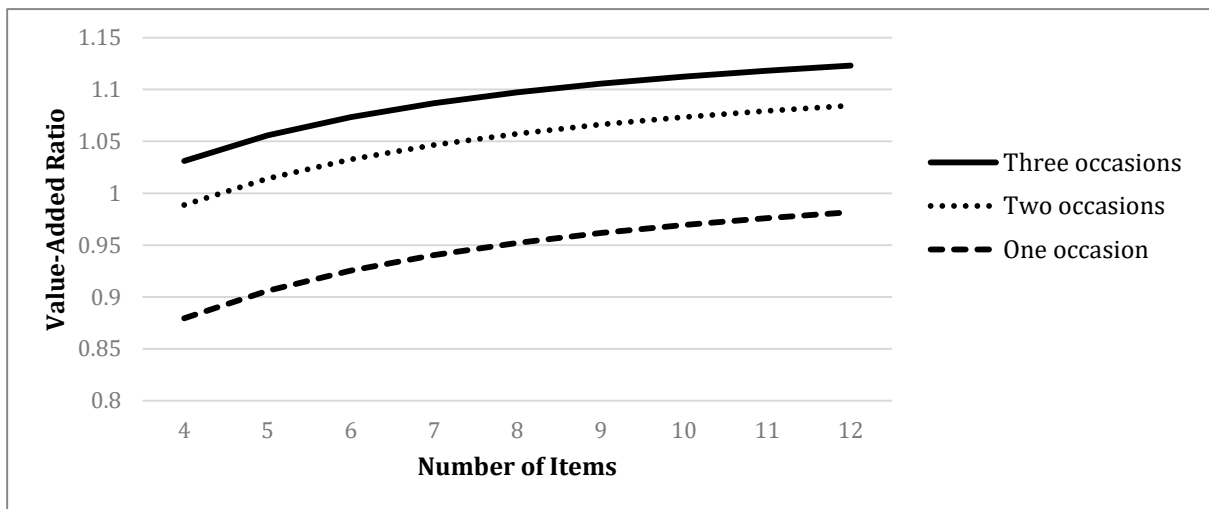


**Figure S4.3 Prophecy Graphs for Subscale Score: Creative Imagination**

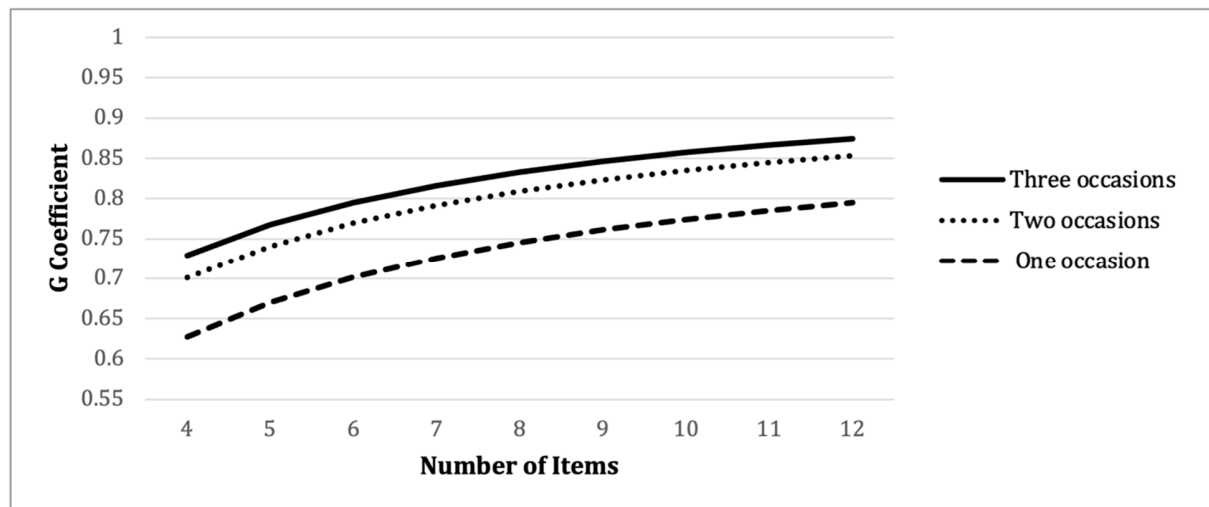


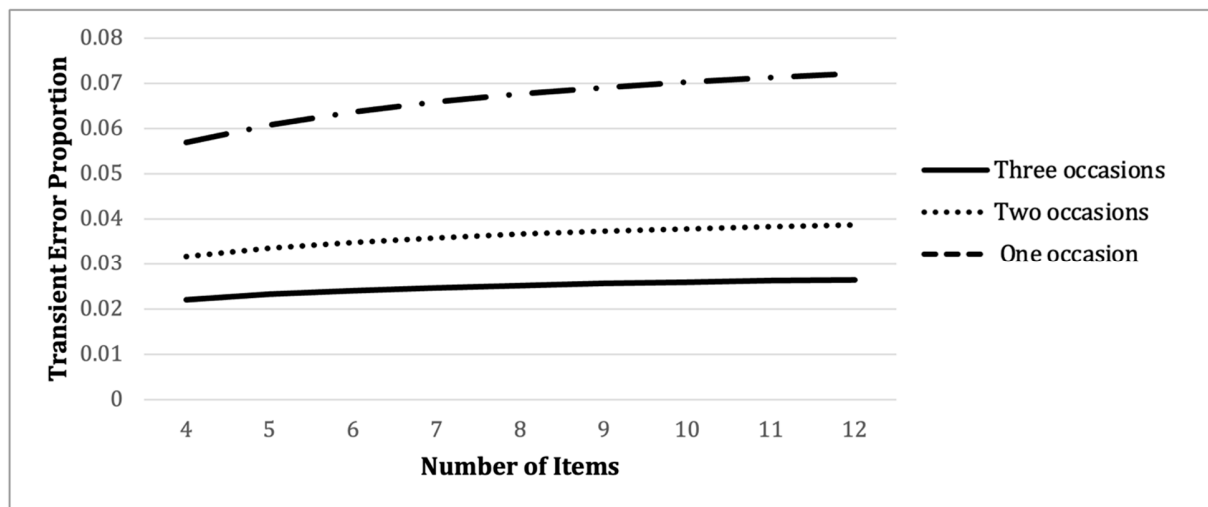
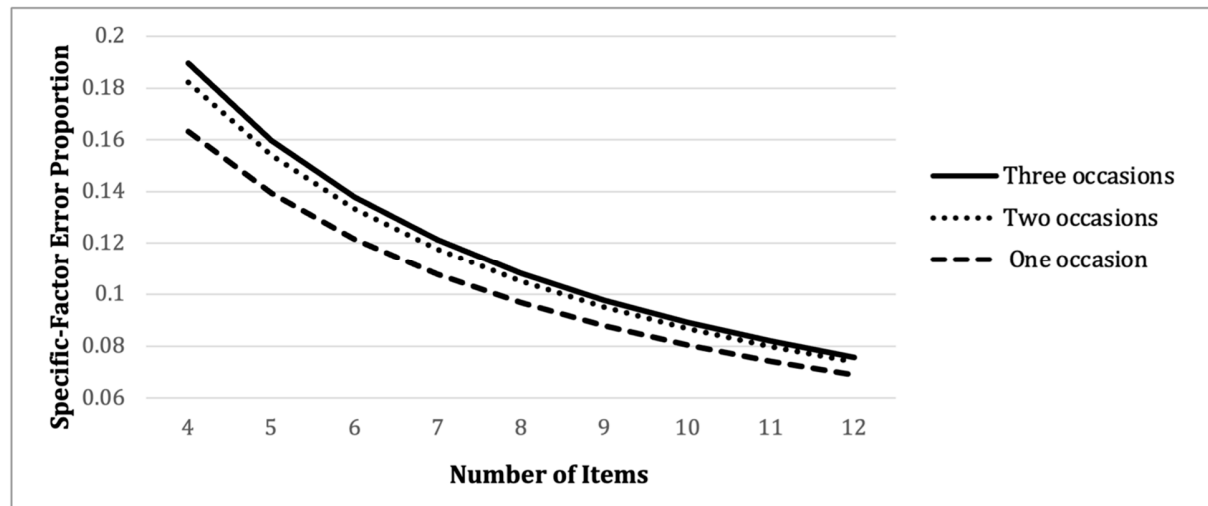
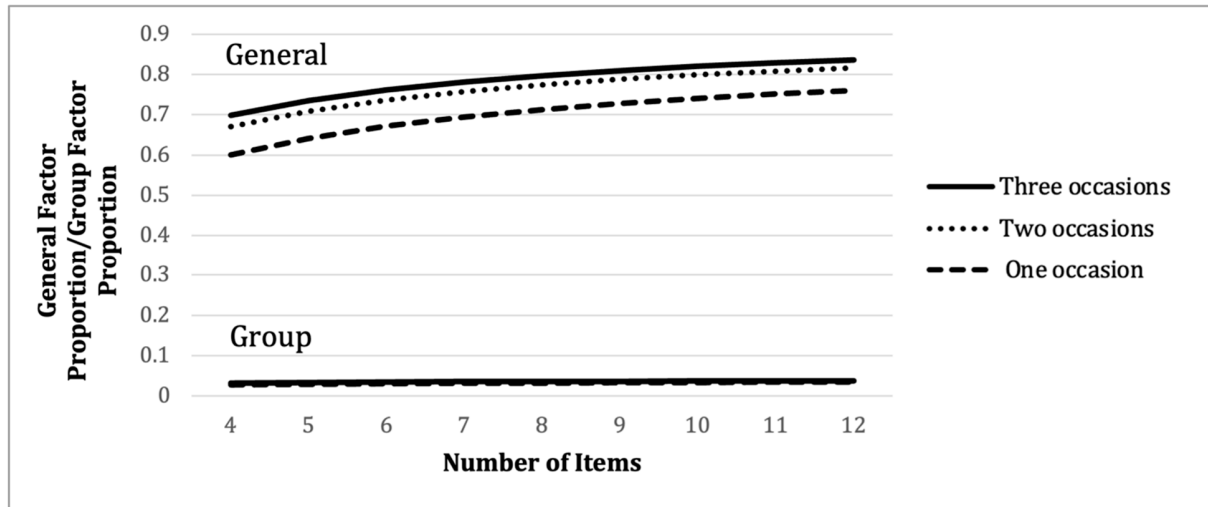


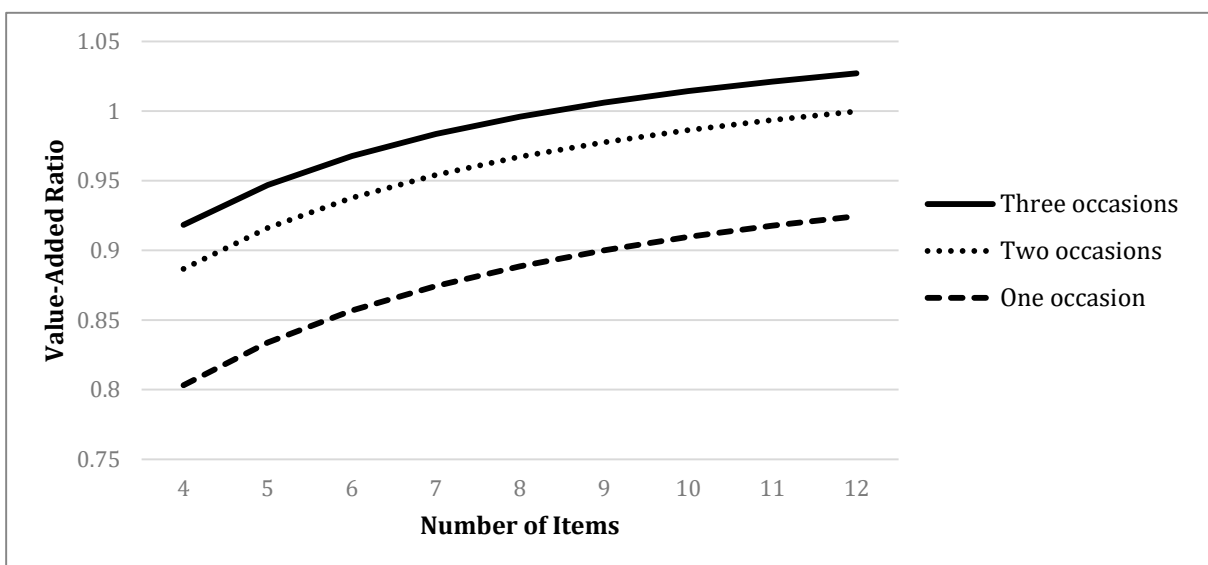
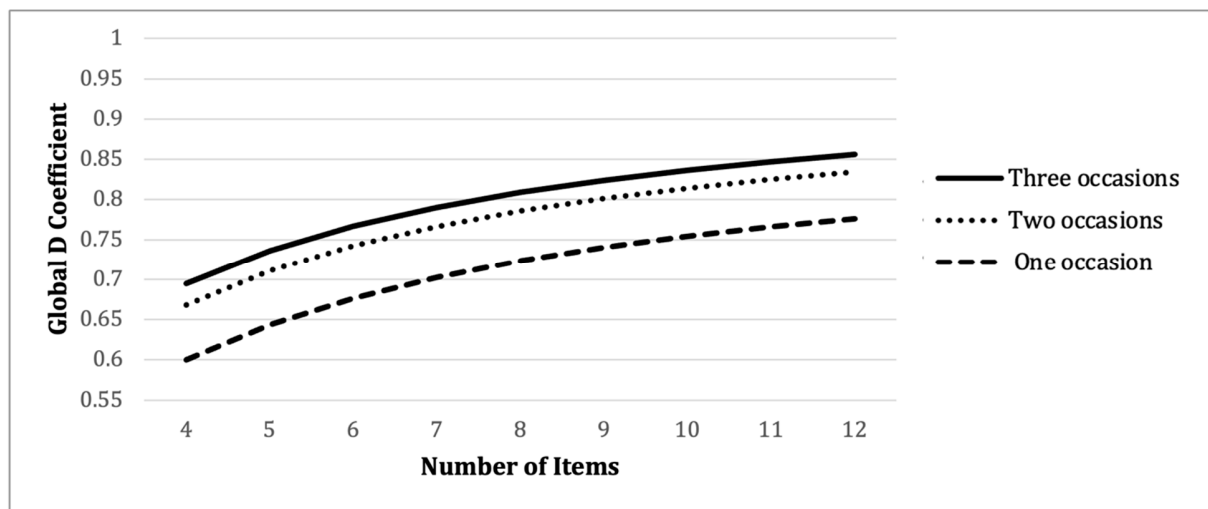
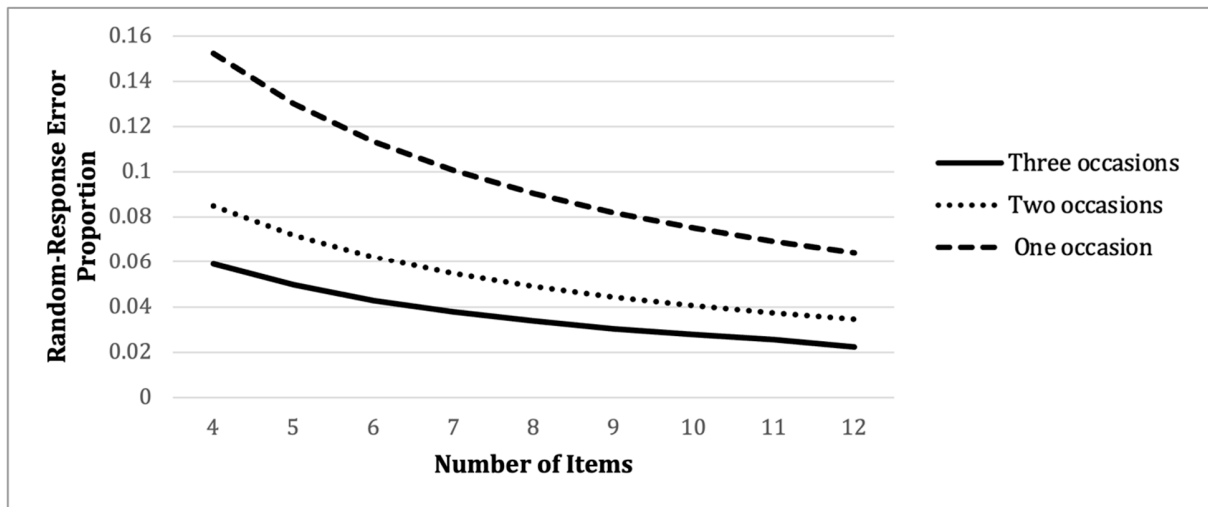




**Figure S4.4 Prophecy Graphs for Subscale Score: Intellectual Curiosity**







## Abbreviations used throughout the supplement

GT: Generalizability theory

BFI-2: Big Five Inventory Form 2

G\_COEF : G coefficient

SFE : Specific-factor error

TE: Transient error

RRE: Random-response error

Tot\_E: Total error

PRMSE : Proportional reduction in mean squared error

VAR: Value-added ratio

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