Electronic Supplementary Information (ESI)

Title: Before the Lecture Begins: Unpacking How Affective Measures Impact performance in General Chemistry 1

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Table of Contents

A: Internal Structure

Descriptive statistics and determination of sampling adequacy

The investigation of data distributions enables early detection of non-normal properties that may affect correlations and subsequent analyses. In this study, data normality and variability were assessed using descriptive statistics, including histograms, means, standard deviations, skewness, and kurtosis. Data for Science Currency (SciCur) were collected only at the start of the semester, as this construct pertains to students science resources as a child and their parental influence. In contrast, data for social belonging, imposter syndrome, and academic mindset were collected at two time points: early semester (first two weeks) and end of semester (last two weeks, prior to finals). Because the social belonging instrument had been previously used at the same institution and course, only confirmatory factor analysis (CFA) was conducted to confirm its internal structure. For Academic Mindset and Imposter Syndrome, however, both exploratory and confirmatory factor analyses (EFA and CFA) were performed.

The full, early-semester (pr_) dataset (N = 398) was randomly split in half: one subgroup (G1) was used for exploratory factor analysis (EFA), while the other (G2) was reserved for CFA. For each construct, we created a testing and training dataset. Further details for each construct are described below. Descriptive statistics (not-reverse scored/coded to show true distribution) were calculated for G1, followed by assumption checks to determine suitability for factor analysis. For multidimensional models that include both positive and negative phrasing of survey questions– such as academic mindset and social belonging, it is recommended that negatively worded items (academic mindset entity and social belonging: belonging uncertainty) be reverse scored/coded to avoid additional problems with skewness (Streiner and Kottner, 2014; Komperda*, et al.*, 2018). Multivariate normality was examined using Mardia's test ($p < .05$ indicating deviation from normality). Due to violations of multivariate normality detected by Mardia's test across all measures, Polychoric correlations were used for the EFAs. The Polychoric correlation matrix was examined to ensure that a substantial number of correlations exceeded .30, indicating sufficient intercorrelation among items to justify factor analysis (Watkins, 2018). Specifically, sampling adequacy was evaluated using the Kaiser-Meyer-Olkin (KMO) measure ($KMO > 0.80$), and factorability was assessed with Bartlett's test of sphericity ($p < .001$). Multicollinearity was assessed for measures with more than one factor via Variance Inflation Factors ($VIFs < 10.0$), and potential outliers were identified using Mahalanobis D^2, with significance determined by the chi-square distribution based on the number of items per measure ($p < .001$). If the measure does not include values excluded due to Mahalanobis D^2, then outliers were not excluded. Below, we present our descriptive statistics, assumption checks, EFAs, and CFAs for each measure used in this study.

EFA and Estimation Methods

EFA is a multivariate technique for uncovering the underlying structure of relationships among a set of observed variables (items) by identifying their common underlying dimensions (Beaujean, 2014; Hair*, et al.*, 2019). This method does not rely on prior assumptions about the factor structure; factors (latent variables) are extracted from a dataset without pre-specifying the number of factors or the pattern of factor loadings between the observed and latent factors. To

identify the appropriate number of factors to retain for rotation, two post-estimations were conducted: minimum average partial (MAP) (Velicer, 1976) and scree plots (Cattell, 1978). For extraction method, Minimum Residual (MinRes) was chosen. Oblique rotation was chosen because it allows the factors to be correlated, which more accurately reflects the reality that social science variables are often interrelated (Meehl, 1990). Promax, an oblique rotation method, was selected as the extraction method because it allows factors to be correlated (Finch, 2020). Due to oblique rotation, close attention was paid to both the pattern coefficients (to interpret the meaning of each factor) and the factor intercorrelations (to understand how much the factors overlap (Bandalos and Gerstner, 2016; Bandalos, 2018). To ensure both practical (10% variance explained) and statistical $(p < .05)$ significance of eigen loadings, the threshold for salience was originally set at 0.32 (Morin*, et al.*, 2020). Factor models were checked to ensure that the proportion (no more than 20% of data) of residual coefficients did not exceed absolute values of .05 and .10 (Flora and Flake, 2017). Close model fit, meaning the ability of a model to reproduce the data, was indicated by an RMSR value of 0.05 or smaller.

CFA Guidelines

CFA is a theory-driven statistical method used to test hypotheses about the relationships between observed variables (items) and their underlying latent constructs (factors). This method involves specifying a predefined measurement model, estimating the covariance matrix implied by this model, and comparing it to the observed covariance matrix to evaluate how well the model fits the data.

Goodness-of-fit Satorra Bentler

Due to the multivariate non-normality distribution of our data, a Satorra-Bentler scaled chi-squared test for model goodness of fit was selected, which is robust to non-normality (Satorra and Bentler, 1994). The chi-square goodness of fit statistic evaluates the size of the difference between the sample and fitted covariance matrices (Hu and Bentler, 1999). For good model fit, Schreiber et al. (2006) recommended a non-significant chi-square p-value.

RMSEA

The Root Mean Square Error of Approximation (RMSEA) is an index to evaluate a "badness of fit," where zero indicates a perfect fit and higher values indicate a lack of fit (Browne and Cudeck, 1993; Watkins, 2021). Hu and Bentler (1999) recommended RMSEA values <.06 to .08.

CFI

The Comparative Fit Index (CFI) represents the amount of variance that has been accounted for in a covariance matrix (Watkins, 2021). Higher CFI values indicate a better model fit. Hu and Bentler recommend a CFI index bigger than or equal to 0.95 for a good model fit; whereas, a CFI index > 0.90 is an adequate model fit (Hu and Bentler, 1999; Sivo*, et al.*, 2006).

TLI

The Tucker-Lewis Index (TLI) (Tucker and Lewis, 1973), also known as the non-normed fit index (NNFI) (Bentler and Bonett, 1980), is an incremental fit index that measures the proportionate improvement of fit by comparing models to a more restricted, hypothetical baseline model

(Woods and Edwards, 2007). Hu and Bentler recommend a TLI index bigger than or equal to 0.95 for a good model fit; whereas, a TLI index > 0.90 is an adequate model fit (Hu and Bentler, 1999; Sivo*, et al.*, 2006)

SRMR

The Standardized Root Mean Square Residual is an absolute measure of fit and is the square root of the discrepancy between the sample covariance matrix and the model covariance matrix. Hu and Bentler (1999) recommend an SRMR value of < 0.08.

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I. Academic Mindset

Prompt: Using a 6-point Likert-Scale where (1) “Strongly Disagree” (2) “Disagree” (3) “Somewhat Disagree” (4) “Somewhat Agree” (5) “Agree” (6) “Strongly Agree.” rate your agreement to the following questions.

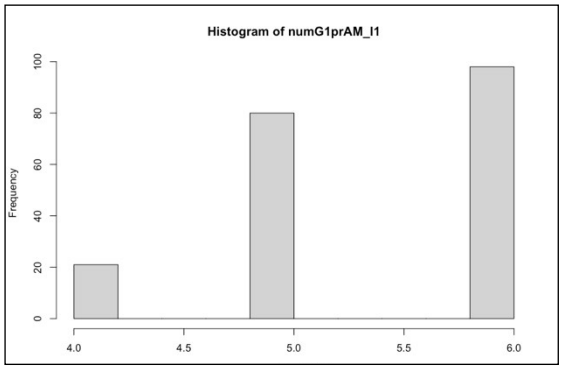
Self-theory Incremental: (**4 questions total**)

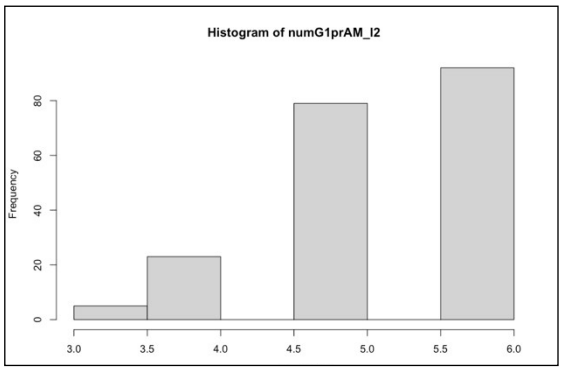
1. With enough time and effort, I think I could significantly improve my intelligence level in chemistry.
2. I believe I can always substantially improve my intelligence in chemistry.
3. Regardless of my current chemistry intelligence level, I think I have the capacity to change it quite a bit.
4. I believe I have the ability to change my basic intelligence level in chemistry considerably over time.

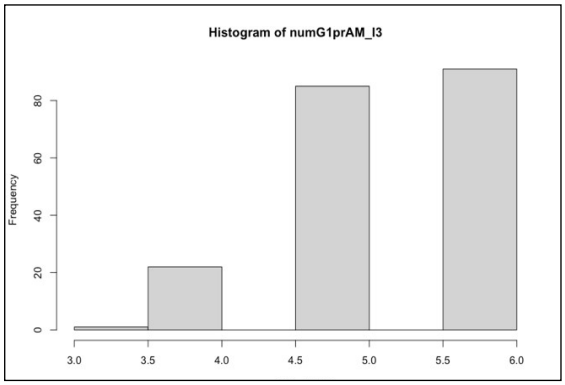
Self-Theory Entity: (**4 questions total**)

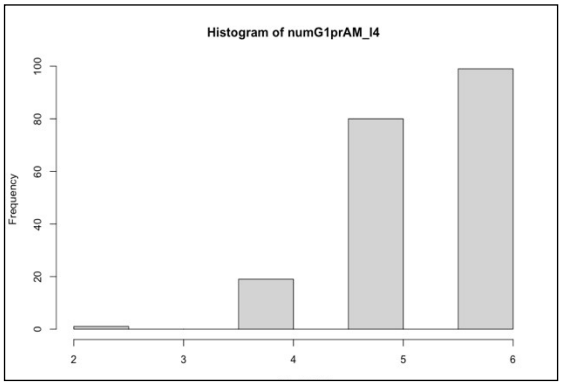
1. I don’t think I personally can do much to increase my chemistry intelligence.
2. My chemistry intelligence is something about me that I personally can’t change very much.
3. To be honest, I don’t think I can really change how intelligent I am in chemistry.
4. I can learn new things, but I don’t have the ability to change my basic intelligence in chemistry.

Academic Mindset: Incremental Histograms

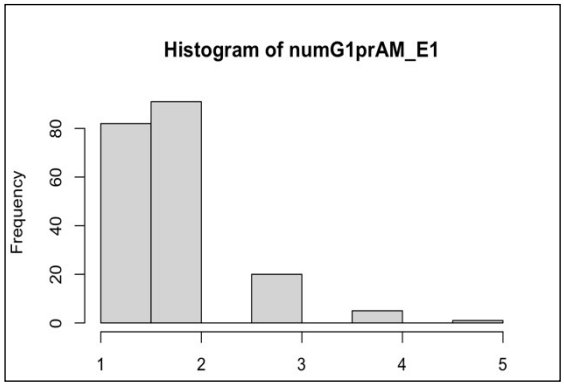


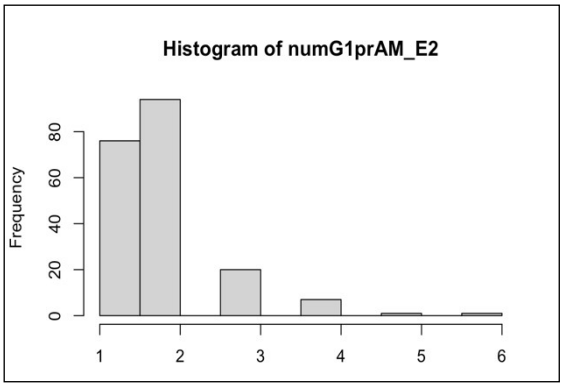


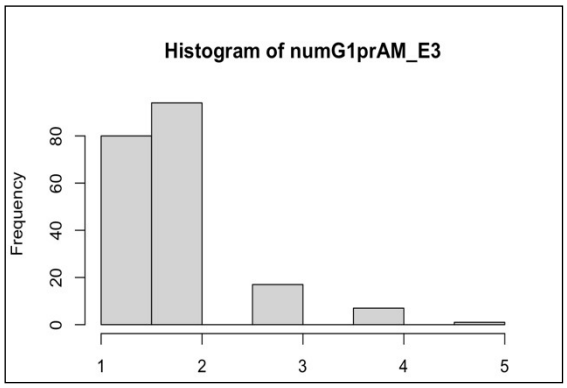


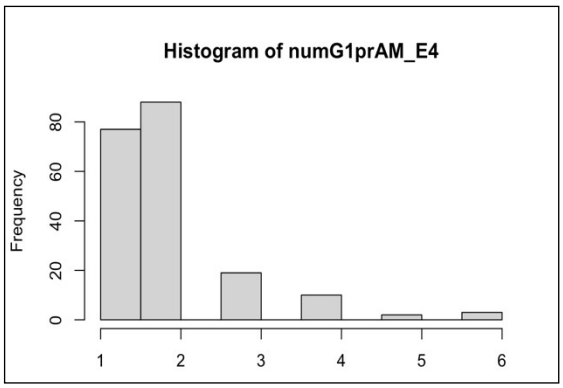


Academic Mindset: Entity Histograms







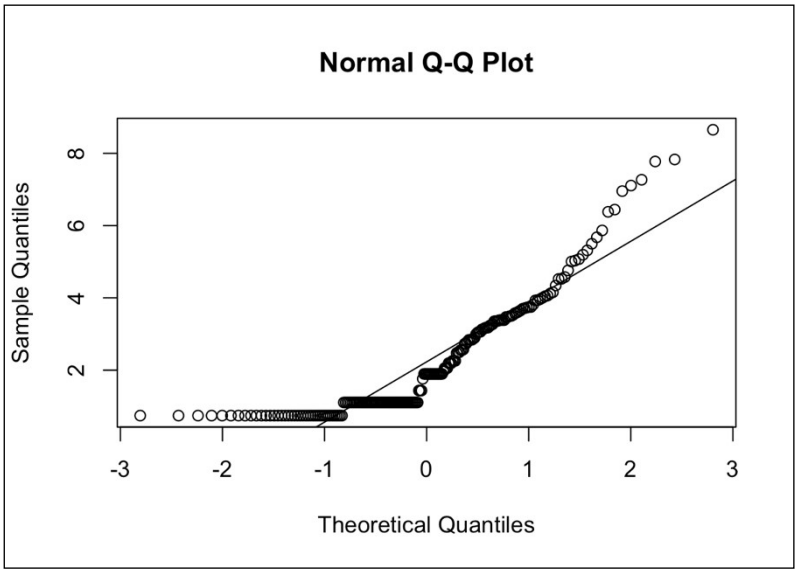


G1-Skewness, Kurtosis, SD, and Means for pr_Academic Mindset (8 items, outliers NOT removed). Entity items are not reverse coded.

	Skewness	Kurtosis	Mean	SD
G1-item I1	-0.6375602	2.334194	5.386935	0.6712194
G1-item I2	-0.8937528	3.274324	5.296482	0.7703716
G1-item I3	-0.6453332	2.649527	5.336683	0.690638
G1-item I4	-1.050449	4.584285	5.386935	0.7006708
G1-item E1	1.042203	4.408739	1.753769	0.7750356
G1-item E2	1.383645	6.203767	1.824121	0.8493736
G1-item E3	1.111957	4.57311	1.824121	0.7893446
G1-item E4	1.638515	6.497605	1.899497	1.005013

Mardia's Test of Academic Mindset (Incremental and Entity ; Entity Items are Reverse Coded)

```
Call: mardia(x = G1NumAllprAM)

Mardia tests of multivariate skew and kurtosis
Use describe(x) the to get univariate tests
n.obs = 199   num.vars =  8
b1p =  62.01   skew =  2056.72  with probability  <=  0
 small sample skew =  2094.71  with probability <=  0
b2p =  205.35   kurtosis =  69.9  with probability <=  0
```



Mardia's test of multivariate skewness (b1p = 62.01, $p < .001$) and kurtosis (b2p = 205.35, $p < .001$; kurtosis = 69.9) indicated significant departures from multivariate normality for the 8 variables in the sample (n = 199). These results suggest the data do not meet the assumption of multivariate normality.

Polychoric Correlation Matrix

	E1	E2	E3	E4	I1	I2	I3	I4
numG1prAM_E1	1							
numG1prAM_E2	0.839189	1						
numG1prAM_E3	0.855882	0.910815	1					
numG1prAM_E4	0.694275	0.701001	0.747273	1				
numG1prAM_I1	0.689688	0.57101	0.631057	0.555983	1			
numG1prAM_I2	0.697624	0.59142	0.625921	0.541888	0.861182	1		
numG1prAM_I3	0.702965	0.604536	0.662522	0.540387	0.839722	0.836635	1	
numG1prAM_I4	0.604896	0.521549	0.558873	0.525441	0.775407	0.778201	0.835736	1

Kaiser-Myer Olkin Test (KMO)

```
> kmo_G1prAM <- kmo_optimal_solution(G1NumAllprAM, squared = FALSE)
Final Solution Achieved!> kmo_G1prAM[["results"]]
$overall
[1] 0.9054591

$individual
                   MSA
numG1prAM_E1 0.9508088
numG1prAM_E2 0.8625234
numG1prAM_E3 0.8556312
numG1prAM_E4 0.9501328
numG1prAM_I1 0.9134098
numG1prAM_I2 0.9161016
numG1prAM_I3 0.9007254
numG1prAM_I4 0.9115451

$AIS
            [,1]         [,2]        [,3]          [,4]        [,5]          [,6]         [,7]
[1,]  0.19988138 -0.050482483 -0.03942762 -0.0277544898 -0.02027463 -0.0264753640 -0.016737919
[2,] -0.05048248  0.152936552 -0.08965293 -0.0092031741  0.02013869 -0.0118447182  0.009696078
[3,] -0.03942762 -0.089652929  0.12383150 -0.0652585775 -0.01074994  0.0120847967 -0.024767901
[4,] -0.02775449 -0.009203174 -0.06525858  0.4114384243 -0.02092791  0.0004787711  0.034390111
[5,] -0.02027463  0.020138692 -0.01074994 -0.0209279070  0.19967961 -0.0933310195 -0.049723804
[6,] -0.02647536 -0.011844718  0.01208480  0.0004787711 -0.09333102  0.2009515090 -0.044710892
[7,] -0.01673792  0.009696078 -0.02476790  0.0343901113 -0.04972380 -0.0447108924  0.175899311
[8,]  0.01108034 -0.008238082  0.01661960 -0.0533561234 -0.02936405 -0.0368983472 -0.102702900
             [,8]
[1,]  0.011080340
[2,] -0.008238082
[3,]  0.016619598
[4,] -0.053356123
[5,] -0.029364051
[6,] -0.036898347
[7,] -0.102702900
[8,]  0.267421193

$AIR
            [,1]        [,2]        [,3]        [,4]        [,5]        [,6]        [,7]        [,8]
[1,]  0.95080879 -0.28873464 -0.25061027 -0.09678201 -0.10148454 -0.13210223 -0.08926541  0.04792576
[2,] -0.28873464  0.86252342 -0.65146827 -0.03668847  0.11524146 -0.06756526  0.05911645 -0.04073545
[3,] -0.25061027 -0.65146827  0.85563124 -0.28911433 -0.06836338  0.07660871 -0.16781917  0.09132865
[4,] -0.09678201 -0.03668847 -0.28911433  0.95013283 -0.07301406  0.00166506  0.12783480 -0.16085477
```

Barlett's Test of Sphericity

```
> cortest.bartlett(G1NumAllprAM_SpearMatrix, n=199)
$chisq
[1] 1934.882

$p.value
[1] 0

$df
[1] 28

>
> format(result$p.value, scientific = TRUE)
[1] "0e+00"
```

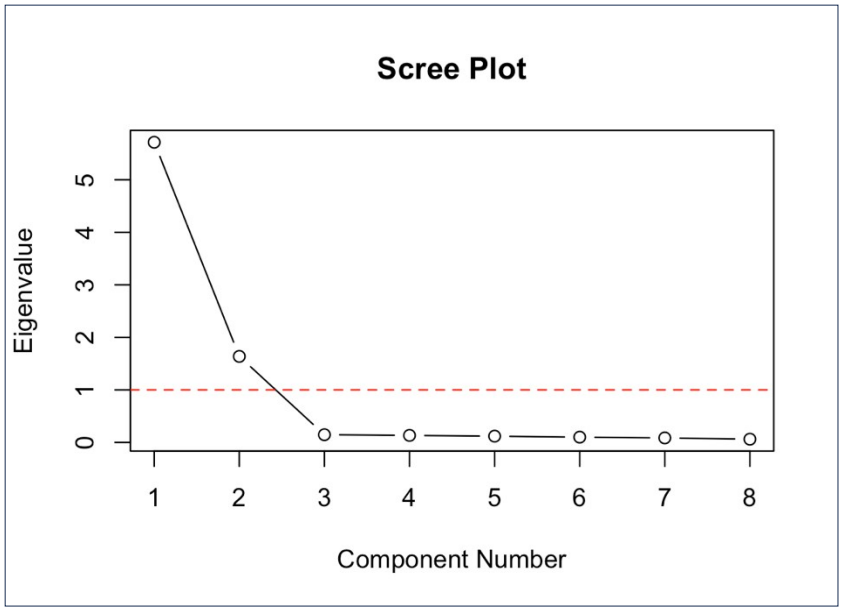
Check for Multicollinearity Using VIFs

```
numG1prAM_I1 numG1prAM_I2 numG1prAM_I3 numG1prAM_I4
    4.822204     4.779815     5.199445     3.624004
```

Minimum Average Partial (MAP) test

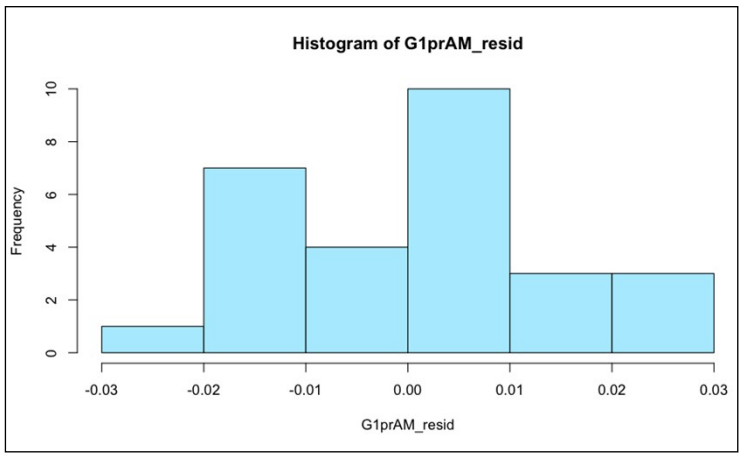
```
> vss_result <- vss(G1NumAllAM, n.obs = nrow(G1NumAllAM), rotate = "varimax", fm = "minres")
> # View the results
> print(vss_result)

Very Simple Structure
Call: vss(x = G1NumAllAM, rotate = "varimax", fm = "minres", n.obs = nrow(G1NumAllAM))
VSS complexity 1 achieves a maximimum of 0.92  with  1  factors
VSS complexity 2 achieves a maximimum of 1  with  3  factors

The Velicer MAP achieves a minimum of 0.05  with  2  factors
BIC achieves a minimum of  -49.34  with  2  factors
Sample Size adjusted BIC achieves a minimum of  -8.16  with  2  factors

Statistics by number of factors
  vss1 vss2   map dof   chisq     prob sqresid  fit RMSEA BIC SABIC complex  eChisq    SRMR  eCRMS eBIC
1 0.92 0.00 0.460  20 1.0e+03 4.6e-203   2.865 0.92 0.501 913 975.9     1.0 4.0e+02 1.9e-01 0.2240  293
2 0.75 1.00 0.054  13 1.9e+01  1.1e-01   0.100 1.00 0.050 -49  -8.2     1.2 4.1e-01 6.1e-03 0.0089  -68
3 0.75 1.00 0.104   7 7.1e+00  4.1e-01   0.081 1.00 0.009 -30  -7.7     1.2 1.5e-01 3.7e-03 0.0074  -37
4 0.75 0.96 0.165   2 3.8e-01  8.3e-01   0.064 1.00 0.000 -10  -3.9     1.3 6.2e-03 7.5e-04 0.0028  -11
5 0.75 1.00 0.257  -2 2.9e-05       NA   0.065 1.00    NA  NA    NA     1.2 4.7e-07 6.5e-06     NA   NA
6 0.75 1.00 0.432  -5 1.5e-07       NA   0.065 1.00    NA  NA    NA     1.2 2.7e-09 4.9e-07     NA   NA
7 0.75 1.00 1.000  -7 0.0e+00       NA   0.064 1.00    NA  NA    NA     1.2 1.2e-15 3.3e-10     NA   NA
8 0.75 1.00    NA  -8 0.0e+00       NA   0.064 1.00    NA  NA    NA     1.2 1.2e-15 3.3e-10     NA   NA
```

Scree Plot–*red line signifies the Kaiser criterion reference line*



Residuals for pr_AM:

	E1	E2	E3	E4	I1	I2	I3	I4
numG1prAM_E1								
numG1prAM_E2	0.007636							
numG1prAM_E3	-0.01022	0.000336						
numG1prAM_E4	0.001549	-0.00891	0.010085					
numG1prAM_I1	0.006176	-0.01143	0.001216	0.006557				
numG1prAM_I2	0.011557	0.005171	-0.00762	-0.00998	0.02569			
numG1prAM_I3	0.001369	0.004018	0.01381	-0.02421	-0.01219	-0.01438		
numG1prAM_I4	-0.01879	0.001558	-0.00636	0.026828	-0.01643	-0.01245	0.029734	



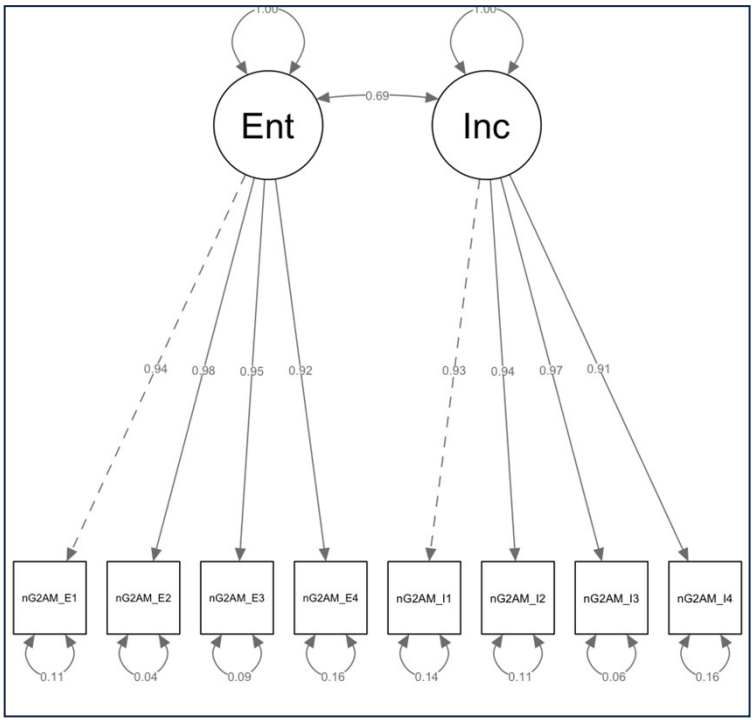
- No residuals are greater than |0.05|
- Residuals are normally distributed

Exploratory Factor Analysis, *promax rotation*

Factor Loadings of Exploratory Factor Analysis (EFA) of Early-Semester Academic Mindset				
Survey Item	Factor 1	Factor 2	Uniqueness u^2	Communality h^2
G1-item E1	**0.93**	0.01	0.120	0.88
G1-item E2	**0.97**	0.01	0.052	0.95
G1-item E3	**0.95**	-0.02	0.114	0.89
G1-item E4	**0.91**	0.03	0.149	0.85
G1-item I1	-0.05	**0.98**	0.084	0.92
G1-item I2	-0.02	**0.95**	0.116	0.88
G1-item I3	0.08	**0.90**	0.102	0.90
G1-item I4	0.04	**0.91**	0.123	0.88
N = 199; ; Factor loadings reported following a promax (oblique) factor rotation.				

Multidimensional Confirmatory Factor Analysis on G2 Data

Estimator: MLM

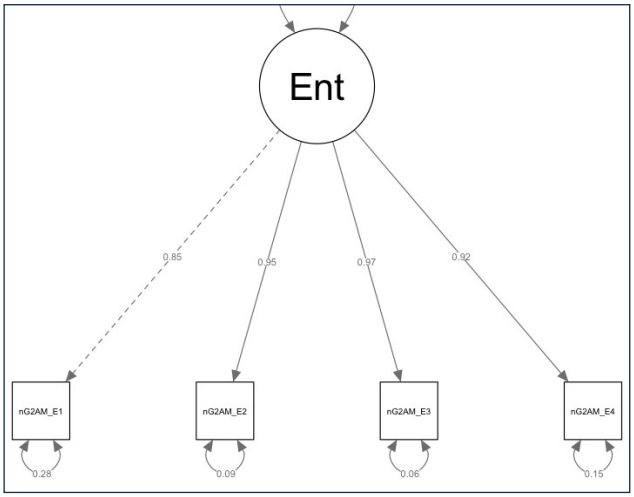


N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	23.586 (19, 0.213)	0.062	0.994	0.991	0.023

Unidimensional Confirmatory Factor Analysis on G2 Data

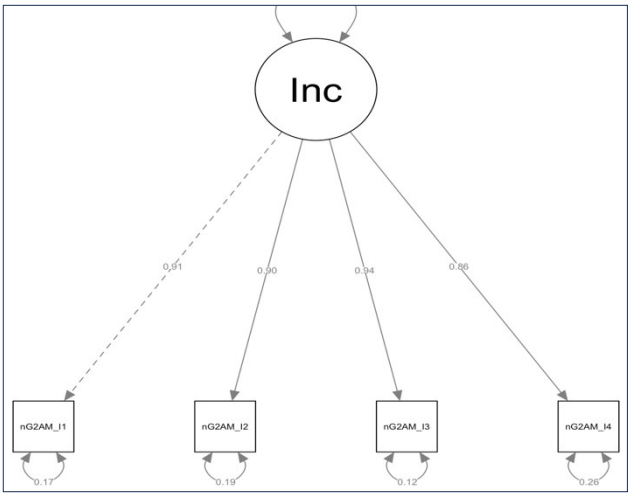
Estimator: MLM

Academic Mindset Entity (4 items loading on one factor)



N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	2.628 (2, 0.269)	0.073	0.998	0.993	0.012

Academic Mindset Incremental (4 items loading on one factor)



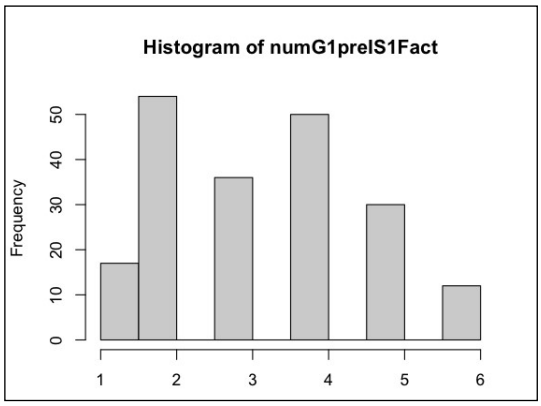
N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	2.910 (2, 0.233)	0.075	0.997	0.991	0.012

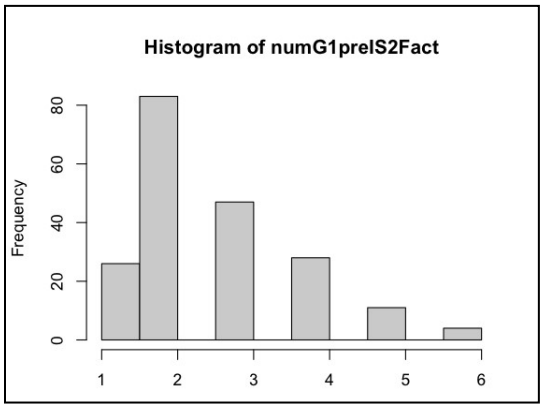
II. Imposter Syndrome

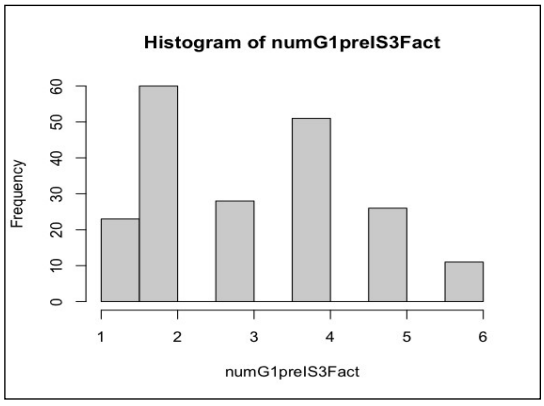
Prompt: Using a 6-point Likert-Scale where (1) “Strongly Disagree” (2) “Disagree” (3) “Somewhat Disagree” (4) “Somewhat Agree” (5) “Agree” (6) “Strongly Agree.” rate your agreement to the following questions.

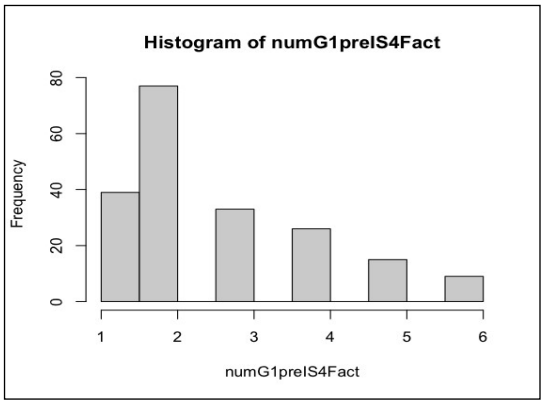
1. In class, I felt like people might find out that I am not as capable as they think I am.
2. Today, I felt like my successes in class were due to some kind of luck.
3. In class, I felt afraid others would discover how much knowledge or ability I really lack.
4. In class, I felt like an "imposter."

Imposter Syndrome Histograms







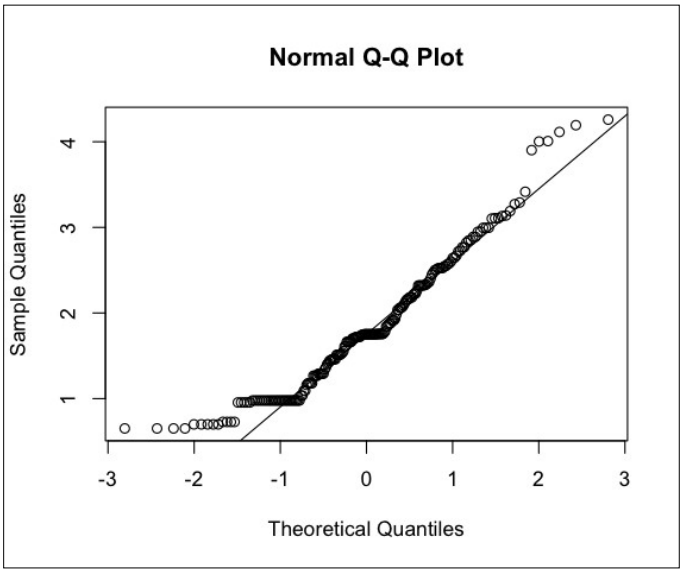


G1-Skewness and Kurtosis for pr_IS (4 items, outliers NOT removed)

	Skewness	Kurtosis	Mean	SD
G1-item IS1	0.1582299	2.078994	3.291457	1.39098
G1-item IS2	0.7643049	3.197778	2.633166	1.163895
G1-item IS3	0.227524	2.040708	3.150754	1.423961
G1-item IS4	0.8101957	2.846062	2.638191	1.374276

Mardia’s Test

```
Call: mardia(x = G1NumAll_prIS)

Mardia tests of multivariate skew and kurtosis
Use describe(x) the to get univariate tests
n.obs = 199   num.vars =  4
b1p =  3.15   skew =  104.34  with probability  <=  2.1e-13
 small sample skew =  106.56  with probability <=  8.3e-14
b2p =  27.77   kurtosis =  3.84  with probability <=  0.00012
```



Mardia's test indicated significant multivariate skewness (b1p = 3.15, skew = 104.34, p < .001) and kurtosis (b2p = 27.77, kurtosis = 3.84, p = .00012) for the set of 4 variables (n = 199). These results suggest the data deviate significantly from multivariate normality.

Polychoric Correlation Matrix

	IS1	IS2	IS3	IS4
G1-item IS1	1	0.57487	0.834457	0.686891
G1-item IS2	0.57487	1	0.62777	0.652307
G1-item IS3	0.834457	0.62777	1	0.730005
G1-item IS4	0.686891	0.652307	0.730005	1

Kaiser-Myer Olkin Test (KMO)

```
> kmo_G1prIS <- kmo_optimal_solution(G1NumAll_prIS, squared = FALSE)
Final Solution Achieved!> kmo_G1prIS[["results"]]
$overall
[1] 0.8032075

$individual
                       MSA
numG1preIS1Fact 0.7677055
numG1preIS2Fact 0.8768113
numG1preIS3Fact 0.7494982
numG1preIS4Fact 0.8565618
```

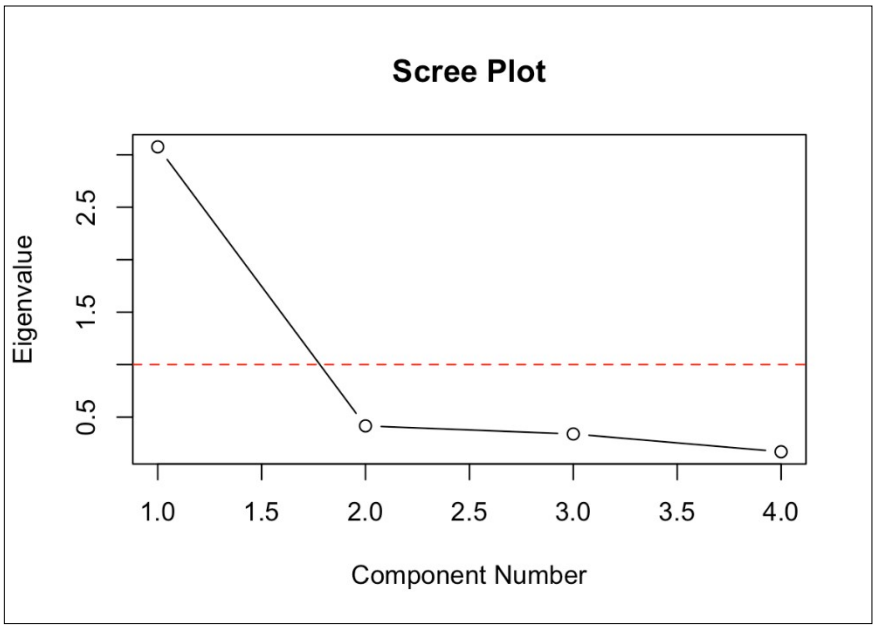
Barlett's Test of Sphericity

```
> BartRes <- cortest.bartlett(G1AllprISEXPolMatrix, n=199)
> BartRes
$chisq
[1] 517.5119

$p.value
[1] 1.418467e-108

$df
[1] 6

> format(BartRes$p.value, scientific = TRUE)
[1] "1.418467e-108"
```

Minimum Average Partial (MAP) test

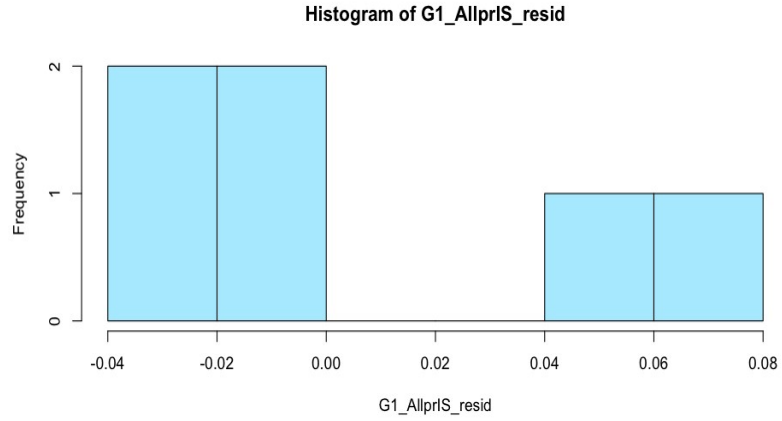
```
> vss_result <- vss(G1NumAll_IS, n.obs = nrow(G1NumAll_IS), rotate = "varimax", fm = "minres")
> print(vss_result)

Very Simple Structure
Call: vss(x = G1NumAll_IS, rotate = "varimax", fm = "minres", n.obs = nrow(G1NumAll_IS))
VSS complexity 1 achieves a maximimum of 0.96  with  1  factors
VSS complexity 2 achieves a maximimum of 0.96  with  2  factors

The Velicer MAP achieves a minimum of 0.12  with  1  factors
BIC achieves a minimum of  -9.14  with  1  factors
Sample Size adjusted BIC achieves a minimum of  -2.8  with  1  factors

Statistics by number of factors
  vss1 vss2  map dof   chisq prob sqresid  fit RMSEA  BIC SABIC complex  eChisq    SRMR eCRMS eBIC
1 0.96 0.00 0.12   2 1.4e+00 0.48    0.43 0.96     0 -9.1  -2.8     1.0 2.2e-01 9.7e-03 0.017  -10
2 0.45 0.96 0.45  -1 3.2e-10   NA    0.37 0.96    NA   NA    NA     1.8 2.1e-10 3.0e-07    NA   NA
3 0.32 0.73 1.00  -3 0.0e+00   NA    0.37 0.96    NA   NA    NA     2.7 3.8e-21 1.3e-12    NA   NA
4 0.32 0.73   NA  -4 0.0e+00   NA    0.37 0.96    NA   NA    NA     2.7 3.8e-21 1.3e-12    NA   NA
```

Scree Plot–*red line signifies the Kaiser criterion reference line*



Residuals for pr_IS:

	IS1	IS2	IS3	IS4
numG1preIS1Fact				
numG1preIS2Fact	-0.03915441			
numG1preIS3Fact	0.04479128	-0.01870787		
numG1preIS4Fact	-0.01676051	0.06175765	-0.03108526	



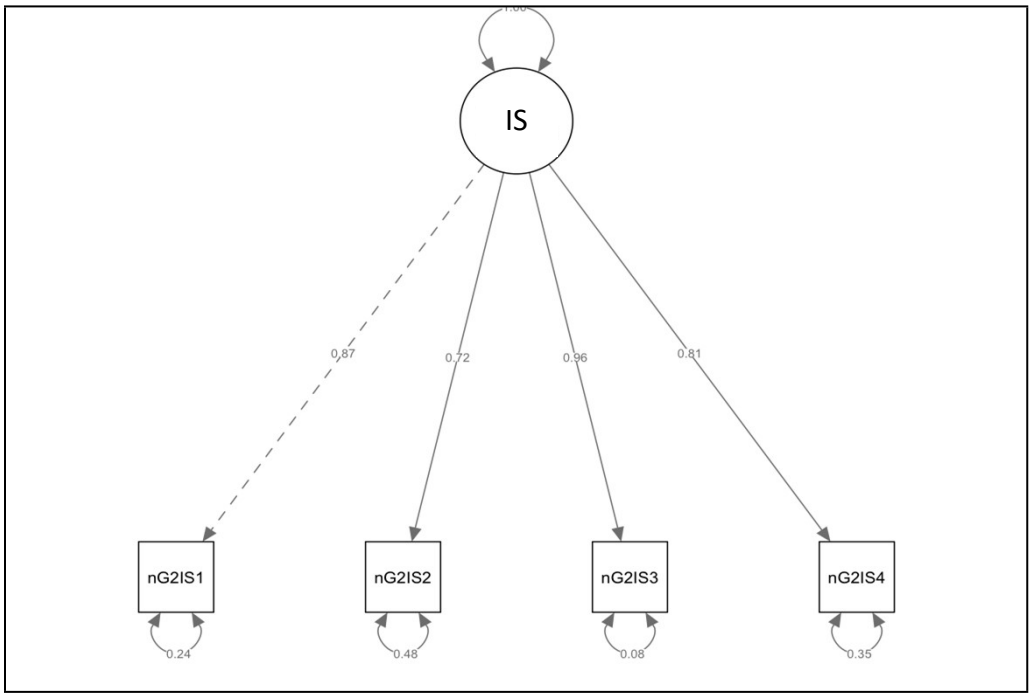
- 1 residual |0.05|
- Residuals are bimodal (not normally distributed)

Exploratory Factor Analysis

Factor Loadings of Exploratory Factor Analysis (EFA) of Early-Semester Imposter Syndrome			
Survey Item	Factor 1	Uniqueness u^2	Communality h^2
G1-item IS1	0.86	0.26	0.74
G1-item IS2	0.69	0.52	0.48
G1-item IS3	0.91	0.17	0.83
G1-item IS4	0.82	0.33	0.67

Confirmatory Factor Analysis on G2 Data

Estimator: MLM



N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	2.648 (2, 0.266)	0.048	0.998	0.995	0.017

III. Social Belonging

Prompt: Using a 6-point Likert-Scale where (1) “Strongly Disagree” (2) “Disagree” (3) “Somewhat Disagree” (4) “Somewhat Agree” (5) “Agree” (6) “Strongly Agree.” rate your agreement to the following questions:

Factor 1: Social Belonging (4 items)

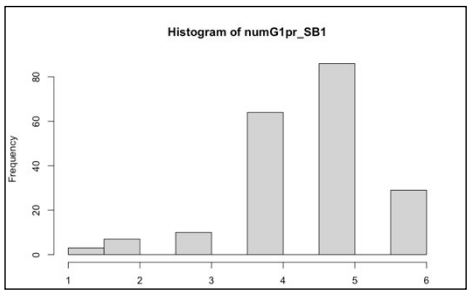
1. In (Course name), I feel like I fit in.
2. In (Course name), I feel comfortable with my peers and classmates.
3. In (Course name), I feel comfortable with my instructor.
4. In (Course name), setting aside my performance in class, I feel like belong.

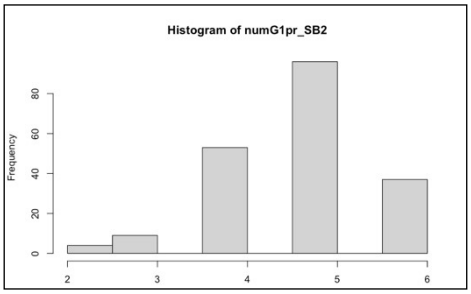
Factor 2: Belonging Uncertainty (2 items)

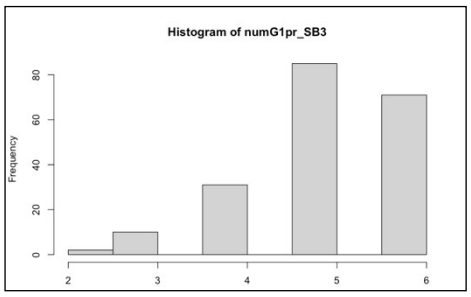
5. In (Course name), I feel uncertain about my belonging (i.e., sometimes I feel like I belong, and sometimes I don’t)
6. In (Course name), when I don’t perform well, I feel like maybe I don’t belong.

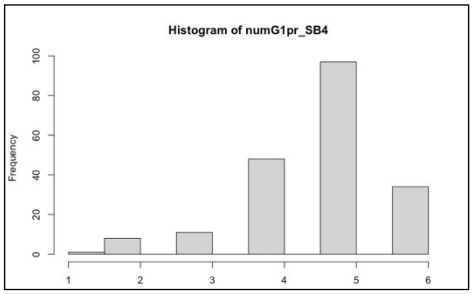
**The actual course name in the course catalog was provided to students taking the survey*

Social Belonging: Sense of Belonging Histograms

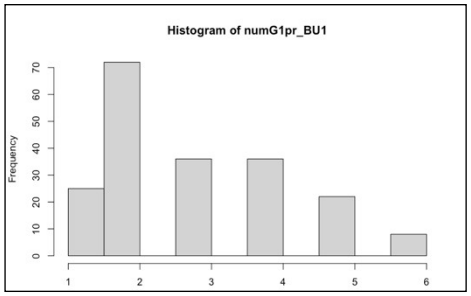


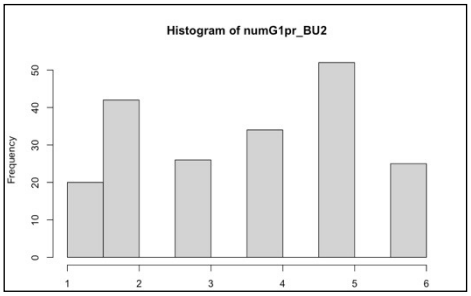






Social Belonging: Belonging Uncertainty Histograms



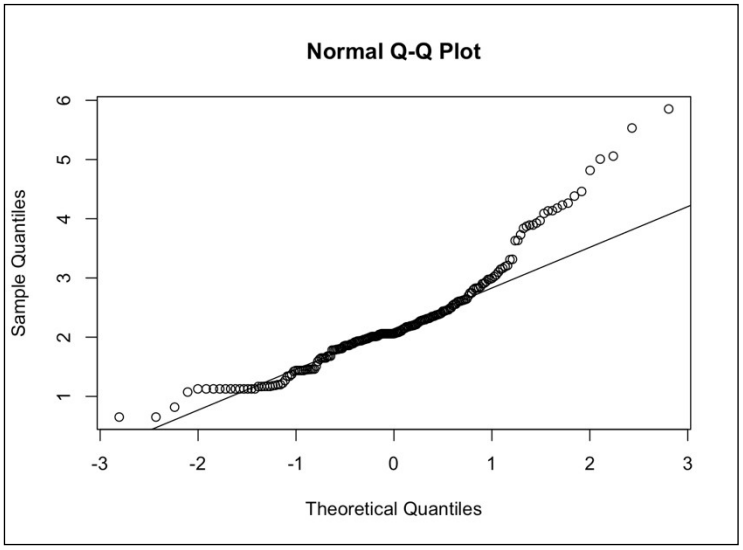


G1-Skewness and Kurtosis for pr_SB (8 items, outliers NOT removed). Belonging Uncertainty items are not reverse coded)

	Skewness	Kurtosis	Mean	SD
G1-item SB1	-0.9928954	4.608839	4.557789	1.017735
G1-item SB2	-0.6709456	3.708735	4.768844	0.8743449
G1-item SB3	-0.8978892	3.582352	5.070352	0.8961621
G1-item SB4	-0.9899429	4.239582	4.678392	0.9883592
G1-item BU1	0.5140961	2.346084	2.909548	1.36028
G1-item BU2	-0.1585015	1.765008	3.658291	1.59349

Mardia's Test of Social Belonging (Belonging Uncertainty Items are Reverse Coded)

```
Mardia tests of multivariate skew and kurtosis
Use describe(x) the to get univariate tests
n.obs = 199   num.vars =  6
b1p =  8.65   skew =  286.98  with probability  <=  9.3e-33
 small sample skew =  292.56  with probability <=  9.6e-34
b2p =  64.48   kurtosis =  11.86  with probability <=  0
```



Mardia's test revealed significant multivariate skewness (b1p = 8.65, skew = 286.98, $p < .001$) and kurtosis (b2p = 64.48, kurtosis = 11.86, $p < .001$) in the sample of 199 cases with 6 variables, indicating that the data violate the assumption of multivariate normality.

Polychoric Correlation Matrix

	G1-item SB1	G1-item SB2	G1-item SB3	G1-item SB4	G1-item BU1	G1-item BU2
G1-item SB1	1	0.5713034	0.4385196	0.696397	-0.3829081	-0.2680428
G1-item SB2	0.5713034	1	0.4398253	0.6733059	-0.4125862	-0.2454769
G1-item SB3	0.4385196	0.4398253	1	0.4932444	-0.3469125	-0.1563792
G1-item SB4	0.696397	0.6733059	0.4932444	1	-0.4575087	-0.2368835
G1-item BU1	-0.3829081	-0.4125862	-0.3469125	-0.4575087	1	0.5099199
G1-item BU2	-0.2680428	-0.2454769	-0.1563792	-0.2368835	0.5099199	1

Kaiser-Myer Olkin Test (KMO)

```
> kmo_G1prIS <- kmo_optimal_solution(NumAllG1_prSB, squared = FALSE)
Final Solution Achieved!> kmo_G1prIS[["results"]]
$overall
[1] 0.8029734

$individual
                  MSA
numG1pr_SB1 0.8221726
numG1pr_SB2 0.8529301
numG1pr_SB3 0.9059124
numG1pr_SB4 0.7687289
numG1pr_BU1 0.7737911
numG1pr_BU2 0.6765609
```

Bartlett's Test of Sphericity

```
> BartRes <- cortest.bartlett(G1AllprSBEXPolMatrix, n=199)
> BartRes
$chisq
[1] 434.8098

$p.value
[1] 3.277067e-83

$df
[1] 15

> format(BartRes$p.value, scientific = TRUE)
[1] "3.277067e-83"
```

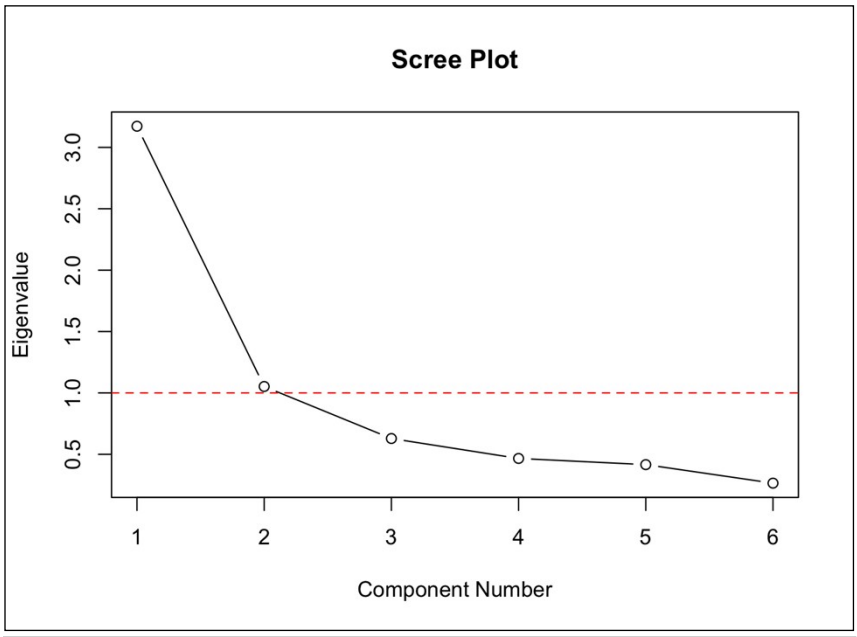
Check for Multicollinearity Using VIFs

```
> vif(sense_model)
numG1pr_SB1 numG1pr_SB2 numG1pr_SB3 numG1pr_SB4
   2.048225    1.939413    1.380861    2.589168
> vif(uncertainty_model)
numG1pr_BU1 numG1pr_BU2
   1.351385    1.351385
```

Minimum Average Partial (MinAp) Test

```
Call: vss(x = NumAllG1_prSB, rotate = "varimax", fm = "minres", n.obs = nrow(NumAllG1_prSB))
VSS complexity 1 achieves a maximimum of 0.81  with  1  factors
VSS complexity 2 achieves a maximimum of 0.9  with  2  factors

The Velicer MAP achieves a minimum of 0.07  with  1  factors
BIC achieves a minimum of  -17.59  with  2  factors
Sample Size adjusted BIC achieves a minimum of  -4.92  with  2  factors

Statistics by number of factors
  vss1 vss2   map dof   chisq    prob sqresid  fit RMSEA   BIC SABIC complex
1 0.81 0.00 0.069   9 4.6e+01 4.9e-07    2.26 0.81  0.14  -1.2  27.4     1.0
2 0.73 0.90 0.117   4 3.6e+00 4.7e-01    1.19 0.90  0.00 -17.6  -4.9     1.2
3 0.69 0.83 0.256   0 6.1e-01      NA    0.99 0.92    NA    NA    NA     1.4
4 0.61 0.87 0.523  -3 4.4e-10      NA    1.00 0.92    NA    NA    NA     1.6
5 0.72 0.85 1.000  -5 0.0e+00      NA    0.98 0.92    NA    NA    NA     1.5
6 0.72 0.85    NA  -6 0.0e+00      NA    0.98 0.92    NA    NA    NA     1.5
   eChisq    SRMR eCRMS  eBIC
1 4.2e+01 8.4e-02 0.108  -5.5
2 1.6e+00 1.6e-02 0.031 -19.6
3 1.9e-01 5.7e-03    NA    NA
4 1.4e-10 1.6e-07    NA    NA
5 1.1e-19 4.3e-12    NA    NA
6 1.1e-19 4.3e-12    NA    NA
```

Scree Plot–*red line signifies the Kaiser criterion reference line*



Residuals for pr_SB:

	IS1	IS2	IS3	IS4
numG1preIS1Fact				
numG1preIS2Fact	-0.03915441			
numG1preIS3Fact	0.04479128	-0.01870787		
numG1preIS4Fact	-0.01676051	0.06175765	-0.03108526	

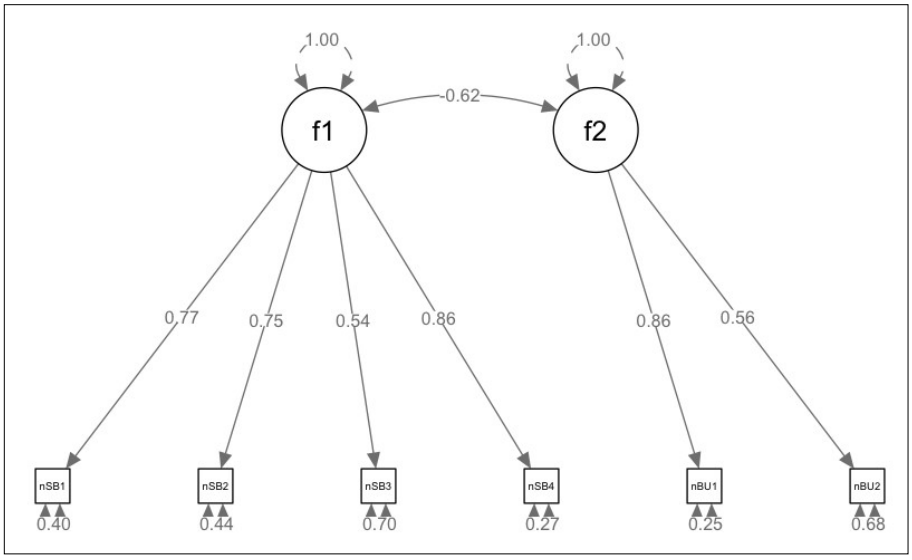
- 1 residual |0.05|
- Residuals are bimodal (not normally distributed)

Note: EFA was not conducted on SB as this instrument's internal structure has been confirmed in previous studies at the same institution (Edwards, *et al.*, 2021; Edwards, *et al.*, 2022; Edwards, *et al.*, 2023).

Multidimensional Confirmatory Factor Analysis of pr_ Social Belonging (pr_SB and pr_BU) Construct

2 factors, 4 items one each factor

Estimator: MLM



N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
398	11.142 (8, 0.194)	0.033	0.996	0.992	0.019

Unidimensional Confirmatory Factor Analysis of pr_ Belonging Uncertainty G2 Data

2 items on one factor

Estimator: MLR

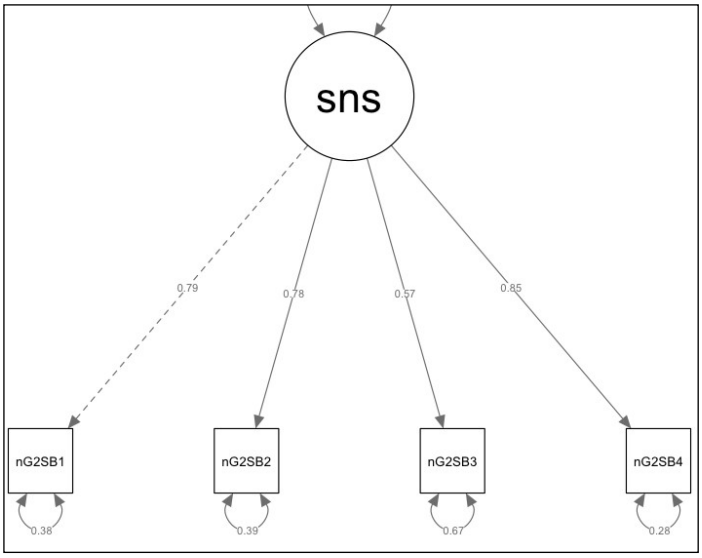
```
> G2prBU_CFA1 <- cfa(G2prBU_model,G2NumAllprSB, estimator= "mlr")
Warning message:
lavaan->lav_model_vcov():
   The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive
   definite! The smallest eigenvalue (= -2.272077e+03) is smaller than zero. This may be a symptom that the
   model is not identified. > summary(G2prBU_CFA1, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
Error in if (!is.finite(X2) || !is.finite(df) || !is.finite(X2.null) ||  :
  missing value where TRUE/FALSE needed
```

Note: Belonging uncertainty unidimensional model does not have an adequate internal structure to support 2 items on one factor.

Unidimensional Confirmatory Factor Analysis of pr_Sense of Belonging G2 Data

4 items on one factor

Estimator: MLR



N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	1.538 (2, 0.464)	0.0*	1.00*	1.00*	0.014

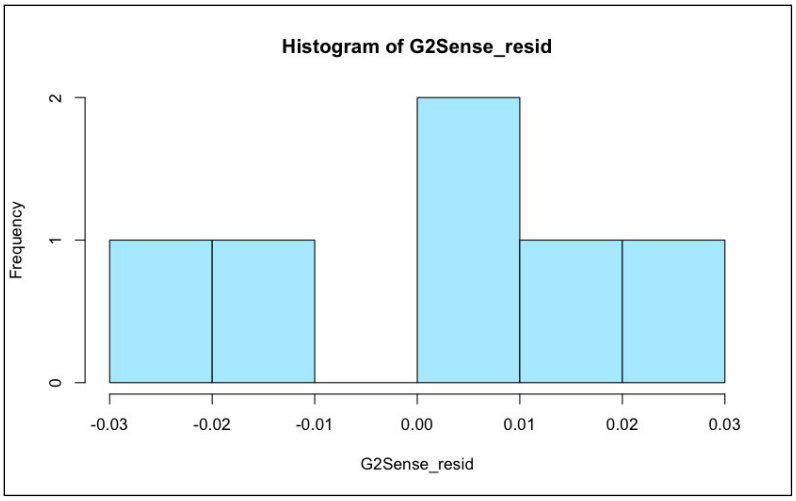
**To further support these fit indices, we provide additional "checkpoints" to support the use of this model. Please see modification indices, as well as residuals.*

Modification Indices

```
> modindices(G2prSB_CFA1)
          lhs op         rhs    mi     epc sepc.lv sepc.all sepc.nox
10 numG2prSB1 ~~ numG2prSB2 0.606  0.045   0.045    0.123    0.123
11 numG2prSB1 ~~ numG2prSB3 1.804 -0.062  -0.062   -0.126   -0.126
12 numG2prSB1 ~~ numG2prSB4 0.280  0.038   0.038    0.115    0.115
13 numG2prSB2 ~~ numG2prSB3 0.280  0.021   0.021    0.049    0.049
14 numG2prSB2 ~~ numG2prSB4 1.804 -0.082  -0.082   -0.279   -0.279
15 numG2prSB3 ~~ numG2prSB4 0.606  0.034   0.034    0.086    0.086
```

Modification indices are not large enough to warrant kicking out any items: MI are not greater than 3.84 and expected parameter change (EPC) are not large enough to impact assessment (Gunzler and Morris, 2015).

Residuals:



	numG2prSB1	numG2prSB2	numG2prSB3	numG2prSB4
numG2prSB1				
numG2prSB2	0.003830442			
numG2prSB3	-0.02627202	0.02077674		
numG2prSB4	0.015308576	-0.018549108	0.004695667	

- No residual is over 0.05
- Bimodal distribution

References

Edwards J. D., Barthelemy R. S. and Frey R. F., (2021), Relationship between course-level social belonging (sense of belonging and belonging uncertainty) and academic performance in General Chemistry 1, *Journal of Chemical Education*, **99**, 71-82.

Edwards J. D., Laguerre L., Barthelemy R. S., De Grandi C. and Frey R. F., (2022), Relating students' social belonging and course performance across multiple assessment types in a calculus-based introductory physics 1 course, *Physical Review Physics Education Research*, **18**, 020150.

Edwards J. D., Torres H. L. and Frey R. F., (2023), The effect of social belonging on persistence to General Chemistry 2, *Journal of Chemical Education*.

Gunzler D. D. and Morris N., (2015), A tutorial on structural equation modeling for analysis of overlapping symptoms in co-occurring conditions using MPlus, *Statistics in medicine*, **34**, 3246-3280.

IV. Childhood Science Currency

From Turnbull's Self-Concept (**20 total questions**):

Prompt: Using a 6-point Likert-Scale where (1) "Strongly Disagree" (2) "Disagree" (3) "Somewhat Disagree" (4) "Somewhat Agree" (5) "Agree" (6) "Strongly Agree." rate your agreement to the following questions:

1. I find science difficult.
2. If I study hard, I will do well in my science courses.
3. I am just not good at science.
4. My parents/guardians think science is interesting.
5. My parents/guardians think it is important for me to learn science.
6. My parents/guardians would like it if I work in science.
7. My parents/guardians have explained to me that science is useful for my future.

Parents

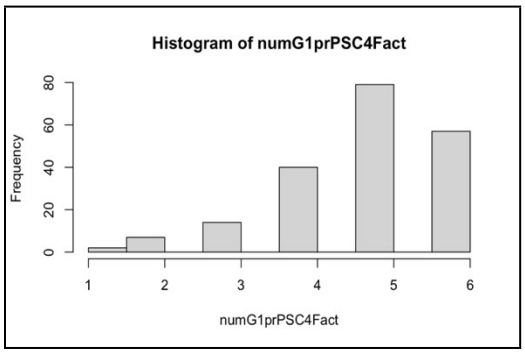
8. My friends see me as a "science person".
9. My friends think that science is important.
10. My friends think that science is cool.
11. My friends care about their university grades.
12. Growing up, did you do science activities (e.g., science kits, nature walks, do experiments)?
13. Growing up, did you read books or magazines about science?
14. Growing up, did you look up things online about science or nature?
15. Growing up, did you watch TV programs about science or nature?
16. ~~Growing up, did you go to a lunchtime or after-school science club?~~

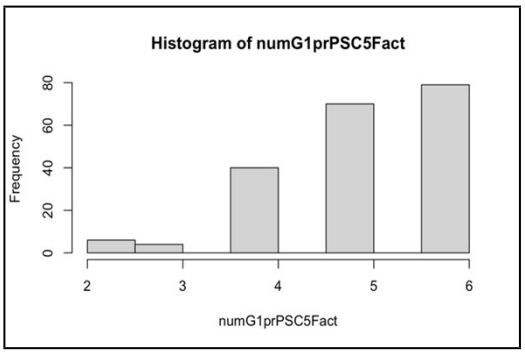
Science Resources

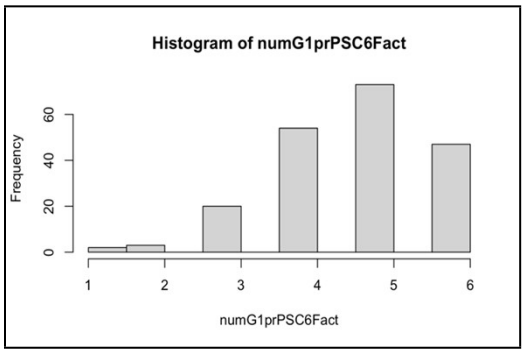
17. I would like to study more science in the future.
18. I would like to have a job that uses science.
19. I would like to become a scientist.
20. I think I could be a good scientist one day.

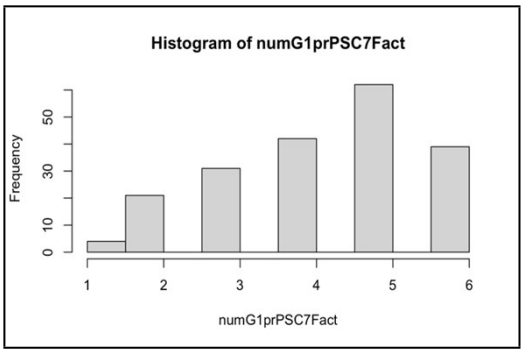
*Items 4-7 are *Parental Influence*, and items 12-15 are *Science Resources*. Together, these two factors make up *Childhood Science Currency.*

Science Currency: Parental Influence Histograms

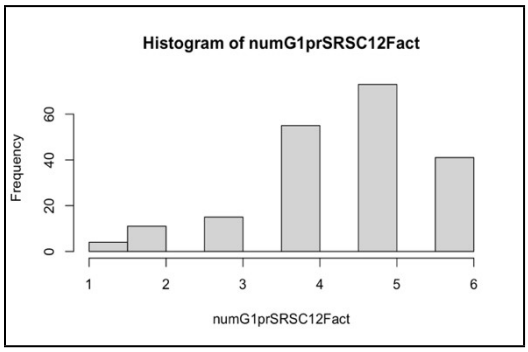


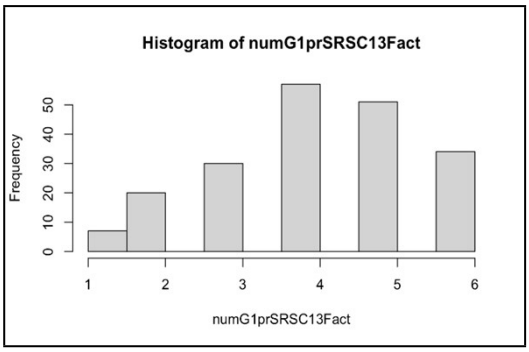


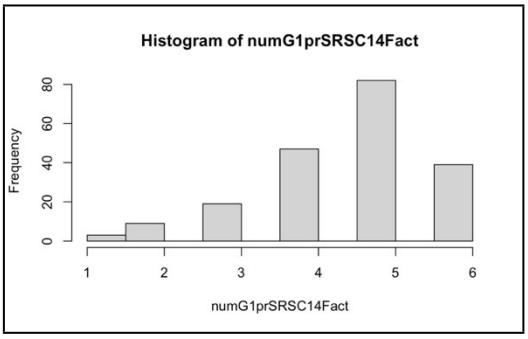


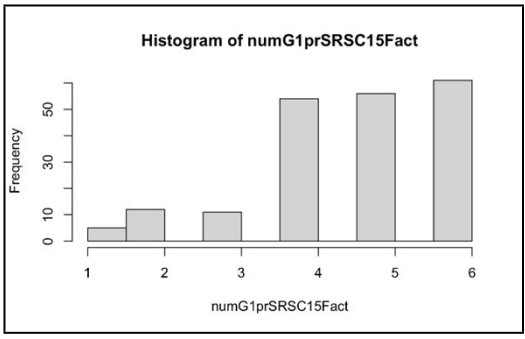


Science Currency: Science Resources Histograms







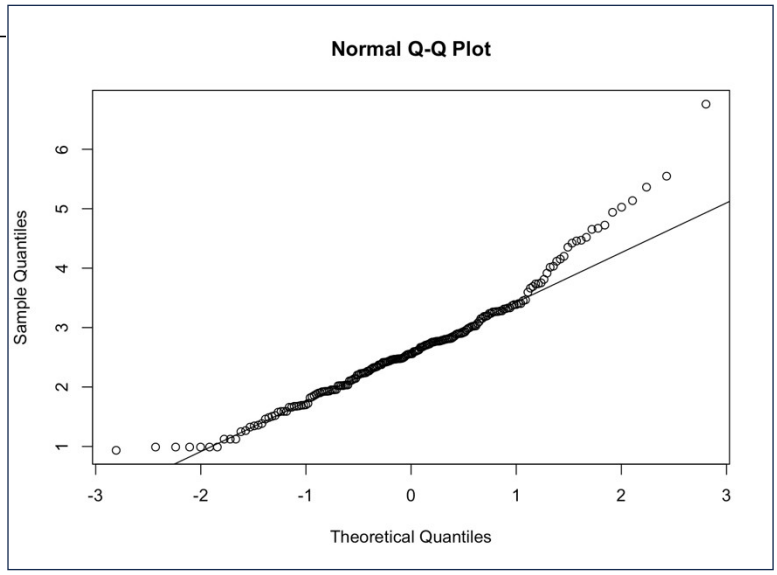


G1-Skewness and Kurtosis for pr_SciCur (4 items, outliers NOT removed)

	Skewness	Kurtosis	Mean	SD
G1-item SciCur4	-1.008289	3.898005	4.798995	1.100872
G1-item SciCur5	1.04908	4.01551	5.065327	0.9748109
G1-item SciCur6	-0.6843867	3.450833	4.678392	1.052695
G1-item SciCur7	-0.4887209	2.334714	4.276382	1.336736
G1-item SciCur12	-0.8647786	3.555075	4.532663	1.179663
G1-item SciCur13	-0.4343093	2.489555	4.140704	1.341001
G1-item SciCur14	-0.8784902	3.586468	4.572864	1.134165
G1-item SciCur15	-0.9087916	3.392004	4.643216	1.274593

Mardia's Test

```
> mardia(G1_AllprSciCur)
Call: mardia(x = G1_AllprSciCur)

Mardia tests of multivariate skew and kurtosis
Use describe(x) the to get univariate tests
n.obs = 199   num.vars =  8
b1p =  12.76   skew =  423.27  with probability  <=  2e-35
 small sample skew =  431.09  with probability <=  1.2e-36
b2p =  100.27   kurtosis =  11.3  with probability <=  0
```



Mardia's test of multivariate skewness (b1p = 12.76, p < .001) and kurtosis (b2p = 100.27, p < .001; kurtosis = 11.3) indicated significant departures from multivariate normality for the 8 variables in the sample (n = 199). These results suggest the data do not meet the assumption of multivariate normality.

Polychoric Matrix

	Factor 1				Factor 2			
	PSC4	**PSC5**	**PSC6**	**PSC7**	**SRSC12**	**SRSC13**	**SRSC14**	**SRSC15**
PSC4	1.00000	0.65706	0.36231	0.48754	0.24620	0.13899	0.17359	0.04222
PSC5	0.65706	1.00000	0.55212	0.61009	0.23310	0.24020	0.13957	0.16519
PSC6	0.36231	0.55212	1.00000	0.60544	0.13865	0.09304	0.12125	0.15872
PSC7	0.48754	0.61009	0.60544	1.00000	0.24246	0.27685	0.17487	0.15895
SRS12	0.24620	0.23310	0.13865	0.24246	1.00000	0.60049	0.61257	0.46965
SRS13	0.13899	0.24020	0.09304	0.27685	0.60049	1.00000	0.66733	0.57321
SSC14	0.17359	0.13957	0.12125	0.17487	0.61257	0.66733	1.00000	0.62773
SRS15	0.04222	0.16519	0.15872	0.15895	0.46965	0.57321	0.62773	1.00000

Kaiser-Myer Olkin Test (KMO)

```
Final Solution Achieved!> kmo_G1prSciCur[["results"]]
$overall
[1] 0.762362

$individual
                         MSA
numG1prPSC4Fact    0.6853804
numG1prPSC5Fact    0.7228075
numG1prPSC6Fact    0.7192873
numG1prPSC7Fact    0.7899876
numG1prSRSC12Fact 0.8633140
numG1prSRSC13Fact 0.7684113
numG1prSRSC14Fact 0.7519852
numG1prSRSC15Fact 0.8070368
```

Barlett's Test of Sphericity

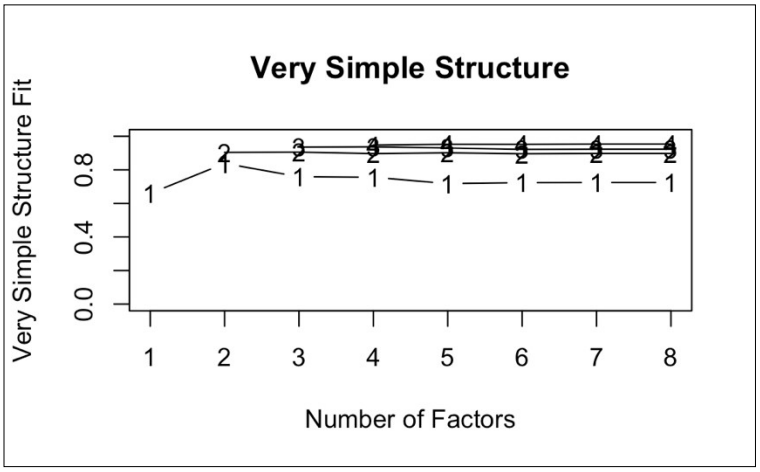
```
> BartRes <- cortest.bartlett(G1AllprSciCurEXPolMatrix, n=199)
> BartRes
$chisq
[1] 698.1981

$p.value
[1] 4.663306e-129

$df
[1] 28

> format(BartRes$p.value, scientific = TRUE)
[1] "4.663306e-129"
```

Check for Multicollinearity Using VIFs

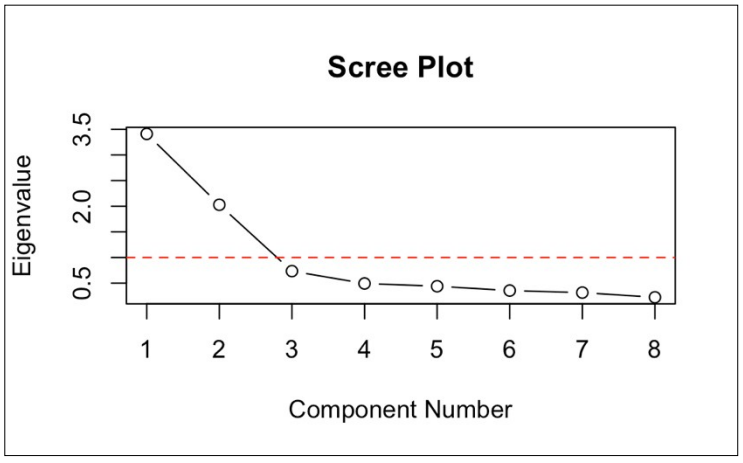
```
> vif(parent_model)
numG1prPSC4Fact numG1prPSC5Fact numG1prPSC6Fact numG1prPSC7Fact
       1.805451        2.370936        1.730965        1.957964
> vif(SciRes_model)
numG1prSRSC12Fact numG1prSRSC13Fact numG1prSRSC14Fact numG1prSRSC15Fact
         1.796271          2.135818          2.378865          1.781831
```

Minimum Average Partial (MAP) test

```
Very Simple Structure
Call: vss(x = G1_AllprSciCur, rotate = "varimax", fm = "minres", n.obs = nrow(G1_AllprSciCur))
VSS complexity 1 achieves a maximimum of 0.84  with  2  factors
VSS complexity 2 achieves a maximimum of 0.91  with  3  factors

The Velicer MAP achieves a minimum of 0.06  with  2  factors
BIC achieves a minimum of  -15.89  with  3  factors
Sample Size adjusted BIC achieves a minimum of  -1.77  with  4  factors

Statistics by number of factors
  vss1 vss2   map dof   chisq    prob sqresid  fit RMSEA   BIC SABIC complex  eChisq    SRMR eCRMS  eBIC
1 0.66 0.00 0.149  20 3.5e+02 7.1e-62    5.79 0.66 0.287 243.1 306.5     1.0 4.6e+02 2.0e-01 0.241 355.4
2 0.84 0.90 0.064  13 5.5e+01 3.9e-07    1.63 0.90 0.127 -13.7  27.5     1.1 2.1e+01 4.3e-02 0.063 -48.0
3 0.76 0.91 0.101   7 2.1e+01 3.5e-03    1.09 0.94 0.101 -15.9   6.3     1.2 5.3e+00 2.2e-02 0.044 -31.8
4 0.76 0.90 0.160   2 2.5e+00 2.9e-01    0.89 0.95 0.034  -8.1  -1.8     1.3 6.9e-01 7.8e-03 0.029  -9.9
5 0.72 0.90 0.262  -2 7.1e-07      NA    0.78 0.95    NA    NA    NA     1.5 1.7e-07 3.9e-06    NA    NA
6 0.72 0.90 0.451  -5 1.9e-09      NA    0.72 0.96    NA    NA    NA     1.5 3.8e-10 1.8e-07    NA    NA
7 0.72 0.90 1.000  -7 6.5e-11      NA    0.69 0.96    NA    NA    NA     1.5 8.7e-12 2.8e-08    NA    NA
8 0.72 0.90    NA  -8 6.5e-11      NA    0.69 0.96    NA    NA    NA     1.5 8.7e-12 2.8e-08    NA    NA
```



Scree Plot–*red line signifies the Kaiser criterion reference line*

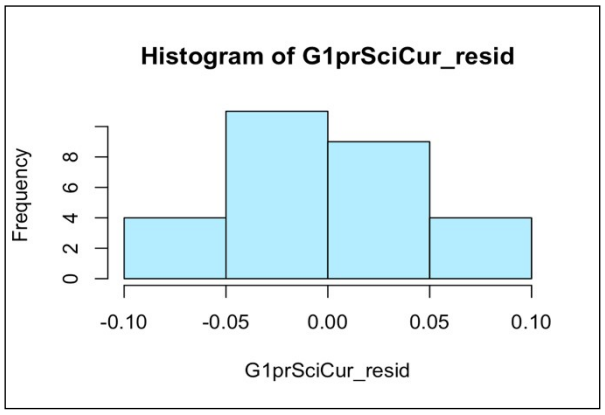


Exploratory Factor Analysis

Factor Loadings of Exploratory Factor Analysis (EFA) of Childhood Science Currency				
Survey Item	Factor 1	Factor 2	Uniqueness u^2	Communality h^2
PSC4	0.00	**0.67**	0.55	0.45
PSC5	-0.01	**0.87**	0.25	0.75
PSC6	-0.03	**0.67**	0.56	0.44
PSC7	0.05	**0.76**	0.40	0.60
SRS12	**0.69**	0.08	0.48	0.52
SRS13	**0.80**	0.02	0.34	0.66
SSC14	**0.87**	-0.06	0.26	0.74
SRS15	**0.72**	-0.04	0.50	0.50
N = 199; ; Factor loadings reported following a promax (oblique) factor rotation.				

Residuals

	PSC4	PSC5	PSC6	PSC7	SRSC12	SRSC13	SRSC14	SRSC15
PSC4								
PSC5	0.079928							
PSC6	-0.07833	-0.01746						
PSC7	-0.02788	-0.05584	0.098269					
SRSC12	0.055854	-0.01058	-0.03116	-0.01131				
SRSC13	-0.03022	0.024206	-0.05296	0.041863	0.020782			
SRSC14	0.0427	-0.02667	0.014866	-0.01929	0.005692	-0.02395		
SRSC15	-0.07269	0.019075	0.063982	-0.00897	-0.03076	0.004027	0.023348	

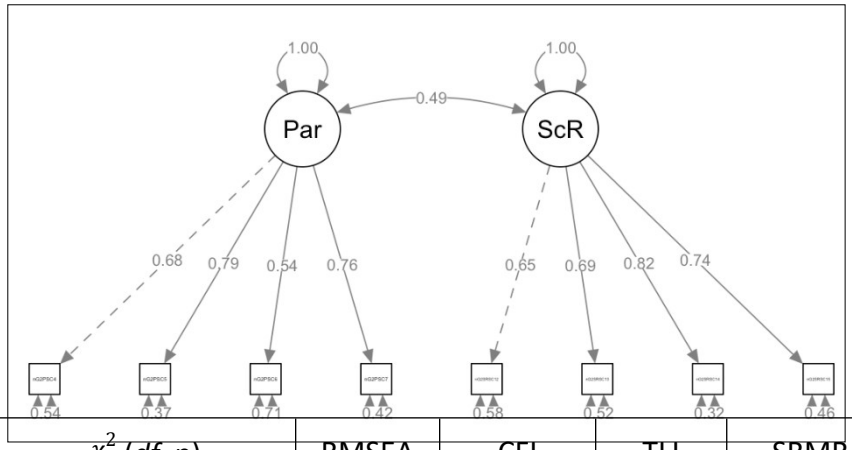


- 8 residuals over |0.05|
- Residuals are normally distributed

Multidimensional Confirmatory Factor Analysis on G2 Data

Two factors, 4 items per factor

Estimator: MLR

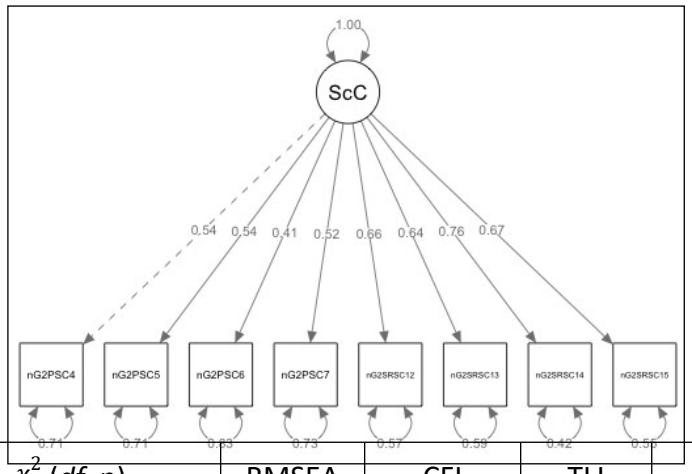


N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	27.692 (19, 0.090)	0.053	0.980	0.970	0.046

Unidimensional Confirmatory Factor Analysis on G2 Data

One factor, 8 items on one factor

Estimator: MLR

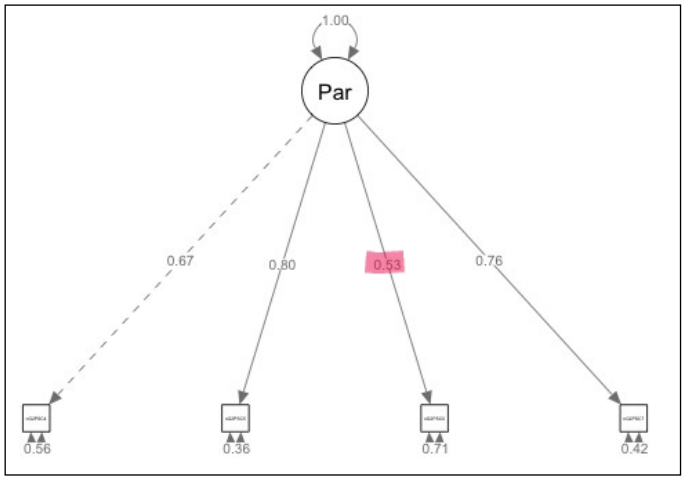


N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	165.540 (20, 0.000)	0.197	0.706	0.589	0.121

Unidimensional Confirmatory Factor Analysis on G2 Data

One factor, 4 items (Parents) on one factor

Estimator: MLR

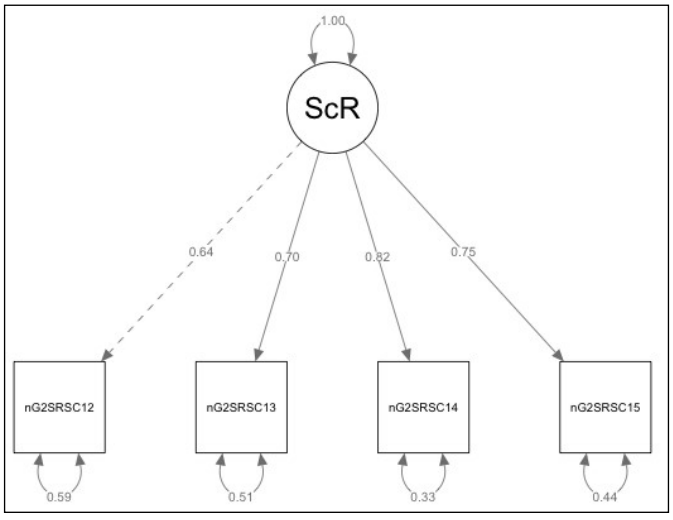


N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	5.409 (2, 0.067)	0.115	0.977	0.930	0.037

Unidimensional Confirmatory Factor Analysis on G2 Data

One factor, 4 items (Science Resources) on one factor

Estimator: MLR



N	χ^2 (*df*, p)	RMSEA	CFI	TLI	SRMR
199	2.883 (2, 0.237)	0.055	0.995	0.986	0.022

V. Removal of Outliers

Due to poor factor loadings ONLY in the Science Currency CFA (as seen above), outliers were removed from both G1 and G2 to improve loadings. Below are the Mahalanobis Distance and p-value for the outliers that were removed. As these outliers were removed in the CFA process, these outliers are reflected in the sample size used for the SEM path analysis (*N* = 354).

G1		
Outlier	**Mahalanobis**	***P-value***
1	21.64852	7.72E-05
2	19.98303	1.71E-04
3	30.77309	9.49E-07
4	24.40113	2.06E-05
5	28.75677	2.52E-06
6	16.94708	7.25E-04
7	19.54489	2.11E-04
8	17.2418	6.30E-04
9	18.94269	2.81E-04
10	17.63502	5.23E-04
11	21.81673	7.12E-05
12	26.37599	7.96E-06
13	25.2592	1.36E-05
14	22.31574	5.61E-05
15	45.68392	6.62E-10
16	19.86995	1.81E-04
17	20.41725	1.39E-04

G2		
Outlier	**Mahalanobis**	***P-value***
1	16.4674	9.09E-04
2	18.17021	4.06E-04
3	17.75627	4.94E-04
4	33.02121	3.19E-07
5	26.48027	7.57E-06
6	16.46969	9.08E-04
7	25.13782	1.44E-05
8	16.74886	7.96E-04
9	20.28557	1.48E-04
10	25.85656	1.02E-05
11	18.129	4.14E-04
12	16.79003	7.81E-04
13	17.36623	5.94E-04
14	23.04049	3.96E-05
15	17.13085	6.64E-04
16	18.85624	2.93E-04
17	28.38584	3.01E-06
18	18.25816	3.89E-04
19	17.69778	5.08E-04
20	26.14141	8.91E-06
21	29.10906	2.12E-06

Total outliers in childhood science currency = 38

***N* = 398 (original sample) – 38 (outliers) = 360**

** It was also found that 6 consenting students, who completed both surveys, had missing grades for either their midterm exams or their preassessments. In order to avoid Type I errors for future statistical analysis involving student performance, these seven students were also removed from future analysis. Thus, leaving us with a final sample of **354**, which is reflected in the SEM analysis portion.*

B: SEM Path Models

Structural Equation Modeling (SEM) is a statistical technique used to explore relationships among observed (measured) and latent (unobserved) variables, whereby direct and indirect effects can be evaluated (Hancock and Mueller, 2013). Path Analysis**,** on the other hand, is a specialized form of multiple regression analysis that uses diagrams (path models) to visually represent hypothesized causal relationships among observed variables (Beaujean, 2014). Conveniently, path models adhere to common drawing conventions utilized in SEM models: ovals represent latent variables, squares represent observed variables, directional relations are indicated by straight, single-headed, and double-headed arrows represent covariance. Importantly, path analysis is not to be used to establish causality or to determine whether a specific model is correct (Streiner, 2005). Path analysis can only determine whether the data are consistent with the path model specified. When paired together, SEM path analysis provides a comprehensive approach for analyzing both simple and intricate relationships displayed in a given path model (Chavance*, et al.*, 2010).

Just as with factor analysis, assumption checks were conducted for these path models to determine suitability. These include ensuring correct model tracings, ample sample size, and a properly identified model. According to Wright's tracing rules, there can be a maximum of one double-headed arrow included in one path (covariance), there is no going forward and then backward (once you have traveled along a route forward, you cannot travel backward to get to the variable at the end point), and there can be no loops (non-recursive models) (Wright, 1918; Wright, 1934). Please see models presented in the main text or the example model below (**Example for Model 1a)** for models that follow Wright's Rules. To determine ample sample size, samples of 100 to 200 are generally considered the minimum necessary to obtain stable, unbiased estimates, while samples of fewer than 100 cases are often viewed as indefensible for most models (Kline, 2011). Others have indicated that at least 10 to 20 cases per free factor loadings $(q; Equation\ 1)$ are needed to provide a minimal basis for unbiased estimation and inference (Bentler and Chou, 1987; Wolf*, et al.*, 2013). All SEM path models use the entire sample size (*N* = 354), which satisfies the requirement provided by Kline. Additionally, we calculated the suggested sample size required by Bentler & Chou and Wolf et al. below.

Determination of an Ample Sample Size

Sample Size (***N***) = 354
Free Factor Loadings (q):

Constructs	Indicators	Factors	(Indicators – Factors)
Imposter Syndrome	4	1	3
Academic Mindset Entity	4	1	3
Sense of Belonging	4	1	3
Science Resources	4	1	3

$$Free\ Loadings\ (q) = \Sigma(indicators/latent\ variable\ - fixed\ loadings/latent\ variable) \quad (1)$$

$$(q) = 12$$

Minimum Recommended Sample Size = (# of cases) x (q:$Free\ Factor\ Loadings$)

= 10 x 12 = 120

Upper/Conservative Recommended Range = (# of cases) x (q:$Free\ Factor\ Loadings$)

= 20 x 12 = 240

Model Identification

Model identification should be considered to ensure that parameters are uniquely estimated. Simply put, the number of free factor loadings $(q;Equation\ 1)$ should be less than or equal to the number of non-redundant elements in the sample covariance matrix (p^*). Where p^* is calculated using **Equation 2,** and p is the sum of manifest variables (items/observed variables) in the model.

$$p^* = \frac{p(p+1)}{2} \tag{2}$$

Example calculation of p and p^*:

p = 4 items (sense of belonging)
+ 4 items (academic mindset entity)
+ 4 items (imposter syndrome)
+ 4 items (science resources)
+ 1 observed var. (preassessment)
+ 1 observed var. (exam variable: Exam 1 or Final Exam)

p = 18

$$p^* = \frac{18(18+1)}{2} = 171$$

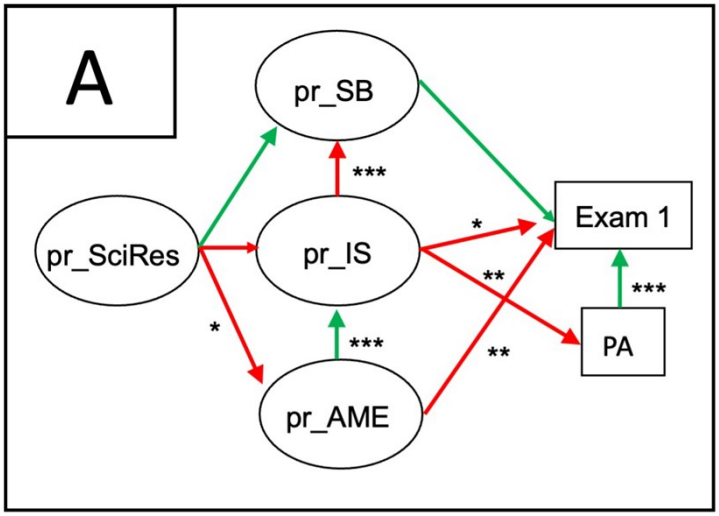
$12 < 171$, $q < p^*$ Therefore, **this path model is overidentified**

If $q > p^*$ the model is underidentified (not enough information to estimate all parameters). If $q = p^*$ the model is just-identified (a unique solution exists for each parameter, but the model cannot be tested for fit). If $q < p^*$ the model is overidentified (the model can be tested for fit, and parameter estimates are possible in multiple ways). The total parameters (k) can be found by summing the free factor loadings (q) + observed variable residual variances (Count each observed variable's residual variance as one estimated parameter) + latent variable variances + latent variable covariance + endogenous latent variable residual variances (Count each observed variable's residual variance as one estimated parameter) + number of structural paths (Bentler

and Chou, 1987). It's also important to note that the number of parameters affects the degrees of freedom. A positive df is desirable because it indicates that your model is over-identified, meaning there is more information than unknowns, increasing the stability and reliability of the estimates. If df is zero, the model is just-identified, and if df is negative, the model is under-identified, meaning it's unlikely to produce stable or reliable results. The formula for this is provided in **Equation 3**.

$$df = \frac{p(p+1)}{2} - k \tag{3}$$

Example calculation for df:



Example for Model 1a

Degrees of Freedom

$$Total\ parameters\ (k) = free\ factor\ loadings\ (q) + observed\ variable\ residual\ variances + latent\ variable\ variances + latent\ variable\ covariances + endogenous\ latent\ variable\ residual\ variances + number\ of\ structural\ paths$$

Total parameters (k) = 12 + 18 + 4 + 6 + 3 + 10 = 53

$$df = \frac{p(p+1)}{2} - k = 171 - 53 = 118$$

$$q = 12$$
$$p = 18$$
$$p^* = 171$$
$$k = 53$$
$$df = 118$$

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I. Main Text Model with FDR corrections and bootstrapped results

Model A Fit (in main text)											
		CFI	TLI	RMSEA	SRMR	AIC	BIC	β	β^*	*p-value*	FDR Corr. *p-value*
	Model Fit	0.988	0.986	0.030	0.045	13397.376	13568.851				
Path 1	pr_IS → pr_SB							**-0.312**	**-0.412**	$2.580 * 10^{-10}$	$4.270 * 10^{-10}$
Path 2	pr_AME → pr_IS							**0.558**	**0.409**	$1.327 * 10^{-12}$	$2.655 * 10^{-12}$
Path 3	pr_SciRes → pr_IS							0.041	0.030	$6.473 * 10^{-1}$	$7.225 * 10^{-1}$
Path 4	pr_SciRes → pr_SB							**0.133**	**0.131**	$5.262 * 10^{-2}$	$6.014 * 10^{-2}$
Path 5	pr_SciRes → pr_AME							**-0.159**	**-0.161**	$1.837 * 10^{-2}$	$2.204 * 10^{-2}$
Path 6	pr_IS → Exam1							**-0.025**	**-0.148**	$2.029 * 10^{-2}$	$2.375 * 10^{-2}$
Path 7	pr_AME → Exam1							**-0.040**	**-0.172**	$5.139 * 10^{-3}$	$6.325 * 10^{-3}$
Path 8	pr_SB → Exam1							0.003	0.014	$8.092 * 10^{-1}$	$8.828 * 10^{-1}$
Path 9	PA_perc → Exam1							**0.268**	**0.304**	$9.417 * 10^{-10}$	$1.507 * 10^{-9}$
Path 10	pr_IS → PA_perc							**-0.032**	**-0.163**	$1.140 * 10^{-3}$	$1.478 * 10^{-3}$

Model A Bootstrapped Results

Estimator: ML
Test: Bollen.Stine
Iterations: 5000
Parameter Estimates: BCA.simple
*Significant paths bolded

	Paths	S.E	β	ULCI	LLCI
Path 1	pr_IS → pr_SB	**0.050**	**-0.302**	**-0.418**	**-0.222**
Path 2	pr_AME → pr_IS	**0.081**	**0.558**	**0.413**	**0.737**
Path 3	pr_SciRes → pr_IS	0.089	0.041	-0.140	0.215
Path 4	pr_SciRes → pr_SB	0.070	0.133	0.005	0.285
Path 5	pr_SciRes → pr_AME	**0.068**	**-0.159**	**-0.307**	**-0.037**
Path 6	pr_IS → Exam1	**0.011**	**-0.025**	**-0.048**	**-0.004**
Path 7	pr_AME → Exam1	**0.015**	**-0.040**	**-0.069**	**-0.012**
Path 8	pr_SB → Exam1	0.014	0.003	-0.024	0.033
Path 9	PA → Exam1	**0.044**	**0.268**	**0.179**	**0.351**
Path 10	pr_IS → PA	**0.010**	**-0.032**	**-0.051**	**-0.013**

Model B Fit (in main text)											
		CFI	TLI	RMSEA	SRMR	AIC	BIC	β	β^*	*p-value*	FDR Corr. *p-value*
	Model Fit	0.990	0.988	0.027	0.045	13452.010	13623.485				
Path 1	pr_IS → pr_SB							**-0.312**	**-0.412**	$2.629 * 10^{-10}$	$4.206 * 10^{-10}$
Path 2	pr_AME → pr_IS							**0.558**	**0.409**	$1.358 * 10^{-12}$	$2.716 * 10^{-12}$
Path 3	pr_SciRes → pr_IS							0.040	0.030	$6.561 * 10^{-1}$	$7.324 * 10^{-1}$
Path 4	pr_SciRes → pr_SB							0.133	0.131	$5.260 * 10^{-2}$	$6.011 * 10^{-2}$
Path 5	pr_SciRes → pr_AME							**-0.159**	**-0.161**	$1.819 * 10^{-2}$	$2.144 * 10^{-2}$
Path 6	pr_IS → Final Exam							**-0.027**	**-0.028**	$1.832 * 10^{-2}$	$2.144 * 10^{-2}$
Path 7	pr_AME → Final Exam							**-0.049**	**-0.0.38**	$7.209 * 10^{-3}$	$8.873 * 10^{-3}$
Path 8	pr_SB → Final Exam							0.005	0.004	$7.251 * 10^{-1}$	$7.910 * 10^{-1}$
Path 9	PA_perc → Final Exam							**0.296**	**0.296**	$2.456 * 10^{-10}$	$4.065 * 10^{-10}$
Path 10	pr_IS → PA_perc							**-0.032**	**-0.034**	$1.139 * 10^{-3}$	$1.477 * 10^{-3}$

Model B Bootstrapped Results

Estimator: ML
Test: Bollen.Stine
Iterations: 5000
Parameter Estimates: BCA.simple
*Significant paths bolded

	Paths	S.E	β	ULCI	LLCI
Path 1	pr_IS → pr_SB	0.050	**-0.312**	**-0.417**	**-0.220**
Path 2	pr_AME → pr_IS	0.082	**0.558**	**0.404**	**0.732**
Path 3	pr_SciRes → pr_IS	0.090	-0.040	-0.140	0.212
Path 4	pr_SciRes → pr_SB	0.070	**0.133**	**0.008**	**0.282**
Path 5	pr_SciRes → pr_AME	0.069	**-0.159**	**-0.311**	**-0.042**
Path 6	pr_IS → Final Exam	0.011	**-0.027**	**-0.049**	**-0.004**
Path 7	pr_AME → Final Exam	0.018	**-0.049**	**-0.083**	**-0.013**
Path 8	pr_SB → Final Exam	0.015	-0.005	-0.033	0.026
Path 9	PA → Final Exam	0.047	**0.296**	**0.202**	**0.386**
Path 10	pr_IS → PA	0.010	**-0.032**	**-0.052**	**-0.012**

II. Additional Models tested (not included in the main text)

Switched Path, pr_IS → pr_AME								
		CFI	TLI	RMSEA	SRMR	AIC	BIC	β	FDR *p-value*
	Model Fit	0.990	0.988	0.029	0.045	13675.221	13838.902		
Path 1	pr_IS → pr_SB							-0.310	$6.349 * 10^{-10}$
Path 2	**pr_IS → pr_AME**							0.292	$1.410 * 10^{-9}$
Path 3	pr_SciRes → pr_SB							0.125	$8.478 * 10^{-2}$
Path 4	pr_SciRes → pr_AME							-0.147	$1.840 * 10^{-2}$
Path 5	pr_SciRes → pr_IS							-0.051	$6.833 * 10^{-1}$
Path 6	pr_IS → PA							-0.032	$1.552 * 10^{-3}$

Switch Path, pr_AME → pr_IS								
		CFI	TLI	RMSEA	SRMR	AIC	BIC	β	FDR *p-value*
	Model Fit	0.990	0.988	0.029	0.046	13672.442	13828.328		
Path 1	pr_IS → pr_SB							-0.313	$4.419 * 10^{-10}$
Path 2	**pr_AME → pr_IS**							0.557	$2.659 * 10^{-12}$
Path 3	pr_SciRes → pr_SB							0.126	$7.742 * 10^{-2}$
Path 4	pr_SciRes → pr_AME							-0.159	$2.138 * 10^{-2}$
Path 5	pr_SciRes → pr_IS							0.038	$7.342 * 10^{-1}$
Path 6	pr_IS → PA							-0.032	$1.651 * 10^{-3}$

Switch Path, pr_SB → pr_IS								
		CFI	TLI	RMSEA	SRMR	AIC	BIC	β	FDR *p-value*
	Model Fit	0.987	0.984	0.034	0.068	13684.121	13836.110		
Path 1	**pr_SB → pr_IS**							-0.457	$1.107 * 10^{-6}$
Path 2	pr_AME → pr_IS							0.466	$1.0812 * 10^{-10}$
Path 3	pr_SciRes → pr_SB							0.152	$6.893 * 10^{-2}$
Path 4	pr_SciRes → pr_AME							-0.163	$1.809 * 10^{-2}$
Path 5	pr_SciRes → pr_IS							0.090	$2.754 * 10^{-1}$
Path 6	pr_IS → PA							-0.032	$2.347 * 10^{-3}$

**Though AIC does not have a meaningful scale, the model with the smallest AIC value is the most likely to replicate and helpful for model selection (Klin, 2023)*

pr_SB → Exam 1, pr_AME → Exam 1									
		CFI	TLI	RMSEA	SRMR	AIC	BIC	Estimate	*p-value*
	Model Fit	0.989	0.983	0.055	0.044	3722.608	3734.926		
Path 1	pr_SB → pr_AME							**-0.175**	$3.615 * 10^{-3}$
Path 2	pr_AME → Exam 1							**-0.050**	$9.211 * 10^{-5}$
Path 3	pr_SB → Exam 1							0.017	$1.131 * 10^{-1}$
Path 4	PA → Exam 1							**0.275**	$1.316 * 10^{-10}$

pr_SB → Final Exam, pr_AME → Final Exam									
		CFI	TLI	RMSEA	SRMR	AIC	BIC	Estimate	*p-value*
	Model Fit	0.991	0.987	0.049	0.044	3778.045	3844.296		
Path 1	pr_SB → pr_AME							**-0.186**	$2.426 * 10^{-3}$
Path 2	pr_AME → Final Ex							**-0.059**	$2.254 * 10^{-4}$
Path 3	pr_SB → Final Ex							0.011	$2.947 * 10^{-1}$
Path 4	PA → Final Ex							**0.305**	$7.773 * 10^{-12}$

C. Mediation Analysis

Mediation analysis, or more commonly thought of as models with direct and indirect effects, are commonly used in the behavioral sciences (Mayer*, et al.*, 2014). Mediation analysis is useful whenever researchers assume that the effects of a presumed caused on an outcome of interest might be transmitted though one or more intermediate variables. However, many SEM parameters, particularly indirect effects, do not follow a normal distribution and are often skewed or kurtotic, violating the assumptions of standard statistical inference. Traditional methods for calculating standard errors and confidence intervals (like the delta method or Sobel test) rely on normality assumptions, which can lead to inaccurate or misleading results for non-normally distributed estimates. Additionally, due to the complex nature of SEM models: often involving multiple mediators, latent variables, and non-linear relationships, analytical formulas for standard errors and confidence intervals can become intractable or unavailable for such models. Therefore, bootstrapping is

In this study, we used the *manymome* package, an RStudio package developed by Cheung and Cheung (2024), which can be used to estimate and calculate confidence intervals (C.I) for indirect, direct, and total effects. This is done using a two-step approach where model parameter are estimated by SEM using *lavaan*, and then the coefficients are used to compute the requested effects and form confidence intervals (Cheung and Cheung, 2024).

Traditionally, there are two approaches to mediation analysis: the difference method and the product method. Below, I will briefly describe the method used in the manymome package–the product method, using a mathematical breakdown. Consider the following the equations (**equations 4-6**). In these equations, Y_0 is the dependent variable, X is the independent variable, X_M is the mediating variable, τ' codes the relation between the independent variable, and the dependent variable, α codes the relation between the independent variable and the dependent variable adjusted for the effects of the mediating variable, β codes the relation between the independent variable and the mediating variable, and codes the relation between the mediating variable and the dependent variable adjusted for the independent variable. The residuals are coded by ε_1, ε_2 , and ε_3 and have expected values of zero. The intercepts are coded by β_{01}, β_{02} , and β_{03}. In the first regression equation, the dependent variable (Y_0) is regressed on only the independent variable (X). In the second regression equation, the dependent variable (Y_0) is regressed on both the independent variable (X) and the mediating variable (X_M). The indirect effect equals the difference in the estimated independent variable coefficients in the two regression equations (Judd & Kenny, 1981)

$$Y_0 = \beta_{01} + \tau X + \varepsilon_1 \tag{4}$$

$$Y_0 = \beta_{02} + \tau' X + \beta X_M + \varepsilon_2 \tag{5}$$

$$X_M = \beta_{03} + \alpha X + \beta X_M + \varepsilon_3 \tag{6}$$

Total effects consist of all paths from one variables to another mediated by at least one additional variable (Bollen, 1987). In other words, total effects are equal to the sum of the direct and indirect path effects (MacKinnon*, et al.*, 2004) as shown in **Figure 1** and **Equation 7-8.**

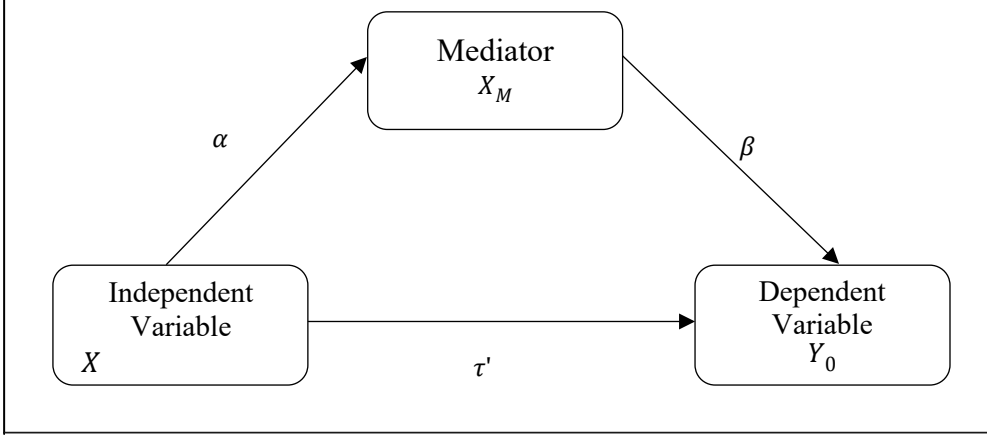

Figure 1: Visual depiction of path effects of a mediated model.

$$Direct\ Effect = \tau' \quad (7)$$

$$Indirect\ Effect = \alpha\beta \quad (8)$$

$$Total\ Effects = \alpha\beta + \tau' \quad (9)$$

Calculation of indirect and total effects

Path of interest: **pr_AME → pr_IS → pr_SB**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct pr_AME --> pr_SB	-0.060	0.063	-0.193	0.070
Indirect **pr_AME --> pr_IS --> pr_SB**	**-0.146**	**0.039**	**-0.231**	**-0.080**
Total Effects	**-0.205**	**0.065**	**-0.341**	**-0.087**

Path of interest: **pr_SciRes → pr_AME → pr_IS**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct pr_SciRes --> pr_IS	0.037	0.354	-0.143	0.218
Indirect **pr_SciRes --> pr_AME --> pr_IS**	**-0.88**	**0.156**	**-0.179**	**-0.020**
Total Effects	-0.051	0.394	-0.257	0.145

Path of interest: **pr_SciRes → pr_AME → Exam 1**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct pr_SciRes --> Exam1	-0.021	0.049	-0.046	0.004
Indirect **pr_SciRes --> pr_AME--> Exam1**	**0.007**	**0.016**	**0.001**	**0.017**
Total Effects	-0.014	0.050	-0.040	0.011

Path of interest: **pr_AME → pr_IS → Exam1**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct **pr_AME --> Exam1**	-0.040	0.015	-0.068	-0.011
Indirect	-0.013	0.006	-0.025	-0.002

pr_AME --> pr_IS--> Exam1				
Total Effects	-0.053	0.012	-0.078	-0.028

Path of interest: **pr_IS → PA → Exam1**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct **pr_IS --> Exam1**	-0.025	0.011	-0.046	-0.003
Indirect **pr_IS--> PA --> Exam1**	-0.009	0.003	-0.015	-0.003
Total Effects	-0.033	0.011	-0.055	-0.011

Path of interest: **pr_SciRes → pr_AME → Final Exam**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct **pr_SciRes --> Final Exam**	0.009	0.009	-0.008	0.027
Indirect **pr_SciRes --> pr_AME--> Final Exam**	0.005	0.002	0.000	0.011
Total Effects	0.014	0.009	-0.004	0.033

Path of interest: **pr_AME → pr_IS → Final Exam**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct **pr_AME --> Final Exam**	-0.014	0.006	-0.027	-0.002
Indirect **pr_AME --> pr_IS--> Final Exam**	-0.048	0.019	-0.083	-0.010
Total Effects	-0.062	0.016	-0.093	-0.029

Path of interest: **pr_IS → PA → Final Exam**

Pathway	Estimate	Boot S.E	Boot LLCI	Boot ULCI
Direct **pr_IS --> Final Exam**	-0.009	0.003	-0.016	-0.003
Indirect	-0.036	0.011	-0.048	-0.004

pr_IS--> PA --> Final Exam				
Total Effects	-0.036	0.011	-0.058	-0.013

References

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