Scale Building with Confirmatory Factor Analysis

PRE 906: Structural Equation Modeling
Lecture #7 – March 4, 2015

Today's Class

- Scale building with confirmatory factor analysis
  - Model Fit
  - Model Modification
  - Scale Interpretation
  - Item information

- Additional Psychometric Issues:
  - Construct Maps
  - Item Design
  - Item Information

Key Questions for Today's Class

1. What methods are used to remove mis-fitting items from a one-factor model?

2. What is item information?
   1. What does it quantify?
   2. How is it calculated?

Data for Today's Class

- Data were collected from two sources:
  - 144 "experienced" gamblers
    - Many from an actual casino
  - 1192 college students from a "rectangular" midwestern state
    - Many never gambled before

- Today, we will combine both samples and treat them as homogenous – one sample of 1346 subjects
  - Later we will test this assumption – measurement invariance (called differential item functioning in item response theory literature)

- We will build a scale of gambling tendencies using the first 24 items of the GRI
  - Focused on long-term gambling tendencies

Pathological Gambling: DSM Definition

- To be diagnosed as a pathological gambler, an individual must meet 5 of 10 defined criteria:

1. Is preoccupied with gambling
2. Needs to gamble with increasing amounts of money in order to achieve the desired excitement
3. Has repeated unsuccessful efforts to control, cut back, or stop gambling
4. Is restless or irritable when attempting to cut down or stop gambling
5. Gambles as a way of escaping from problems or relieving a dysphoric mood
6. After losing money gambling, often returns another day to get even
7. Lies to family members, therapist, or others to conceal the extent of involvement with gambling
8. Has committed illegal acts such as forgery, fraud, theft, or embezzlement to finance gambling
9. Has jeopardized or lost a significant relationship, job, educational, or career opportunity because of gambling
10. Relies on others to provide money to relieve a desperate financial situation caused by gambling

Our 24 GRI Items

- The first 24 items of the GRI were written to represent the 10 DSM criteria in the gambling tendencies construct:

Criterion	Item Count
1	3
2	2
3	4
4	1
5	4
6	4
7	2
8	2
9	1
10	1

BUILDING OUR GAMBLING SCALE

Building our Gambling Scale

- The 41 items of the GRI represent the full set of items generated to study the tendency to gamble as a construct
  - The 10 DSM criteria were the basis for the items of the GRI
  - We will use the first 24 items as our item pool

- Our goal: to create a scale that accurately measures **one overall "gambling tendencies" factor**

- The key: make sure the one-factor model fits the data
  - If the model does not fit, inferences cannot be made

- The problem: balancing model fit with the construct
  - Not all items will be retained – so the final construct will likely be different from the original construct

First Step: Analysis of 24 Items

- The first step in our analysis is to examine how the one-factor model fits the entire item pool

```
model01.syntax = "

#factor specification statement (only statement needed)
  gambling =~ GRI1 + GRI2 + GRI3 + GRI4 + GRI5 + GRI6 + GRI7 + GRI8 + GRI9 + GRI10 + GRI11 + GRI12 +
              GRI13 + GRI14 + GRI15 + GRI16 + GRI17 + GRI18 + GRI19 + GRI20 + GRI21 + GRI22 + GRI23 + GRI24
"

#model estimation
model01.fit = sem(model01.syntax, data=gri_data, mimic="Mplus", estimator = "MLR")

#display model output
summary(model01.fit, fit.measures = TRUE, standardized = TRUE)
```

Step #1: Assessment of Model Fit

```
lavaan (0.5-17) converged normally after  51 iterations

  Number of observations                          1304

  Number of missing patterns                         5

  Estimator                                         ML      Robust
  Minimum Function Test Statistic             3729.276    2697.490
  Degrees of freedom                               252         252
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  1.382
    for the Yuan-Bentler correction (Mplus variant)

Model test baseline model:

  Minimum Function Test Statistic            11790.193    8007.561
  Degrees of freedom                               276         276
  P-value                                        0.000       0.000

User model versus baseline model:

  Comparative Fit Index (CFI)                    0.698       0.684
  Tucker-Lewis Index (TLI)                       0.669       0.654

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -43696.259  -43696.259
  Scaling correction factor                                  2.023
    for the MLR correction
  Loglikelihood unrestricted model (H1)     -41831.621  -41831.621
  Scaling correction factor                                  1.525
    for the MLR correction

  Number of free parameters                         72          72
  Akaike (AIC)                               87536.519   87536.519
  Bayesian (BIC)                             87908.988   87908.988
  Sample-size adjusted Bayesian (BIC)        87680.279   87680.279

Root Mean Square Error of Approximation:

  RMSEA                                          0.103       0.086
  90 Percent Confidence Interval          0.100  0.106       0.084  0.089
  P-value RMSEA <= 0.05                          0.000       0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.087       0.087
```

The model χ^2 indicated the model did not fit better than the saturated model – but this statistic can be overly sensitive

The model CFI and TLI indicated the model did not fit well (want these to be > .95)

The model RMSEA indicated the model did not fit well (want this to be < .05)

The SRMR indicated the model did not fit well (want this to be < .08)

Assessment of Global Model Fit

- **Assessment of global model fit:**
  - Recall that item intercepts, factor means, and variances are just-identified
    - ***<u>Therefore, misfit comes from inaccurately modeled covariances</u>***
  - χ^2 is sensitive to large sample size
  - Pick at least one global fit index from each class; hope they agree (e.g., CFI, RMSEA)
  - If model fit is not good, you should NOT be interpreting the model estimates
    - They will change as the model changes
    - All models are approximations – close approximations are best
  - If model fit is not good, it's your job to find out WHY
  - If model fit is good, it does not mean you are done, however…
    - You can have good fit and poorly functioning items

Step #2: Assessment of Model Misfit

- Our one-factor model ended up not fitting well
  - We must make modifications before we can conclude we have built a good scale to measure gambling tendencies

- Because the model did not fit well, we **cannot** look at any model-based parameters to give us indications of misfit
  - These are likely to be biased (= wrong or misleading)

- The modification indices for this approach won't work
  - Nothing to modify with only one factor

- What we must examine is the **residual covariance matrix** using the **normalized residual covariances**
  - Normalized residual covariances are like z-scores (bigger than +/- 2 indicate significant misfit)

Normalized Residual Covariances

- Normalized residual covariances are like z-scores
  - Values bigger than +/- 2 indicate significant misfit
- Positive residuals: items are more related than your model predicts them to be
  - Something other than the factor created the relationship
- Negative residuals: items are less related than your model predicts them to be
  - The overall model causes these to be off
- Evidence of model misfit tells you where the problems with the model lie, but not what to do about fixing them

Normalized Residual Covariances

- These are hard to read when there are a lot of items

```
> residuals(model01.fit, type="normalized")
$cov
       GRI1   GRI2   GRI3   GRI4   GRI5   GRI6   GRI7   GRI8   GRI9   GRI10  GRI11  GRI12  GRI13  GRI14  GRI15  GRI16  GRI17  GRI18  GRI19
GRI1    0.000
GRI2    2.718  0.000
GRI3    0.661  1.690  0.000
GRI4    1.165  6.206  1.943  0.000
GRI5    0.133  1.457  0.192  3.027  0.000
GRI6   -0.556 -1.995  0.683 -2.536  0.302  0.000
GRI7   -0.597 -0.525  0.430  4.256  2.408  0.843  0.000
GRI8    2.310  3.673  0.500  4.075  1.042 -0.183  0.867  0.000
GRI9    0.134  0.256  0.098 -0.187  1.379  0.836  0.292  0.575  0.000
GRI10  -0.351 -1.106  0.486  0.359  0.399  1.346  1.021  0.745  1.277  0.083
GRI11  -1.792 -4.137 -0.740 -3.404 -0.947  0.718 -0.446 -2.131 -0.240  0.319  0.000
GRI12   0.100  3.384 -3.627  7.637 -0.541 -4.348  0.139  4.783 -2.354 -1.312 -0.921  0.000
GRI13  -0.214 -1.429 -0.030 -1.626 -0.493  0.109 -0.143 -0.816  0.281 -0.356 -0.054 -1.727  0.000
GRI14   0.120 -2.912  0.117  1.132  0.311 -1.933  1.936 -1.987 -0.783 -0.393  3.523  1.760 -0.894 -0.004
GRI15   1.511  2.008 -1.443  0.857 -1.774 -1.619  0.212  1.975 -1.736 -1.039 -1.784  6.281  0.098  1.410 -0.002
GRI16  -0.998 -1.722  0.025 -5.197 -2.128  0.943 -3.172 -1.842 -1.781 -0.720  1.311 -0.360  0.331 -0.915  1.244  0.000
GRI17  -2.464 -3.780 -0.419 -3.498 -1.548 -0.566 -1.355 -4.163 -1.750 -0.900  2.168 -2.894  0.304  3.558  1.114  3.046  0.000
GRI18   0.157 -1.431 -0.893 -6.003 -0.950 -0.552 -2.854 -0.716 -1.419 -2.417  2.498  1.251 -0.067 -1.329 -0.018  3.348  1.244  0.000
GRI19   3.729  3.141 -0.736 -0.406 -2.957 -2.075 -4.808  2.086 -1.364 -1.554 -1.761  5.772 -0.772 -3.592  4.617  2.814 -0.919  4.002  0.000
GRI20   2.601  6.605 -0.967 14.083  1.934 -6.870  1.724  5.783 -3.529 -1.037 -4.721 14.643 -3.416  0.993  8.642 -2.564 -4.003 -1.539  7.795
GRI21  -0.742 -0.519 -0.406 -2.749 -0.690 -0.461 -1.997 -2.392  0.058 -0.750  0.144 -3.072  1.299 -0.926 -0.514  1.930  1.395  1.484  1.630
GRI22  -1.251 -9.327 -2.011 -12.660 -1.845 4.389 -1.552 -3.866 -0.104  0.847  5.822 -5.207  0.492  4.022 -5.065  1.593  3.524  5.217 -4.726
GRI23  -1.489  0.355 -0.831  2.207 -0.301 -1.228  0.947 -1.000 -0.802 -0.759  1.793 -0.470  0.524  0.306  0.659  0.968  2.554  0.122 -0.173
GRI24  -0.540 -5.130 -1.032 -7.446 -2.023  1.378 -3.646 -2.037  0.116  0.258  1.114 -2.248  1.461  2.001 -4.120  1.839  4.263  2.592 -1.465
       GRI20  GRI21  GRI22  GRI23  GRI24
GRI1
GRI2
GRI3
GRI4
GRI5
GRI6
GRI7
GRI8
GRI9
GRI10
GRI11
GRI12
GRI13
GRI14
GRI15
GRI16
GRI17
GRI18
GRI19
GRI20   0.034
GRI21  -1.301  0.000
GRI22 -15.947  1.969  0.000
GRI23   3.193  0.344 -2.496  0.000
GRI24  -8.673  3.073 10.542 -1.833  0.000
```

Re-Sorting Normalized Residual Covariances

```
> norm_resid[1:10,]
            normresid  var1  var2
45  -9.32683833600825  GRI2 GRI22
290 -8.67310050087066 GRI20 GRI24
251  8.64240818484154 GRI15 GRI20
281  7.79516530810538 GRI19 GRI20
78    7.6371195942697  GRI4 GRI12
90  -7.44644923002808  GRI4 GRI24
125 -6.87026145595052  GRI6 GRI20
43   6.60514767353204  GRI2 GRI20
213  6.28078559602154 GRI12 GRI15
27   6.20571540924132  GRI2  GRI4
```

GRI 24 Item Analysis Normalized Residuals

- The largest absolute value normalized residuals:
  - -9.32 (Covariance of Item 22 and Item 2)
    - Negative value: model causes misfit
  - -8.67 (Covariance of Item 20 and Item 24)
    - Negative value: model causes misfit
  - 8.64 (Covariance of Item 15 and Item 20)
    - Positive value: additional features causing extra item covariances

- Often, we examine the wording and content of the items for clues as to why they do not fit the model:
  - Item 20: When gambling, I have an amount of money in mind that I am willing to lose, and I stop if I reach that point. (6R)
  - Item 22: Gambling has hurt my financial situation. (10)
  - Item 4: I enjoy talking with my family and friends about my past gambling experiences. (7R)
  - Item 12: When I lose money gambling, it is a long time before I gamble again. (6R)

Ways of Fixing The Model #1: Adding Parameters – Increasing Complexity

- A common source of misfit is due to items that have a significant residual covariance
  - Items are still correlated after accounting for the common factor
  - For a one-factor model – this indicates that one factor does not fit data (so theory of one-factor is incorrect)

- Solutions that increase model complexity:
  - **Add additional factors** (recommended solution)
    - Factors are additional dimensions (constructs) that are measured by the items
  - **Add a residual covariance between items** (dangerous solution)
    - Use modification indices to determine which to add
    - Error covariances are unaccounted for multi-dimensionality
      - This means you have measured your factor **and** something else that those items have in common (e.g. stem, valence, specific content, additional factors)

Solution #1: Adding Factors

- Adding a factor is equivalent to stating that the hypothesized one-factor model does not fit the data
  - The evidence suggests a one-factor model is not adequate

- The GRI was created to measure each of the 10 criteria of the DSM, not one general gambling factor
  - Likely, gambling tendencies have more than one factor

- We will revisit adding an additional factor next week
  - When we look at multidimensional factor models

- For now, our focus will be on building a one-factor scale

Solution #2: Examining Modification Indices for Residual Covariances

- Note: this solution is not recommended as it weakens the argument that a single factor underlies a scale
  - It also is seen as a trick to improve model fit

- The largest modification indices for residual covariances:

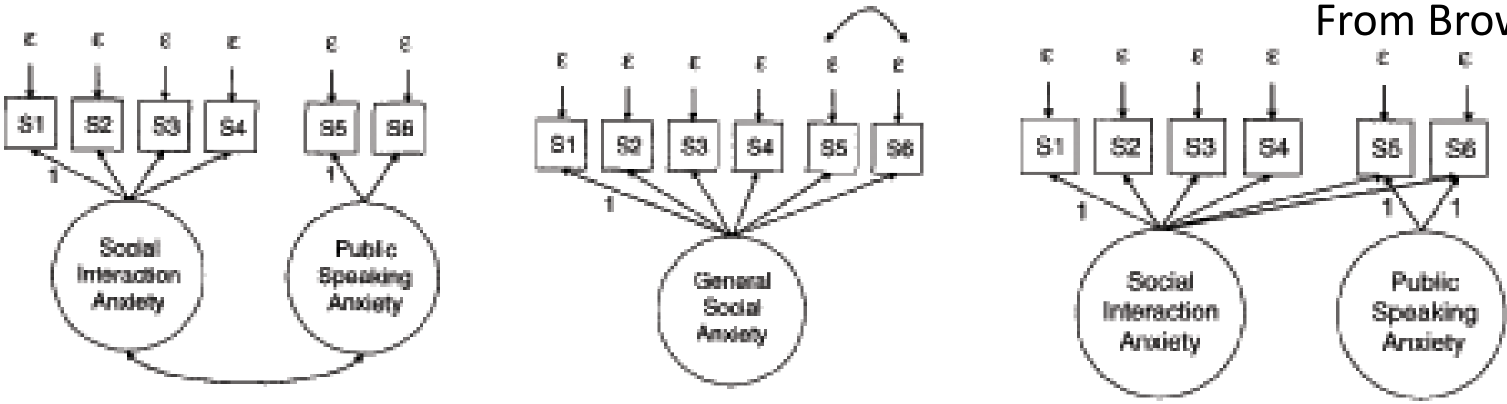
```
> model01.mi[1:10,]
     lhs op   rhs      mi mi.scaled    epc sepc.lv sepc.all sepc.nox
1   GRI4 ~~ GRI20 269.642   195.040  1.065   1.065    0.403    0.403
2  GRI20 ~~ GRI22 238.767   172.707 -1.404  -1.404   -0.405   -0.405
3  GRI12 ~~ GRI20 225.551   163.147  1.498   1.498    0.399    0.399
4  GRI22 ~~ GRI24 180.710   130.713  0.697   0.697    0.325    0.325
5   GRI4 ~~ GRI22 150.710   109.013 -0.741  -0.741   -0.304   -0.304
6   GRI1 ~~ GRI19 119.367    86.342  0.250   0.250    0.224    0.224
7  GRI15 ~~ GRI20 104.120    75.313  0.581   0.581    0.248    0.248
8  GRI19 ~~ GRI20  99.265    71.801  0.511   0.511    0.239    0.239
9  GRI20 ~~ GRI24  92.818    67.138 -0.537  -0.537   -0.231   -0.231
10  GRI2 ~~ GRI22  80.579    58.285 -0.666  -0.666   -0.231   -0.231
```

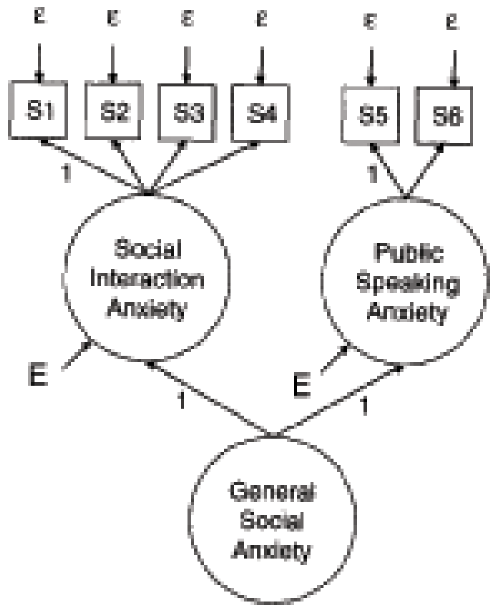
- Most of these items are reverse coded
  - Indication that wording of items elicits different response
  - Potential for a reverse-worded method factor

- We will not add these to our model – we want our single factor to be only thing that "explains" items

Error Covariances Actually Represent Multidimensionality

From Brown (2006)





Here there is a general factor of “Social Interaction Anxiety” that includes two items dealing with public speaking specifically.

The extra relationship between the two public speaking items can be modeled in many different, yet statistically equivalent ways… error covariances really represent another factor (which is why you should be able to explain and predict them if you include them).

Ways of Fixing The Model #2: Removing Terms – Decreasing Complexity

- Solution #1: When multiple factors are correlated > .85 may suggest a simpler structure – remove factors
  - Nested model comparison: fix factor variances to 1 so factor covariance becomes factor correlation, then test correlation ≠1 at $p < .10$

- Solution #2: Dropping Items; Drop items with:
  - **Non-significant loadings:** If the item isn't related, it isn't measuring the construct, and you most likely don't need it
  - **Negative loadings**: Make sure to reverse-coded as needed ahead of time – otherwise, this indicates a big problem!
  - **Problematic leftover positive covariances between two items** – such redundancy implies you may not need both items

- However – models with differing items are **NOT COMPARABLE AT ALL** because their Log-Likelihood values are based on different data!
  - No model comparisons of any kind (including AIC and BIC)
  - To do a true comparison, you'd need to leave the item in the model but remove its loading (≈ original test of its loading)

List of Items to Remove

- Because our model fit is terrible we will modify our model by dropping items that do not fit well
  - This will change our gambling construct but will allow us to (hopefully) have one factor measured by the test
- There are 9 items with 10 or more significant normalized residual covariances:

GRI22	16
GRI4	15
GRI20	15
GRI2	13
GRI8	13
GRI19	13
GRI24	13
GRI12	12
GRI17	12

Item Removal Logic and Details

- By dropping items with a number of significant normalized residual covariances we will reduce the number of items in our analysis thereby reducing the number of terms in the saturated covariance matrix

- This can make it easier to achieve a reasonable approximation as the number of covariances increases exponentially with each additional item, but the number of statistical parameters increases by two (factor loading and unique variance)
  - We would be trying to approximate a lot of covariances terms with only a few parameters

- We will remove the 9 items from the list on the previous page, leaving us with a 15-item analysis

GRI 15 Item Analysis Model Fit Information

```
lavaan (0.5-17) converged normally after  48 iterations

  Number of observations                          1304

  Number of missing patterns                         5

  Estimator                                         ML      Robust
  Minimum Function Test Statistic              691.824     420.480
  Degrees of freedom                                90          90
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  1.645
    for the Yuan-Bentler correction (Mplus variant)

Model test baseline model:

  Minimum Function Test Statistic             6791.150    3726.133
  Degrees of freedom                               105         105
  P-value                                        0.000       0.000

User model versus baseline model:

  Comparative Fit Index (CFI)                    0.910       0.909
  Tucker-Lewis Index (TLI)                       0.895       0.894

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -23888.184  -23888.184
  Scaling correction factor                                  2.404
    for the MLR correction
  Loglikelihood unrestricted model (H1)     -23542.272  -23542.272
  Scaling correction factor                                  1.898
    for the MLR correction

  Number of free parameters                         45          45
  Akaike (AIC)                               47866.367   47866.367
  Bayesian (BIC)                             48099.161   48099.161
  Sample-size adjusted Bayesian (BIC)        47956.218   47956.218

Root Mean Square Error of Approximation:

  RMSEA                                          0.072       0.053
  90 Percent Confidence Interval          0.067  0.077       0.049  0.057
  P-value RMSEA <= 0.05                          0.000       0.100

Standardized Root Mean Square Residual:

  SRMR                                           0.042       0.042
```

The model χ^2 indicated the model did not fit better than the saturated model – but this statistic can be overly sensitive

The model CFI and TLI indicated the model adequately (want these to be > .95)

The model RMSEA indicated acceptable model fit (want this to be < .05; .06-.08 is acceptable)

The SRMR indicated the fit well (want this to be < .08)

Examining the Normalized Residuals

- The normalized residuals from the analysis indicated that several items had questionable fit:
  - Items 7, 16, and 18 had four significant normalized residuals
  - The rest had 2 or fewer (4 items had none)

- At this point, the choice of removal of additional items is ultimately up to theory
  - The fit of the model is adequate – removal of items may make the model fit better
  - The construct may be significantly altered by removing items measuring certain features

- We will choose to omit items 7, 16, and 18 from the scale, and rerun the analysis with 12 items

GRI 12 Item Analysis

- The 12 item analysis gave this model fit information:

```
lavaan (0.5-17) converged normally after  42 iterations

  Number of observations                          1304

  Number of missing patterns                         5

  Estimator                                         ML      Robust
  Minimum Function Test Statistic              296.920     185.178
  Degrees of freedom                                54          54
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  1.603
    for the Yuan-Bentler correction (Mplus variant)

Model test baseline model:

  Minimum Function Test Statistic             5186.873    2802.860
  Degrees of freedom                                66          66
  P-value                                        0.000       0.000

User model versus baseline model:

  Comparative Fit Index (CFI)                    0.953       0.952
  Tucker-Lewis Index (TLI)                       0.942       0.941

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -18988.425  -18988.425
  Scaling correction factor                                  2.431
    for the MLR correction
  Loglikelihood unrestricted model (H1)     -18839.965  -18839.965
  Scaling correction factor                                  1.934
    for the MLR correction

  Number of free parameters                         36          36
  Akaike (AIC)                               38048.850   38048.850
  Bayesian (BIC)                             38235.085   38235.085
  Sample-size adjusted Bayesian (BIC)        38120.730   38120.730

Root Mean Square Error of Approximation:

  RMSEA                                          0.059       0.043
  90 Percent Confidence Interval          0.052  0.065       0.038  0.049
  P-value RMSEA <= 0.05                          0.013       0.981

Standardized Root Mean Square Residual:

  SRMR                                           0.032       0.032
```

Interpreting Parameters

- The one-factor model seems to fit the 12 GRI items so we will interpret the parameters

Item	Unstandardized Loading	Residual Variance	Standardized Loading (STDYX)	R^2
GRI 1	1.000 (0.000)	0.697 (0.066)	.567 (.037)	.322
GRI 3	0.785 (0.073)	0.545 (0.044)	.522 (.036)	.272
GRI 5	1.118 (0.096)	0.499 (0.047)	.673 (.032)	.453
GRI 6	0.815 (0.070)	0.309 (0.024)	.645 (.033)	.416
GRI 9	0.960 (0.059)	0.215 (0.017)	.766 (.023)	.587
GRI 10	1.068 (0.081)	0.369 (0.040)	.711 (.028)	.506
GRI 11	1.012 (0.075)	0.854 (0.078)	.533 (.033)	.284
GRI 13	1.172 (0.073)	0.462 (0.047)	.704 (.028)	.496
GRI 14	1.023 (0.095)	1.837 (0.078)	.398 (.026)	.159
GRI 15	0.857 (0.071)	1.219 (0.078)	.408 (.029)	.166
GRI 21	0.967 (0.071)	0.377 (0.036)	.672 (.028)	.451
GRI 23	1.086 (0.080)	0.514 (0.044)	.657 (.026)	.432

Interpreting Parameters

- Each item had a statistically significant factor loading
  - The item measures the factor/is correlated with the factor
- The standardized factor loadings ranged from .766 (item 9) to .398 (item 14)
- The R^2 is the squared standardized loading
  - Item 9 had an R^2 of .587
    - Items with high R^2 are better for measuring the factor
  - Item 14 had an R^2 of .159
    - Items with low R^2 are not contributing much to the factor

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Interpreting the Scale

- The final gambling scale had a different set of items than the original gambling scale
  - As such, the construct measured by the final scale is different that the construct that would be measured if the full set of items were used (and fit a one-factor model)

Criterion	24-Item Count	12-Item Count
1	3	2
2	2	2
3	4	2
4	1	1
5	4	2
6	4	1
7	2	1
8	2	1
9	1	0
10	1	0

Pathological Gambling: DSM Definition

- To be diagnosed as a pathological gambler, an individual must meet 5 of 10 defined criteria:

1. Is preoccupied with gambling
2. Needs to gamble with increasing amounts of money in order to achieve the desired excitement
3. Has repeated unsuccessful efforts to control, cut back, or stop gambling
4. Is restless or irritable when attempting to cut down or stop gambling
5. Gambles as a way of escaping from problems or relieving a dysphoric mood
6. After losing money gambling, often returns another day to get even
7. Lies to family members, therapist, or others to conceal the extent of involvement with gambling
8. Has committed illegal acts such as forgery, fraud, theft, or embezzlement to finance gambling
9. Has jeopardized or lost a significant relationship, job, educational, or career opportunity because of gambling
10. Relies on others to provide money to relieve a desperate financial situation caused by gambling

Final 12 Items on the Scale

Item	Criterion	Question
GRI1	3	I would like to cut back on my gambling.
GRI3	6	If I lost a lot of money gambling one day, I would be more likely to want to play again the following day.
GRI5	2	I find it necessary to gamble with larger amounts of money (than when I first gambled) for gambling to be exciting.
GRI6	8	I have gone to great lengths to obtain money for gambling.
GRI9	4	I feel restless when I try to cut down or stop gambling.
GRI10	1	It bothers me when I have no money to gamble.
GRI11	5	I gamble to take my mind off my worries.
GRI13	3	I find it difficult to stop gambling.
GRI14	2	I am drawn more by the thrill of gambling than by the money I could win.
GRI15	7	I am private about my gambling experiences.
GRI21	1	It is hard to get my mind off gambling.
GRI23	5	I gamble to improve my mood.

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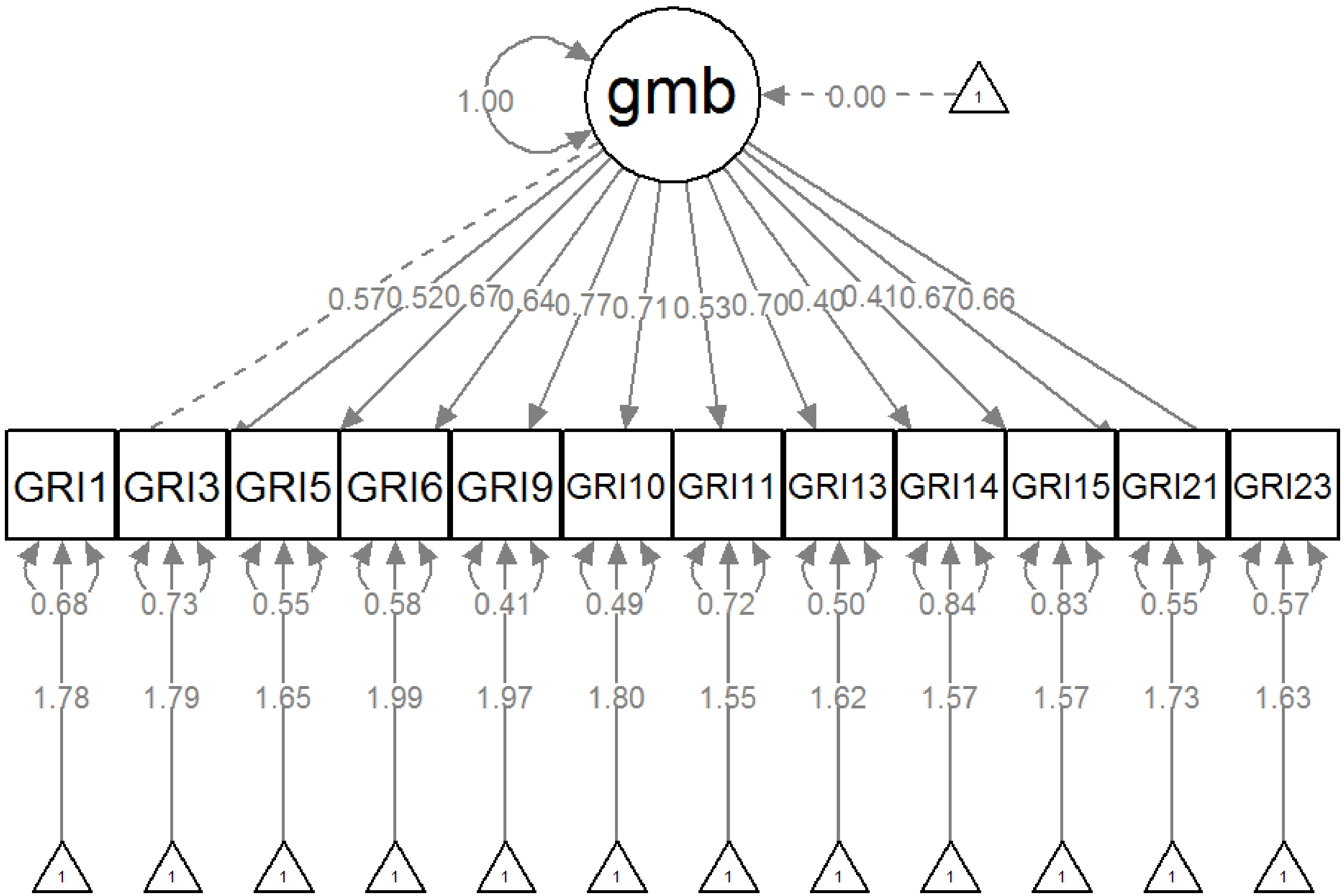
Final Model Path Diagram



QUANTIFYING AN ITEM'S CONTRIBUTION: ITEM INFORMATION

Item Information

- The amount of information an item provides about a factor is a combination of:
  - The size of the factor loading
  - The size of the error variance

- The index of the statistical information that item *i* provides for factor *f* is $\frac{\lambda_{if}^2}{\psi_i^2}$
  - The unstandardized loadings provide the information for a factor with a variance fixed at σ_f^2
  - The standardized loadings provide the information for a factor with a variance of 1
  - The rank order of the information will be the same using either unstandardized or standardized loadings
    - So choice is arbitrary as both work the same way
- Note: as information depends on the model parameters (loadings and unique variances) a model must fit well to have an accurate sense of the information provided by each item

Information of Our Items

- Given that the one-factor model seems to fit the 12 GRI items, we use the parameters to calculate item information

Item	Unstandardized Loading	Residual Variance	Item Information	Info Rank
GRI 1	1.000 (0.000)	0.697 (0.066)	1.434	8
GRI 3	0.785 (0.073)	0.545 (0.044)	1.130	10
GRI 5	1.118 (0.096)	0.499 (0.047)	2.504	4
GRI 6	0.815 (0.070)	0.309 (0.024)	2.148	7
GRI 9	0.960 (0.059)	0.215 (0.017)	4.296	1
GRI 10	1.068 (0.081)	0.369 (0.040)	3.092	2
GRI 11	1.012 (0.075)	0.854 (0.078)	1.201	9
GRI 13	1.172 (0.073)	0.462 (0.047)	2.971	3
GRI 14	1.023 (0.095)	1.837 (0.078)	0.570	12
GRI 15	0.857 (0.071)	1.219 (0.078)	0.602	11
GRI 21	0.967 (0.071)	0.377 (0.036)	2.482	5
GRI 23	1.086 (0.080)	0.514 (0.044)	2.297	6

Using the lavaan ":=" Command to Calculate Item Information

```
#Model 03 w/information =============================================================

model03a.syntax = "

#factor specification statement (only statement needed)
  gambling =~ GRI1 + L3*GRI3 + L5*GRI5 + L6*GRI6 + L9*GRI9 + L10*GRI10 + L11*GRI11 +
              L13*GRI13 + L14*GRI14 + L15*GRI15 + L21*GRI21 + L23*GRI23

#labeling unique variances of indicator variables
  GRI1 ~~ U1*GRI1
  GRI3 ~~ U3*GRI3
  GRI5 ~~ U5*GRI5
  GRI6 ~~ U6*GRI6
  GRI9 ~~ U9*GRI9
  GRI10 ~~ U10*GRI10
  GRI11 ~~ U11*GRI11
  GRI13 ~~ U13*GRI13
  GRI14 ~~ U14*GRI14
  GRI15 ~~ U15*GRI15
  GRI21 ~~ U21*GRI21
  GRI23 ~~ U23*GRI23

#calculating item information with parameter labels:
  info1 := 1 / U1
  info3 := (L3*L3) / U3
  info5 := (L5*L5) / U5
  info6 := (L6*L6) / U6
  info9 := (L9*L9) / U9
  info10 := (L10*L10) / U10
  info11 := (L11*L11) / U11
  info13 := (L13*L13) / U13
  info14 := (L14*L14) / U14
  info15 := (L15*L15) / U15
  info21 := (L21*L21) / U21
  info23 := (L23*L23) / U23
"
#model estimation
```

lavaan Information Output:

```
Defined parameters:
    info1           1.434    0.135   10.638    0.000    1.434    1.475
    info3           1.130    0.241    4.687    0.000    0.374    0.374
    info5           2.504    0.543    4.613    0.000    0.829    0.829
    info6           2.148    0.419    5.131    0.000    0.711    0.711
    info9           4.296    0.635    6.763    0.000    1.423    1.423
    info10          3.092    0.610    5.070    0.000    1.024    1.024
    info11          1.201    0.233    5.143    0.000    0.398    0.398
    info13          2.971    0.507    5.858    0.000    0.984    0.984
    info14          0.570    0.116    4.909    0.000    0.189    0.189
    info15          0.602    0.116    5.203    0.000    0.200    0.200
    info21          2.482    0.435    5.708    0.000    0.822    0.822
    info23          2.297    0.411    5.582    0.000    0.761    0.761
```

Notes About Item Information

- Under CFA (which assumes items that are continuous/normally distributed), information is constant for each item
  - This differs when you have categorical items: Information differs by values of the latent trait (some items measure certain trait levels better than others)

- Because item information is constant under CFA, it gets very little attention
  - By extension, certain types of tests aren't possible with CFA – such as computer adaptive tests (as the best item at each point would be the best item overall)

- Item information can be used to select a set of items to be used to measure a construct
  - A shorter yet efficient test
  - Remember – changing the items changes the construct

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WRAP UP AND REFOCUSING

Key Questions for Today's Class

1. What methods are used to remove mis-fitting items from a one-factor model?

2. What is item information?
   1. What does it quantify?
   2. How is it calculated?

Wrapping Up

- Today, we built a scale using confirmatory factor analysis
  - Model Fit
  - Model Modification (by removing items)
  - Scale Interpretation
  - Item Information

Where We Are Heading

- Next week's lecture: multidimensional CFA models
  - More than one factor
  - Reliability for a total test score no longer applies (each factor is where reliability is important)