Applications of Bifactor Models to Big Five Data

Michael Biderman
University of Tennessee at Chattanooga

www.utc.edu/michael-biderman

Michael-Biderman@utc.edu

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A recording of the presentation is available on the above web site.
Thanks to

Nhung T. Nguyen
Towson University
Collaborator for more than 10 years

International Personality Item Pool
www.ipip.ori.org
Bifactor Model

Confirmatory Factor Analysis (CFA) or Exploratory Factor Analysis (EFA) model applicable to a dataset which may represent both a single overarching construct and multiple subconstructs.

The model contains one general factor and multiple group factors.

The general factor represents the overarching construct and each group factor represents one of the subconstructs.

The general factor influences all indicators. Each group factor influences only the indicators for a subconstruct.

Bifactor models are also called nested models.
Why are we here?

Application of bifactor models has increased dramatically in past 10 years.
Three Examples of Data for which a bifactor model might be applicable

1. WAIS-III Intelligence subtests


14 subtests of intellectual functioning

- Verbal Comprehension
- Perceptual Organization
- Working Memory
- Processing Speed

Overarching construct: General intelligence
Subconstructs: VC, PO, WM, PS
2. The Observer Alexithymia Scale (OAS)


33 observer-rated items

5 groups of items

- Distant
- Uninsightful
- Somatizing
- Humorless
- Rigid

Overarching construct: Alexithymia

Subconstructs: D, U, S, H, R
3. Big Five Questionnaires

For example, the 50-item Sample Questionnaire on the IPIP website at www.ipip.ori.org


5 groups of items

- Extraversion
- Agreeableness
- Conscientiousness
- Stability
- Openness to Experience

Subconstructs: E, A, C, S, and O

Overarching construct: Hmm. General Factor of Personality?

I’ll call it the GFP here.
The basic data for each example

<table>
<thead>
<tr>
<th>WAIS-III</th>
<th>OAS</th>
<th>Big 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information</td>
<td>Distant1</td>
<td>Extrav1</td>
</tr>
<tr>
<td>Vocabulary</td>
<td>Distant2</td>
<td>Extrav2</td>
</tr>
<tr>
<td>Similarities</td>
<td>Distant3</td>
<td>Extrav3</td>
</tr>
<tr>
<td>Compreh</td>
<td>Distant4</td>
<td>Extrav4</td>
</tr>
<tr>
<td>Obj Assem</td>
<td>Distant5</td>
<td>Extrav5</td>
</tr>
<tr>
<td>Blk Design</td>
<td>Distant6</td>
<td>Extrav6</td>
</tr>
<tr>
<td>Pct Compl</td>
<td>Distant7</td>
<td>Extrav7</td>
</tr>
<tr>
<td>Mat Reas</td>
<td>Distant8</td>
<td>Extrav8</td>
</tr>
<tr>
<td>Pict Arrange</td>
<td>Distant9</td>
<td>Extrav9</td>
</tr>
<tr>
<td>Digit Span</td>
<td>Distant10</td>
<td>Extrav10</td>
</tr>
<tr>
<td>Sequencing</td>
<td>Uninsightful1</td>
<td>Agree1</td>
</tr>
<tr>
<td>Arithmetic</td>
<td>Uninsightful2</td>
<td>Agree2</td>
</tr>
<tr>
<td>Dig-Sym</td>
<td>Uninsightful3</td>
<td>Agree3</td>
</tr>
<tr>
<td>Sym Search</td>
<td>Uninsightful4</td>
<td>Agree4</td>
</tr>
<tr>
<td></td>
<td>Uninsightful5</td>
<td>Agree5</td>
</tr>
<tr>
<td></td>
<td>Uninsightful6</td>
<td>Agree6</td>
</tr>
<tr>
<td></td>
<td>Uninsightful7</td>
<td>Agree7</td>
</tr>
<tr>
<td></td>
<td>Uninsightful8</td>
<td>Agree8</td>
</tr>
<tr>
<td></td>
<td>Somaticizing1</td>
<td>Agree9</td>
</tr>
<tr>
<td></td>
<td>Somaticizing2</td>
<td>Agree10</td>
</tr>
<tr>
<td></td>
<td>Somaticizing3</td>
<td>Consc1</td>
</tr>
<tr>
<td></td>
<td>Somaticizing4</td>
<td>Consc2</td>
</tr>
<tr>
<td></td>
<td>Somaticizing5</td>
<td>Consc3</td>
</tr>
<tr>
<td></td>
<td>Humorless1</td>
<td>Consc4</td>
</tr>
<tr>
<td></td>
<td>Humorless2</td>
<td>Consc5</td>
</tr>
<tr>
<td></td>
<td>Humorless3</td>
<td>Consc6</td>
</tr>
<tr>
<td></td>
<td>Humorless4</td>
<td>Consc7</td>
</tr>
<tr>
<td></td>
<td>Humorless5</td>
<td>Consc8</td>
</tr>
<tr>
<td></td>
<td>Humorless6</td>
<td>Consc9</td>
</tr>
<tr>
<td></td>
<td>Humorless7</td>
<td>Consc10</td>
</tr>
<tr>
<td></td>
<td>Humorless8</td>
<td>Stabil1</td>
</tr>
<tr>
<td></td>
<td>Humorless9</td>
<td>Stabil2</td>
</tr>
<tr>
<td></td>
<td>Humorless10</td>
<td>Stabil3</td>
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<tr>
<td></td>
<td>Rigid1</td>
<td>Stabil4</td>
</tr>
<tr>
<td></td>
<td>Rigid2</td>
<td>Stabil5</td>
</tr>
<tr>
<td></td>
<td>Rigid3</td>
<td>Stabil6</td>
</tr>
<tr>
<td></td>
<td>Rigid4</td>
<td>Stabil7</td>
</tr>
<tr>
<td></td>
<td>Rigid5</td>
<td>Stabil8</td>
</tr>
<tr>
<td></td>
<td>Rigid6</td>
<td>Stabil9</td>
</tr>
<tr>
<td></td>
<td>Rigid7</td>
<td>Stabil10</td>
</tr>
</tbody>
</table>

Subtest scores.

Responses to individual items
Possible models of the data sets

1. Single Factor only

2. Multiple correlated factors

3. Higher order factor

4. Bifactor
Model 1: Single factor models of each data set

WAIS-III
- Information
- Vocabulary
- Similarities
- Compreh
- Obj Assem
- Blk Design
- Pct Compl
- Mat Reas
- Pict Arrange
- Digit Span
- Sequencing
- Arithmetic
- Dig-Sym
- Sym Search

OAS
- Distant1
- Distant2
- Distant3
- Distant4
- Distant5
- Distant6
- Distant7
- Distant8
- Distant9
- Distant10
- Uninsightful1
- Uninsightful2
- Uninsightful3
- Uninsightful4
- Uninsightful5
- Uninsightful6
- Uninsightful7
- Uninsightful8
- Somaticizing1
- Somaticizing2
- Somaticizing3
- Somaticizing4
- Somaticizing5
- Humorless1
- Humorless2
- Humorless3
- Humorless4
- Humorless5
- Rigid1
- Rigid2
- Rigid3
- Rigid4
- Rigid5

Alx

GFP
- Extrav1
- Extrav2
- Extrav3
- Extrav4
- Extrav5
- Extrav6
- Extrav7
- Extrav8
- Extrav9
- Extrav10
- Agree1
- Agree2
- Agree3
- Agree4
- Agree5
- Agree6
- Agree7
- Agree8
- Agree9
- Agree10
- Consc1
- Consc2
- Consc3
- Consc4
- Consc5
- Consc6
- Consc7
- Consc8
- Consc9
- Consc10
- Stabil1
- Stabil2
- Stabil3
- Stabil4
- Stabil5
- Stabil6
- Stabil7
- Stabil8
- Stabil9
- Stabil10
- Open1
- Open2
- Open3
- Open4
- Open5
- Open6
- Open7
- Open8
- Open9
- Open10
What’s good about single factor models?

Parsimony – Variance in all of the indicators is accounted for by only one factor

What’s bad?

Differences between / relationships among subconstructs not accounted for
Model 2: Multiple correlated factor models of each data set

WISC-III

VC

PO

WM

PS

Information

Vocabulary

Similarities

Compreh

Obj Assem

Blk Design

Pct Compl

Mat Reas

Pict Arrange

Digit Span

Sequencing

Arithmetic

Dig-Sym

Sym Search

OAS

D

Dist1

Dist2

Dist3

Dist4

Dist5

Dist6

Dist7

Dist8

Dist9

Dist10

Uninsightful1

Uninsightful2

Uninsightful3

Uninsightful4

Uninsightful5

Uninsightful6

Uninsightful7

Uninsightful8

Humorless1

Humorless2

Humorless3

Humorless4

Humorless5

Rigid1

Rigid2

Rigid3

Rigid4

Rigid5

Extrav

Agree

Consc

Stabil

Open

E

A

C

S

O
What’s good about multiple factor models?

Differences / relationships between subconstructs are accounted for

What’s bad?

Can’t parsimoniously account for effects of a single causal factor
Model 3: Higher order factor models of each data set

**WAIS-III**

- g
- VC
- PO
- WM
- PS

**OAS**

- D
- U
- S
- H
- R

**Big 5**

- E
- A
- C
- GFP

**Dimensions:**
- Big 5
- OAS
- VC
- PO
- WM
- PS
- g
- RD
- RU
- RS
- RH
- RR
- RE
- RA
- RC
- R_O

**Variables:**
- Extrav1
- Extrav2
- Extrav3
- Extrav4
- Extrav5
- Extrav6
- Extrav7
- Extrav8
- Extrav9
- Extrav10
- Agree1
- Agree2
- Agree3
- Agree4
- Agree5
- Agree6
- Agree7
- Agree8
- Agree9
- Agree10
- Consc1
- Consc2
- Consc3
- Consc4
- Consc5
- Consc6
- Consc7
- Consc8
- Consc9
- Consc10
- Stabil1
- Stabil2
- Stabil3
- Stabil4
- Stabil5
- Stabil6
- Stabil7
- Stabil8
- Stabil9
- Stabil10
- Open1
- Open2
- Open3
- Open4
- Open5
- Open6
- Open7
- Open8
- Open9
- Open10

**Website:**

www.utc.edu/michael-biderman
What’s good about higher order models?

Represent BOTH effects of a single overarching construct and acknowledge differences between subconstructs

What’s bad?

General factor does not have direct effects on the indicators.

Difficult to show how the unique aspects of the subconstructs (the residuals) are related to the observations
Model 4: Bifactor models of each data set

WAIS-III

- Information
- Vocabulary
- Similarities
- Compreh
- Obj Assem
- Blk Design
- Pct Compl
- Mat Reas
- Pict Arrange
- Digit Span
- Sequencing
- Arithmetic
- Dig-Sym
- Sym Search

PO

VC

OAS

- Dist1
- Dist2
- Dist3
- Dist4
- Dist5
- Dist6
- Dist7
- Dist8
- Dist9
- Dist10

- Uninsightful1
- Uninsightful2
- Uninsightful3
- Uninsightful4
- Uninsightful5
- Uninsightful6
- Uninsightful7
- Uninsightful8

- Somaticizing1
- Somaticizing2
- Somaticizing3
- Somaticizing4
- Somaticizing5

- Humorless1
- Humorless2
- Humorless3
- Humorless4
- Humorless5

- Rigid1
- Rigid2
- Rigid3
- Rigid4
- Rigid5

GFP

- Extrav1
- Extrav2
- Extrav3
- Extrav4
- Extrav5
- Extrav6
- Extrav7
- Extrav8
- Extrav9
- Extrav10

- Agree1
- Agree2
- Agree3
- Agree4
- Agree5
- Agree6
- Agree7
- Agree8
- Agree9
- Agree10

- Consc1
- Consc2
- Consc3
- Consc4
- Consc5
- Consc6
- Consc7
- Consc8
- Consc9
- Consc10

- Stabil1
- Stabil2
- Stabil3
- Stabil4
- Stabil5
- Stabil6
- Stabil7
- Stabil8
- Stabil9
- Stabil10

- Open1
- Open2
- Open3
- Open4
- Open5
- Open6
- Open7
- Open8
- Open9
- Open10

Big 5

E

A

C

S

O

6/11/2013

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What’s good about bifactor models

Represent effects of BOTH the general construct and subconstructs.

**Both** the general factor and group factors are easily included in prediction equations.

Bifactor models are generalizations of the higher-order factor models, so results that support higher-order factor models support these models.


What’s bad?

All factors are orthogonal. This may misrepresent the data.

May require large sample sizes to insure that random variability in sample correlations doesn’t prevent convergence or inappropriate solutions.
The bottom line: which model fits best?

WAIS-III from Brunner et al. (2012) Table 2; N= 1369

<table>
<thead>
<tr>
<th>Model</th>
<th>Chi-square</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Single</td>
<td>1,923</td>
<td>77</td>
<td>.888</td>
<td>.132</td>
<td>.050</td>
</tr>
<tr>
<td>2 Multiple</td>
<td>515</td>
<td>71</td>
<td>.973</td>
<td>.068</td>
<td>.028</td>
</tr>
<tr>
<td>3 H Order</td>
<td>570</td>
<td>73</td>
<td>.970</td>
<td>.071</td>
<td>.032</td>
</tr>
<tr>
<td>4 Bifactor</td>
<td>376</td>
<td>64</td>
<td>.981</td>
<td>.060</td>
<td>.022</td>
</tr>
</tbody>
</table>

Δχ^2(9)=194

OAS from Reise et al. (2010); N=1495

<table>
<thead>
<tr>
<th>Model</th>
<th>Chi-square</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Single</td>
<td>12,407</td>
<td>495</td>
<td>.830</td>
<td>.130</td>
<td></td>
</tr>
<tr>
<td>2 Multiple</td>
<td>4,447</td>
<td>485</td>
<td>.940</td>
<td>.070</td>
<td></td>
</tr>
<tr>
<td>3 H Order</td>
<td>4,818</td>
<td>490</td>
<td>.940</td>
<td>.080</td>
<td></td>
</tr>
<tr>
<td>4 Bifactor</td>
<td>3,152</td>
<td>462</td>
<td>.960</td>
<td>.060</td>
<td></td>
</tr>
</tbody>
</table>

Δχ^2(28)=1,666

Big Five from Biderman et al. (2013); N=547

<table>
<thead>
<tr>
<th>Model</th>
<th>Chi-square</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
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<td>7,898</td>
<td>1175</td>
<td>.317</td>
<td>.102</td>
<td>.121</td>
</tr>
<tr>
<td>2 Multiple</td>
<td>3,959</td>
<td>1165</td>
<td>.716</td>
<td>.066</td>
<td>.081</td>
</tr>
<tr>
<td>3 H Order</td>
<td>3,978</td>
<td>1170</td>
<td>.715</td>
<td>.066</td>
<td>.082</td>
</tr>
<tr>
<td>4 Bifactor</td>
<td>3,483</td>
<td>1125</td>
<td>.760</td>
<td>.062</td>
<td>.069</td>
</tr>
</tbody>
</table>

Δχ^2(45)=495
Comparisons in other Big Five questionnaires

<table>
<thead>
<tr>
<th></th>
<th>Chi-square</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>NEO-FFI</strong>; Biderman, et al. (2011); N=195</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Single</td>
<td>4510</td>
<td>1710</td>
<td>.331</td>
<td>.092</td>
<td>.117</td>
</tr>
<tr>
<td>2 Multiple</td>
<td>3220</td>
<td>1700</td>
<td>.638</td>
<td>.068</td>
<td>.094</td>
</tr>
<tr>
<td>3 H Order</td>
<td>3234</td>
<td>1705</td>
<td>.636</td>
<td>.068</td>
<td>.097</td>
</tr>
<tr>
<td>4 Bifactor</td>
<td>2936 (\Delta \chi^2(55)=298)</td>
<td>1650</td>
<td>.694</td>
<td>.063</td>
<td>.082</td>
</tr>
</tbody>
</table>

| **IPIP “Other” 50-item Questionnaire**; Unpublished data; N=206 |            |     |      |       |      |
| 1 Single             | 3694       | 1175| .347 | .102  | .126 |
| 2 Multiple           | 2667       | 1165| .611 | .079  | .104 |
| 3 H Order            | 2679       | 1170| .609 | .079  | .107 |
| 4 Bifactor           | 2240 \(\Delta \chi^2(45)=439\) | 1125| .711 | .069  | .088 |

| **Thompson MiniMarkers** Questionnaire; Unpublished data; N=206 |            |     |      |       |      |
| 1 Single             | 3736       | 740 | .250 | .140  | .152 |
| 2 Multiple           | 2018       | 730 | .677 | .093  | .103 |
| 3 H Order            | 2031       | 735 | .675 | .093  | .106 |
| 4 Bifactor           | 1593 \(\Delta \chi^2(35)=438\) | 700 | .777 | .079  | .085 |


The bifactor model fit all datasets significantly better than the other models.
The takeaway from the above slides . . .

There is variance common to all items in Big Five questionnaires.

That common variance seems to be represented by a single factor – the bifactor.
General factor importance for the first 3 examples
Loadings are doubly standardized.
Negative indicators reverse-scored

WAIS – III - Brunner et al.

OAS - Reise et al.

IPIP Big 5
Biderman et al.

www.utc.edu/michael-biderman
Convergent Validity of factors of IPIP 50-item scale vs. NEO-FFI
Biderman et al., 2011; N=195
Convergent Validity of IPIP 50-item scale vs. Thompson Minimarkers
Unpublished data; N=206
Convergent Validity of factors of “Original” vs “Other” IPIP scales
Unpublished data; N=206
3 month test-retest correlations of factors of IPIP 50-item scale

Takeaway from the previous slides . . .

Whatever the bifactor is, it exhibits convergent validity across questionnaires and across time
Why should we apply a bifactor model?

If the bifactor model is true, this means that the bifactor affects, i.e., contaminates, each Big 5 response.

This is illustrated in the graphic on this slide . . .

The colored part of each response rectangle is the portion of variance due to the influence of the items’ Big Five trait

The white part is error of measurement

The black part is contamination from the bifactor.

Since the focus of most people using Big five questionnaires is not on the bifactor (yet) but on the Big Five factors, it is to our best interest to remove the effect of the contamination.
The bifactor affects scale scores as well as individual responses

It’s not feasible to remove the contamination due to the bifactor by simply computing scale scores.

Big Five scale scores will be just as contaminated as individual responses.

So analyses involving scale scores will be affected – contaminated – by the bifactor.
Freedom from contamination!!

The solution to the dilemma is to apply a bifactor model to Big Five data and perform analyses involving the Big Five factors in the model.

If the bifactor model fits, the **group factors** in the bifactor model represent purer estimates of each trait than do scale scores for each domain.

Plus we get a free “sixth” Score from the data – the Bifactor score.
Applying Bifactor Models

Specifically, a bifactor **measurement model** must first be applied.

Then a **structural model** – a set of correlations or regressions involving factors from the measurement model – is computed to test whatever hypotheses we might have regarding the Big Five factors.

**Measurement models**

- Amos Graphics
- Amos Program Editor
- EQS
- Mplus

Caution – some of the following slides are pretty dense. Don’t worry, the test over them will be multiple choice.

**Structural Models**

- Amos
- Mplus
Bifactor measurement model – in Amos Graphics

Amos Bifactor Model
Chi-square = \( \chi^2 \)
df = \( df \)
CFI = \( CFI \)
RMSEA = \( RMSEA \)
Bifactor measurement model – in Amos Program Editor

#Region "Header"
Imports System
Imports System.Diagnostics
Imports Microsoft.VisualBasic
Imports AmosEngineLib
Imports AmosGraphics
Imports AmosEngineLib.AmosEngine.TMatrixID
Imports PBayes
#End Region
Module MainModule
  Public Sub Main()
    Dim Sem As AmosEngine
    Sem = New AmosEngine
    Sem.TextOutput = True
    AnalysisProperties(Sem)
    ModelSpecification(Sem)
    Sem.FitAllModels()
    Sem.Dispose()
  End Sub
Sub ModelSpecification(Sem As AmosEngine)
  Sem.GenerateDefaultCovariances(False)
  Sem.BeginGroup("G:\\MDIR1\BalancedScaleStudy\GFP")
End Sub

Paper:
GFP Amos\\1.10DataFiles
  GFP_3DataSets_Corrected_120006.sav" "GFP_3DataSets_Corrected_120008"
  Sem.GroupName("Group number 1")
  Sem.AStructure("e1 = (1) r1 + a + gfp")
  Sem.AStructure("e2 = (1) r2 + a + gfp")
  Sem.AStructure("e3 = (1) r3 + a + gfp")
  Sem.AStructure("e4 = (1) r4 + a + gfp")
  Sem.AStructure("e5 = (1) r5 + a + gfp")
  Sem.AStructure("e6 = (1) r6 + a + gfp")
  Sem.AStructure("e7 = (1) r7 + a + gfp")
  Sem.AStructure("e8 = (1) r8 + a + gfp")
  Sem.AStructure("e9 = (1) r9 + a + gfp")
  Sem.AStructure("e10 = (1) r10 + a + gfp")
  Sem.AStructure("e11 = (1) r11 + a + gfp")
  Sem.AStructure("e1 = (1) r10 + a + gfp")
  Sem.AStructure("e2 = (1) r2 + a + gfp")
  Sem.AStructure("e3 = (1) r3 + a + gfp")
  Sem.AStructure("e4 = (1) r4 + a + gfp")
  Sem.AStructure("e5 = (1) r5 + a + gfp")
  Sem.AStructure("e6 = (1) r6 + a + gfp")
  Sem.AStructure("e7 = (1) r7 + a + gfp")
  Sem.AStructure("e8 = (1) r8 + a + gfp")
  Sem.AStructure("e9 = (1) r9 + a + gfp")
  Sem.AStructure("e10 = (1) r10 + a + gfp")
  Sem.AStructure("e11 = (1) r11 + a + gfp")
  Sem.Model("Default model", "")
End Sub
Sub AnalysisProperties(Sem As AmosEngine)
  Sem.Iterations(50)
  Sem.InputUnbiasedMoments
  Sem.FIMLMoments
  Sem.Seed(1)
End Sub
End Module
Bifactor measurement model - EQS

/VARIABLES=324; CASES=547;

/SPECIFICATIONS
DATA=G:\MDBR\BalancedScaleStudy\GFP Paper\GFP EQS\gfp_big 5 data.ess';

/ANALYSIS=COVARIANCE;
/METHOD=ML;

/EQUATIONS
V15 = 1F1 + 1F6 + E15;
V16 = *F1 + *F6 + E16;
V17 = *F1 + *F6 + E17;
V18 = *F1 + *F6 + E18;
V19 = *F1 + *F6 + E19;
V20 = *F1 + *F6 + E20;
V21 = *F1 + *F6 + E21;
V22 = *F1 + *F6 + E22;
V23 = *F1 + *F6 + E23;
V24 = *F1 + *F6 + E24;
V25 = 1F2 + *F6 + E25;
V26 = *F2 + *F6 + E26;
V27 = *F2 + *F6 + E27;
V28 = *F2 + *F6 + E28;
V29 = *F2 + *F6 + E29;
V30 = *F2 + *F6 + E30;
V31 = *F2 + *F6 + E31;
V32 = *F2 + *F6 + E32;
V33 = *F2 + *F6 + E33;
V34 = *F2 + *F6 + E34;
V35 = 1F3 + *F6 + E35;
V36 = *F3 + *F6 + E36;
V37 = *F3 + *F6 + E37;
V38 = *F3 + *F6 + E38;
V39 = *F3 + *F6 + E39;
V40 = *F3 + *F6 + E40;
V41 = *F3 + *F6 + E41;
V42 = *F3 + *F6 + E42;
V43 = *F3 + *F6 + E43;
V44 = *F3 + *F6 + E44;
V45 = 1F4 + *F6 + E45;
V46 = *F4 + *F6 + E46;
V47 = *F4 + *F6 + E47;
V48 = *F4 + *F6 + E48;
V49 = *F4 + *F6 + E49;
V50 = *F4 + *F6 + E50;
V51 = *F4 + *F6 + E51;
V52 = *F4 + *F6 + E52;
V53 = *F4 + *F6 + E53;
V54 = *F4 + *F6 + E54;
V55 = 1F5 + *F6 + E55;
V56 = *F5 + *F6 + E56;
V57 = *F5 + *F6 + E57;
V58 = *F5 + *F6 + E58;
V59 = *F5 + *F6 + E59;
V60 = *F5 + *F6 + E60;
V61 = *F5 + *F6 + E61;
V62 = *F5 + *F6 + E62;
V63 = *F5 + *F6 + E63;
V64 = *F5 + *F6 + E64;

/VARIANCES
F1 = *;
F2 = *;
F3 = *;
F4 = *;
F5 = *;
F6 = *;
E15 = *;
E16 = *;
E17 = *;
E18 = *;
E19 = *;
E20 = *;
E21 = *;
E22 = *;
E23 = *;
E24 = *;
E25 = *;
E26 = *;
E27 = *;
E28 = *;
E29 = *;
E30 = *;
E31 = *;
E32 = *;
E33 = *;
E34 = *;
E35 = *;
E36 = *;
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E38 = *;
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E43 = *;
E44 = *;
E45 = *;
E46 = *;
E47 = *;
E48 = *;
E49 = *;
E50 = *;
E51 = *;
E52 = *;
E53 = *;
E54 = *;
E55 = *;
E56 = *;
E57 = *;
E58 = *;
E59 = *;
E60 = *;
E61 = *;
E62 = *;
E63 = *;
E64 = *;

/COVARIANCES

/PRINT
FIT=ALL;
TABLE=EQUATION;

/END
TITLE: Bifactor GFP model with items as indicators;

data: FILE IS
  'G:\MdbR\1BalancedScaleStudy\GFP Paper \GFP Mplus\GFPData_120907.dat';
  listwise=on;

variable: names are
  Id wpt age gender ethnic filenum crit ext agr con sta opn
e1 - e10
a1 - a10
c1 - c10
s1 - s10
o1 - o10
dep rse;
usevariables are e1-o10;

analysis: type = general ;
  INFORMATION=EXPECTED;

model:
e by e1-e10*1;
a by a1-a10*1;
c by c1-c10*1;
s by s1-s10*1;
o by o1-o10*1;
gfp by e1-o10*1;
e@1; a@1; c@1; s@1; o@1; gfp@1;
gfp with e-o@0;
e-o with e-o@0;

output:  modindices(20) standardized fsdeterminacy;

savedata: file is
  'G:\MdbR\1BalancedScaleStudy\GFP Paper \GFP Mplus\ZFS_BifactorModel.inp';
save=fscores;
Applying Bifactor Models - Structural Models

**Within-the-program method**

Assess the structural model from within the program that applied the model.

**Factor score method**

Use a program to applied the model to create factor scores of the latent variables in the measurement model.

Put the factor scores in your favorite statistical package.

Perform the regressions using your statistical package.
Assessing a structural model from within Amos Graphics
Assessing criterion related validity of Big Five factors + Bifactor
Criterion (Overall) is supervisor ratings of job performance. N=764.
Assessing a structural model within Amos Program Editor

Imports System
Imports System.Diagnostics
Imports Microsoft.VisualBasic
Imports AmosEngineLib
Imports AmosGraphics
Imports AmosEngineLib.AmosEngine.TMatrixID
Imports PBayes

Module MainModule
    Public Sub Main()
        Dim Sem As AmosEngine
        Sem = New AmosEngine
        Sem.TextOutput = AnalysisProperties(Sem)
        ModelSpecification(Sem)
        Sem.FitAllModels()
        Sem.Dispose()
    End Sub

    Sub ModelSpecification(Sem As AmosEngine)
        Sem.GenerateDefaultCovariances(False)
        Sem.BeginGroup("C:\Users\MichaelAppData\Local\Temp\spss305237426360069.sav", "StatisticsData2233045370426360069", "StatisticsData2233045370426360069")
        Sem.GroupName("Group number 1")
        Sem.AStructure("e1 = (1) re1 + e + gfp")
        Sem.AStructure("e2 = (1) re2 + e + gfp")
        Sem.AStructure("e3 = (1) re3 + e + gfp")
        Sem.AStructure("e4 = (1) re4 + e + gfp")
        Sem.AStructure("e5 = (1) re5 + e + gfp")
        Sem.AStructure("e6 = (1) re6 + e + gfp")
        Sem.AStructure("e7 = (1) re7 + e + gfp")
        Sem.AStructure("e8 = (1) re8 + e + gfp")
        Sem.AStructure("e9 = (1) re9 + e + gfp")
        Sem.AStructure("e10 = (1) re10 + e + gfp")
        Sem.AStructure("a1 = (1) ra1 + a + gfp")
        Sem.AStructure("a2 = (1) ra2 + a + gfp")
        Sem.AStructure("a3 = (1) ra3 + a + gfp")
        Sem.AStructure("a4 = (1) ra4 + a + gfp")
        Sem.AStructure("a5 = (1) ra5 + a + gfp")
        Sem.AStructure("a6 = (1) ra6 + a + gfp")
        Sem.AStructure("a7 = (1) ra7 + a + gfp")
        Sem.AStructure("a8 = (1) ra8 + a + gfp")
        Sem.AStructure("a9 = (1) ra9 + a + gfp")
        Sem.AStructure("a10 = (1) ra10 + a + gfp")
        Sem.AStructure("c1 = (1) rc1 + c + gfp")
        Sem.AStructure("c2 = (1) rc2 + c + gfp")
        Sem.AStructure("c3 = (1) rc3 + c + gfp")
        Sem.AStructure("c4 = (1) rc4 + c + gfp")
        Sem.AStructure("c5 = (1) rc5 + c + gfp")
        Sem.AStructure("c6 = (1) rc6 + c + gfp")
        Sem.AStructure("c7 = (1) rc7 + c + gfp")
        Sem.AStructure("c8 = c + gfp + (1) rc8")
        Sem.AStructure("c9 = (1) rc9 + c + gfp")
        Sem.AStructure("c10 = (1) rc10 + c + gfp")
        Sem.AStructure("s1 = s + gfp + (1) rs1")
        Sem.AStructure("s2 = (1) rs2 + s + gfp")
        Sem.AStructure("s3 = (1) rs3 + s + gfp")
        Sem.AStructure("s4 = s + (1) rs4 + gfp")
        Sem.AStructure("s5 = (1) rs5 + s + gfp")
        Sem.AStructure("s6 = (1) rs6 + s + gfp")
        Sem.AStructure("s7 = (1) rs7 + s + gfp")
        Sem.AStructure("s8 = (1) rs8 + s + gfp")
        Sem.AStructure("s9 = (1) rs9 + s + gfp")
        Sem.AStructure("s10 = (1) rs10 + s + gfp")
        Sem.AStructure("o1 = (1) ro1 + o + gfp")
        Sem.AStructure("o2 = (1) ro2 + o + gfp")
        Sem.AStructure("o3 = (1) ro3 + o + gfp")
        Sem.AStructure("o4 = (1) ro4 + o + gfp")
        Sem.AStructure("o5 = (1) ro5 + o + gfp")
        Sem.AStructure("o6 = (1) ro6 + o + gfp")
        Sem.AStructure("o7 = (1) ro7 + o + gfp")
        Sem.AStructure("o8 = (1) ro8 + o + gfp")
        Sem.AStructure("o9 = (1) ro9 + o + gfp")
        Sem.AStructure("o10 = (1) ro10 + o + gfp")
        Sem.AStructure("Overall = e + a + c + s + o + gfp + (1) Res")
        Sem.Model("Default model", "")
    End Sub

    Sub AnalysisProperties(Sem As AmosEngine)
        Sem.Iterations = 50
        Sem.InputUnbiasedMoments
        Sem.FitMLMoments
        Sem.Standardized
        Sem.Seed = 1
    End Sub

End Module
Assessing a structural model from within Mplus

The data are the same as in the previous slide.

The model statements

```
model:
e by e1-e10*1;
a by a1-a10*1;
c by c1-c10*1;
s by s1-s10*1;
o by o1-o10*1;
gfp by e1-o10*1;
e@0;a@0;c@0;s@0;o@0;gfp@0;
gfp with e-o@0;
e-o with e-o@0;
Overall on e-o gfp;
```

Key portions of the Mplus output

<table>
<thead>
<tr>
<th>OVERALL ON</th>
<th>Estimate</th>
<th>S.E.</th>
<th>Est/S.E.</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>0.033</td>
<td>0.048</td>
<td>0.701</td>
<td>0.483</td>
</tr>
<tr>
<td>A</td>
<td>-0.002</td>
<td>0.045</td>
<td>-0.049</td>
<td>0.961</td>
</tr>
<tr>
<td>C</td>
<td>-0.059</td>
<td>0.056</td>
<td>-1.059</td>
<td>0.290</td>
</tr>
<tr>
<td>S</td>
<td>-0.063</td>
<td>0.049</td>
<td>-1.286</td>
<td>0.198</td>
</tr>
<tr>
<td>O</td>
<td>-0.158</td>
<td>0.047</td>
<td>-3.388</td>
<td>0.001</td>
</tr>
<tr>
<td>GFP</td>
<td>0.104</td>
<td>0.045</td>
<td>2.321</td>
<td>0.020</td>
</tr>
</tbody>
</table>

Measurement Model

Structural Model
Assessing a structural model using **factor scores** from **Mplus** - 1

Key portions of the Mplus program measurement model

```
model:
  e by e1-e10;
a by a1-a10;
c by c1-c10;
s by s1-s10;
o by o1-o10;
gfp by e1-o10;
gfp with e-o@0;
e-o with e-o@0;
```

Note: Measurement model only

```
output: modindices(20) standardized fsdeterminacy;
savedata: file is 'G:\MdbR\1Vikus\FS_1CP10_M_OrthB5.inp';
         save=fscores;
```

Commands to save factor scores

A factor score file saved by Mplus with
1) the raw data, 2) the factor scores, and 3) the standard errors of the factor scores.
Assessing a structural model using factor scores from *Mplus* - 2

“Alt-copy” each factor score column.

Paste the column into a statistical package data editor window.

Continue to “alt-copy” and paste until all data have been moved.
Assessing a structural model using **factor scores** from *Mplus* – 3

The factor Scores in an SPSS data file . . .(renamed as efs, afs, etc.)

The key output from the SPSS analysis

```
Coefficients^a

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td>3.118</td>
<td>.025</td>
<td>125.748</td>
</tr>
<tr>
<td></td>
<td>efs</td>
<td>.054</td>
<td>.060</td>
<td>.036</td>
</tr>
<tr>
<td></td>
<td>afs</td>
<td>.013</td>
<td>.124</td>
<td>.004</td>
</tr>
<tr>
<td></td>
<td>cfs</td>
<td>-.136</td>
<td>.157</td>
<td>-.034</td>
</tr>
<tr>
<td></td>
<td>dfs</td>
<td>-.077</td>
<td>.069</td>
<td>-.044</td>
</tr>
<tr>
<td></td>
<td>offs</td>
<td>-.523</td>
<td>.161</td>
<td>-.124</td>
</tr>
<tr>
<td></td>
<td>gfpfs</td>
<td>.287</td>
<td>.132</td>
<td>.085</td>
</tr>
</tbody>
</table>

^a. Dependent Variable: overall
```
Issues surrounding bifactor models

1) Relationship to common method factors
2) Whether factors should be uncorrelated
3) What the indicators should be
4) Whether the model has to be a CFA
Issues – 1: Relationship to common method factors

The bifactor is a form of common method factor.

It is a factor that influences all behavior collected in administration of the questionnaire.

Issues – 1: Relationship to common method factors

Common method factor model: May be structural relationships between group factors

Bifactor: Group factors often uncorrelated and exogenous.

Bottom line: Much of what we know about common method factors applies to bifactor models
Issues – 2 continued: Should the factors be uncorrelated?

The general factor must be uncorrelated with the group factors – for identification.
Issues – 2
continued:
Should the group factors be uncorrelated?

Hmm.
Issues – 2 continues: Should the Group factors be correlated?

Most applications constrain the group factors to be orthogonal.

There may be bifactor purists who would say that a model is not a bifactor model unless that is the case.

We have explored models in which the group factors have been allowed to correlate with each other. (e.g., Biderman et al., 2011)

Group factors will be assumed to be orthogonal for what follows here.
Issues – 3: What should be the indicators?

Should be the indicators of the factors be items or parcels or scale scores?

Let’s rule out scale scores.

Group factors are contaminated with error of measurement.

So either items or parcels must be indicators.
Issues – 3 continued: Items as indicators

Many models use items as indicators.

**Advantages of items**

- Unambiguity with respect to the effect of item characteristics – content, valence, wording

**Disadvantages of items**

- May require estimation of too many parameters – twice as many loadings as a regular CFA
- Unusual items may have undo influence on results.
- Goodness-of-fit suffers when items are indicators
Issues – 3 continued: Parcels as Indicators

Some applications use parcels as indicators.

**Advantage of parcels**

Parcels more likely to meet normality, etc assumptions.

Parcels may mask *un*interesting item characteristics

Model goodness-of-fit measures are better when parcels are indicators

**Disadvantages of parcels**

Parcels may mask interesting item characteristics – content, valence, wording

Specific choice of parcels may influence the solution.

**In all of what follows, items were indicators.**
Issues 4 – Does a bifactor model have to be a CFA?

The original presentation of bifactor models (Holzinger & Swineford, 1937) was as an exploratory factor model.

Most current applications are CFAs.

Mplus Version 7 can easily apply an EFA bifactor model.

Here’s the Mplus code to specify a bifactor model

```plaintext
usevariables are e1-o10;
analysis: type = EFA 6 6;
  ROTATION = BI-GEOMIN(ORTHOGONAL);
```

All following applications will be CFAs.
Examples of applications of bifactor models to Big Five data

1) Bifactor as a contaminant in Big Five predictions of objective criteria

2) Bifactor and correlations involving Big Five dimensions with measures of affect

3) Bifactor and correlations involving only non Big 5 variables with affective components

4) Bifactor as a predictor
Application Examples – 1: Contaminant of UGPA predictions
Comparing the validity of Conscientiousness scale score with validity of factor scores.

Predictors: Conscientiousness Scale scores vs Conscientiousness Factor Scores
Criterion: Undergraduate GPA or test scores
Questionnaires: IPIP Original 50-item Scale

<table>
<thead>
<tr>
<th>Study</th>
<th>Validity of Scale Scores</th>
<th>Validity of C factor Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biderman, Nguyen, Sebren (2008) N=166</td>
<td>.125</td>
<td>.177</td>
</tr>
<tr>
<td>Biderman, Worthy, Nguyen, Mullins, &amp; Luna (2012) N=328</td>
<td>.079</td>
<td>.080</td>
</tr>
<tr>
<td>Nguyen &amp; Biderman, 2013 N=288</td>
<td>.165</td>
<td>.202</td>
</tr>
</tbody>
</table>

So, there is some evidence that eliminating bifactor contamination results in larger correlations of conscientiousness with UGPA.

Mean loading of C items on bifactor is .21, so only about 4% of variance in C scale scores is due to individual differences in the bifactor. So effect size is small.
Application Examples – 2: Bifactor and correlations of Big 5 dimensions with Positive and Negative Affectivity

Data: N=202

Participants responded to IPIP Original 50-item Scale.

Participants responded to PANAS.

Computed correlations of Big 5 scale scores with PA and NA.

Computed correlations of Big Five factor scores from bifactor model with PA and NA.

Application Examples – 2: Correlations of scale and factor scores with PA

Big Five scale scores all correlated positively with PANAS Positive Affectivity. (p < .05 for red correlations.) N=202

Factor scores from a bifactor model exhibited smaller correlations with PA than did scale scores.
Application Examples – 2: Correlations of scale and factor scores with NA

Same study as above, except that correlations with NA were compared.

Factor scores from the Bifactor model exhibited much smaller correlations with NA than did scale scores.
Application Examples – 2 continued:  Bifactor and Big Five correlations with Self-esteem and Depression

Data: N = 206

Participants responded to IPIP Sample 50-item Questionnaire.

Participants responded to Costello and Comrey (1967) Depression scale.

Participants responded to Rosenberg (1965) Self-esteem scale

Bifactor model was applied to Big Five data.

Big 5 scale scores were correlated with Self-esteem and Depression.

Factors were correlated with Self-esteem and Depression in the following three ways....

Application Examples – 2 continued: Factor correlations of Self-esteem and Depression with factors – 3 ways to evaluate

1) **Within-program** (Mplus) correlations of Big Five with Self-esteem and Depression factors were computed using the following model (m is the bifactor in the model) . . .

2) Bifactor model was applied to only the Big Five data and **factor scores** computed from that model were correlated with Self-esteem and Depression scale scores.

3) Big Five **scale** scores were correlated with Self-esteem and Depression **scale** scores partialling out bifactor factor scores from a Big 5 bifactor model.
Application Examples – 2 continued:
Big Five correlations with Self-esteem and Depression

Correlations in red: p < .05

<table>
<thead>
<tr>
<th></th>
<th>E</th>
<th>A</th>
<th>C</th>
<th>S</th>
<th>O</th>
<th>Bifactor</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Self-esteem</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale correlations</td>
<td>.285</td>
<td>.188</td>
<td>.381</td>
<td>.242</td>
<td>.359</td>
<td></td>
</tr>
<tr>
<td>Factor correlations</td>
<td>.078</td>
<td>-.006</td>
<td>.328</td>
<td>.100</td>
<td>.209</td>
<td>.479</td>
</tr>
<tr>
<td>Factor score correlations</td>
<td>.081</td>
<td>.002</td>
<td>.317</td>
<td>.077</td>
<td>.269</td>
<td>.406</td>
</tr>
<tr>
<td>Scale rs partialling bifactor</td>
<td>-.016</td>
<td>-.085</td>
<td>.335</td>
<td>.073</td>
<td>.230</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>E</th>
<th>A</th>
<th>C</th>
<th>S</th>
<th>O</th>
<th>Bifactor</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Depression</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale correlations</td>
<td>-.202</td>
<td>-.309</td>
<td>-.330</td>
<td>-.284</td>
<td>-.192</td>
<td></td>
</tr>
<tr>
<td>Factor correlations</td>
<td>-.005</td>
<td>-.117</td>
<td>-.328</td>
<td>-.177</td>
<td>.047</td>
<td>-.404</td>
</tr>
<tr>
<td>Factor score correlations</td>
<td>.005</td>
<td>-.124</td>
<td>-.279</td>
<td>-.114</td>
<td>-.075</td>
<td>-.365</td>
</tr>
<tr>
<td>Scale rs partialling bifactor</td>
<td>.099</td>
<td>-.115</td>
<td>-.282</td>
<td>-.145</td>
<td>.049</td>
<td></td>
</tr>
</tbody>
</table>
Application Examples – 2: Correlations with measures of affect

Take away from these examples . . .

1) Controlling for the bifactor diminishes correlations of Big Five dimensions with measures of positive and negative affect.

2) The bifactor estimated from Big Five data is positively correlated with measures of positive affect and negatively correlated with measures of negative affect.

3) Structural correlations
   a) from within program
   b) of factor scores and
   c) of scale scores partialling bifactor
   were similar
Application Examples – 3: Bifactor and correlations among non Big Five variables with affective components

Correlations of Maslach Burnout Scale with Core Self Evaluations, Hardiness, and Extraversion from questionnaire given to 300+ Nurses

Bifactor model applied to only the Big Five data and factor scores computed.

Note: Bifactor was **not** indicated by items from the burnout, hardiness or CSE scales.

All values in red: \( p < .05 \)

<table>
<thead>
<tr>
<th></th>
<th>Hardiness</th>
<th>CSE</th>
<th>Extraversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Correlations with Burnout scale</td>
<td>-.616</td>
<td>-.646</td>
<td>-.265</td>
</tr>
<tr>
<td>Partialling out bifactor factor scores</td>
<td>-.521</td>
<td>-.564</td>
<td>-.019</td>
</tr>
<tr>
<td>Z testing significance of difference</td>
<td>-4.67</td>
<td>-4.57</td>
<td>-6.33</td>
</tr>
</tbody>
</table>

Application Examples – 4
Bifactor as a predictor

These results were presented above. N=764.


www.utc.edu/michael-biderman
What is the bifactor in Big Five data? - 1

Specifically it’s common variation - a tendency to respond slightly more positively or slightly more negatively to items than would be expected on the basis of the respondent’s position on the trait.

It’s a slight elevation of responses to all items or a slight “delevation” of responses to all items.

People high on the bifactor respond with slightly higher responses to all items than if the bifactor were not affecting their responses.

People low on the bifactor respond with slightly lower responses to all items than they would if the bifactor were not affecting their responses.

Interesting result: Since the Big Five factors are essentially orthogonal, a person’s score on the bifactor can be estimated by simply taking the mean of ALL responses on the Big Five questionnaire.
What is the bifactor in Big Five data? – 2

Scatterplots of bifactor factor scores vs. mean of responses to all items.

<table>
<thead>
<tr>
<th>Test</th>
<th>Sample Size</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPIP 50-item</td>
<td>N=547</td>
<td>r = .846</td>
</tr>
<tr>
<td>Minimarkers</td>
<td>N=206</td>
<td>r = .651</td>
</tr>
<tr>
<td>“Other” 50-items</td>
<td>N=206</td>
<td>r = .799</td>
</tr>
<tr>
<td>NEO-FFI</td>
<td>N=189</td>
<td>r = .849</td>
</tr>
</tbody>
</table>
What is the bifactor in Big Five data? - 3

The evidence: Individual differences in the bifactor . . .

are positively correlated with positive affect and self-esteem . . .

are negatively correlated with negative affect and depression . . .

are positively correlated with supervisor evaluations.

These results suggest that the bifactor represents the affective or emotional state of the respondent

High bifactor value – the respondent is feeling good about her/himself – will score high on PA and self-esteem, low on NA and depression, and be evaluated favorably by supervisor

Low bifactor value – the respondent is feeling down - will score low on PA and self-esteem, high on NA and depression and be evaluated less favorably by supervisor.
What is the bifactor in Big Five data? – 4

Déjà vu all over again: Self-report of affective state is not a new concept


“However, the empirical research findings indicate that the five factors are frequently importantly correlated with each other, usually to reflect an overriding evaluative component.”
How is what is presented here different from what’s been done in the past?

Affective state modeled here as a bifactor

Previous applications have sought separate indicators for factors representing affect - not shared indicators.

Modeled here as a part of any Big Five questionnaire

The items on the questionnaires modeled here were chosen to represent the Big Five, not affective state.

Big Five items are typically selected to omit evaluation

Modeled here as orthogonal to the Big Five dimensions

The affect represented by the bifactor is independent of the Big Five
Items and the bifactor - 1

If this expression of affect is coming from the items, how is it related to them?

How are the items of the Big Five related to the bifactor?

What items are most affected by the bifactor?

Bäckström, M., Björklund, F. & Larsson, M. R. (2009). Five-factor inventories have a major general factor related to social desirability which can be reduced by framing items neutrally. *Journal of Research in Personality, 43*, 335-344.

Bäckström et al. showed that neutrally worded items had generally smaller loadings on the bifactor.

What follows is an extension of the work of Bäckström et al.
Items and the bifactor - 2

Looking for what item characteristics are related to the bifactor

Data: N=547

Bifactor model applied to IPIP 50-item Big 5 questionnaire data.

Negatively-worded items were not reverse-scored.

(Results are the same as if items not reverse-scored, except that signs of loadings are reversed.)

Focused on loadings of individual items on the bifactor.
Items and the bifactor – 3

Loadings of 50-item scale items on the bifactor

Filled circles represent positively worded items

Bifactor does not represent blind acquiescence or most loadings would be positive.

Loadings near 0: Bifactor has little effect on those items.

Extreme loadings - far from 0: – Bifactor has a large effect of the bifactor on them.
Items and the bifactor - 4

What is the item characteristic that is related to the loadings?

Our hypothesis was that the salience of an item for the bifactor depends on the item’s **valence**.

Positive valence: Item says something good about you

- I am interested in people.
- I make people feel at ease.

Negative valence: Item says something bad about you

- I insult people.
- I often feel blue.

People feeling good about themselves will agree with the positively valenced items and disagree with the negatively valenced items.
Item valence and bifactor loadings - 1

Data: N=366

We had students estimate valence of each IPIP item.

Instructions:

Think about how people you care about would evaluate you if you had the characteristic mentioned in the statement.

4: “They would say that if I had this characteristic, it would make me look absolutely good.”

... 

0: “They would say that if I had this characteristic, it would make me look absolutely bad.”

Item valence and bifactor loadings - 2

Bifactor Loadings vs. Mean Valence Ratings

Overall $r = 0.884$

$r$ for positively-worded items = 0.592

$r$ for negatively-worded items = 0.240
I make people feel at ease
I feel comfortable around people
I am interested in people
I start conversations
I talk to a lot of different people at parties
I make people feel at ease
I take time out for others
I am not really interested in others
I insult people
I often feel blue
I worry about things
I have a rich vocabulary
I use difficult words
I get stressed out easily
I don’t like to draw attention to myself
I am not really interested in others

Item valence and bifactor loadings - 3

Wordings of selected items.
Takeaway from the previous slides

The bifactor of the Big Five appears to represent the respondent’s affective state.

Influence of the bifactor on items is related to item valence

Persons high on the bifactor will be most likely to agree with items with highest positive valence and to disagree with items with the lowest valence
What to do with the bifactor - 1

Get rid of it.

Following Bäckström et al.

Design scales free of contamination from the bifactor: Items whose valence is least extreme – those around 2 on the 0-4 scale used here - would be expected to have the smallest amount of contamination by the bifactor.

Clearly such information can be used to “purify” scale scores by basing them on items with less extreme valence – less contamination – as Bäckström et al. did.
What to do with the bifactor – 2

Embrace it

Design scales to assess the bifactor along with the Big Five. Select items with extreme valence for questionnaires.

Maximize individual differences in the expression of affect represented by the bifactor.

Use the bifactor to assess affective state by administering a Big Five questionnaire

Use it as a controlling variable to partial out affective state.

Use it as a predictor of performance involving affective characteristics
Summary

1. Strong evidence that there is common item variance in Big Five data – nicely accounted for by a model with a bifactor.

2. Strong evidence that the Big Five bifactor is related to measures that involve affect, suggesting that it is a measure of general affective state.


4. Evidence that items with extreme valence are most strongly related to differences in the bifactor.
Caveats

Big Five bifactor is not identical to bifactors estimated from other questionnaires or Big Five questionnaires obtained under unusual instructional conditions

Item content may overwhelm the valence effect

Instructions and incentives to fake overwhelm the valence effect

Nonconvergence – always a problem with models involving crossed factors.

Multiple solutions – Occasionally, we’ve encountered datasets with two solutions.
Bifactor poem

“Bifactor bifactor where have you been?”

“Hiding among the items so that when you correlate and predict,
my contamination will stick
to your measures like gum on a shoe.
Leaving you with a confusing data stew.”
The End
References - 1

Bäckström, M., Björklund, F. & Larsson, M. (2009). Five-factor inventories have a major general factor related to social desirability which can be reduced by framing items neutrally. *Journal of Research in Personality, 43*, 335- 344.


Bäckström, M., Björklund, F. & Larsson, M. R. (2009). Five-factor inventories have a major general factor related to social desirability which can be reduced by framing items neutrally. *Journal of Research in Personality, 43*, 335- 344.
References - 2


Nguyen, N. T., & Biderman, M. D. (2013). Predicting counterproduct work behavior from a bi-factor model of Big Five personality. Paper accepted for presentation at the annual meeting of the Academy of Management, Orlando, FL.


References - 3


Questions?
Extra slides follow
More detail on loading patterns for Big 5 Questionnaires

Thompson MiniMarker; N=206

NEO – FFI; N=195

IPIP 50-item; N=547

www.utc.edu/michael-biderman
Convergent Validity with a questionnaire of random indicators
This slide shows that the bifactor represents a characteristic of self report that is independent of the specific content of the items.
## Relationships with measures of affect in 4 datasets

<table>
<thead>
<tr>
<th>Study</th>
<th>Scale</th>
<th>Mean of items correlation with</th>
<th>Bifactor scores correlation with</th>
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<tr>
<td></td>
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<td>Negative</td>
<td>Positive</td>
<td>Negative</td>
</tr>
<tr>
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