CIOS Result

1. Cleansing

- I removed missing values, merging 3 variables with other variables(Course variables:5/ Instructor variables: 8) : Using SAS *9554 participants

2. Checked if there is a patterned relationship amongst our variables

1)Determinant score(Haitovsky's test)

- test if this score is significantly different from zero which indicates an absence of multicollinearity.

- check if this score is above the rule of thumb of 0.00001 as this indicates an absence of multicollinearity. :1.038E-5(0.00001038)

2) Confirming an acceptable Kaiser-Meyer-Olkin measures of sample adequacy

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.954
Bartlett's Test of Sphericity	Approx. Chi-Square	131528.575
	df	120
	Sig.	.000

- KMO :0.954 (it is acceptable) / values closer to 1 are better

- Bartlett's Test : p: 0.000 we reject the null hypothesis

(H0: the correlation matrix is an identity matrix)

=> Our data is suitable for EFA

3. Determine the number of significant factors

- 1) Rotated eigenvalues

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	9.344	58.397	58.397	9.344	58.397	58.397	8.638
2	1.385	8.653	67.050	1.385	8.653	67.050	7.239
3	1.093	6.831	73.881	1.093	6.831	73.881	5.609
4	.826	5.159	79.040				
5	.513	3.205	82.245				

- The factors are arranged in the descending order based on the most explained variance.

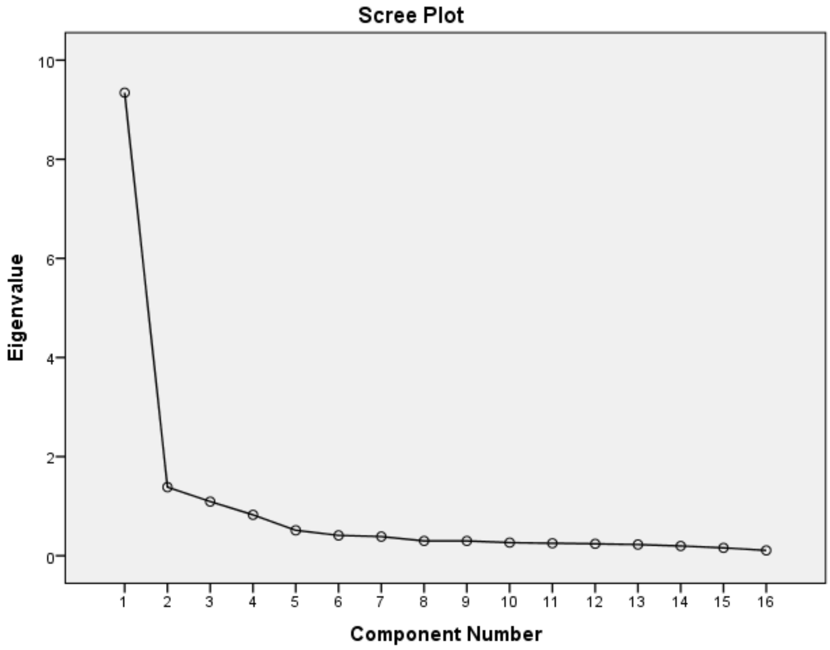
(The first factor will always account for the most variance(and hence have the highes eigenvalue), and the next factor will account for as much of the left over variance as it canm and so on.)

- The Extraction Sums of Squared Loadings is identical to the Initial Eigenvalues except factors that have eigenvalues less than 1 are not shown.

(In this case, three factors are retained. so there are three rows.)

- The Rotation Sums of Squared Loadings show you the eigenvalues after Promax rotation.

2) Scree Plot



-The scree plot graphs the eigenvalue against the factor number. You can see these values in the first two columns of the table immedeiately above. From the third factor on, the line is almost flat, meaning the each successive factor is accounting for smaller and smaller amounts of the total variance.

4. Rotated Factor Matrix

Pattern Matrix[a]

	Component		
	1	2	3
c1		.778	
c2		.755	
c3		.795	
c4		.803	
c5		.784	
s1			.934
s2			.860
s3			.927
i1	.696		
i2	.728		
i3	1.015		
i4	.973		
i5	.688		
i6	.948		
i7	.738		
i8	.854		

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

-This table contains the rotated factor loadings, which represent how the variables are wighted for each factor. (SPSS did not print the correlations that are 0.5 or less, because they are probably not meaningful.)
- We use Promax rotation to attain an optimal simple structure which attempts to have each variable load on a few factors as possible, but maximizes the number of high loadings on each variable. Promax is the one of the common oblique rotation techniques, which is used when the factors are considered to be correlated.

- To determine whether our rotation technique is suitable, I checked the Factor Transformation Matrix's off diagonal elements. A suitable rotation technique will result in a nearly symmetrical off-diagonal element.

- The variables cluster into these three groups.

Component Transformation Matrix

Component	1	2	3
1	1.000	.726	.588
2	.726	1.000	.534
3	.588	.534	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

This transformation matrix has symmetrical off-diagonal elements. So, the rotation we selected is acceptable.

5. Factor Score Covariance Matrix

- Because I did not use an orthogonal rotation, this should not be diagonal.

Component Score Covariance Matrix

Component	1	2	3
1	2.460	2.300	3.014
2	2.300	2.200	2.574
3	3.014	2.574	3.933

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

6. Principal Axis Factor

- I tried to adjust Principal Axis Factor as the data violate the assumption of multivariate normality. (Left skewed)

(Principal Axis Factor is recommended when the data violate the assumption of multivariate normality (Costello & Osborne, 2005)

As shown before, I got three factors, but c1 should be eliminated.

Pattern Matrix[a]

	Factor		
	1	2	3
c1			
c2		.772	
c3		.870	
c4		.793	
c5		.946	

s1			.892
s2			.806
s3			.864
i1	.651		
i2	.663		
i3	.928		
i4	.870		
i5	.633		
i6	.833		
i7	.672		
i8	.851		

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 5 iterations.