

School of Indigenous Education

Programs in this report

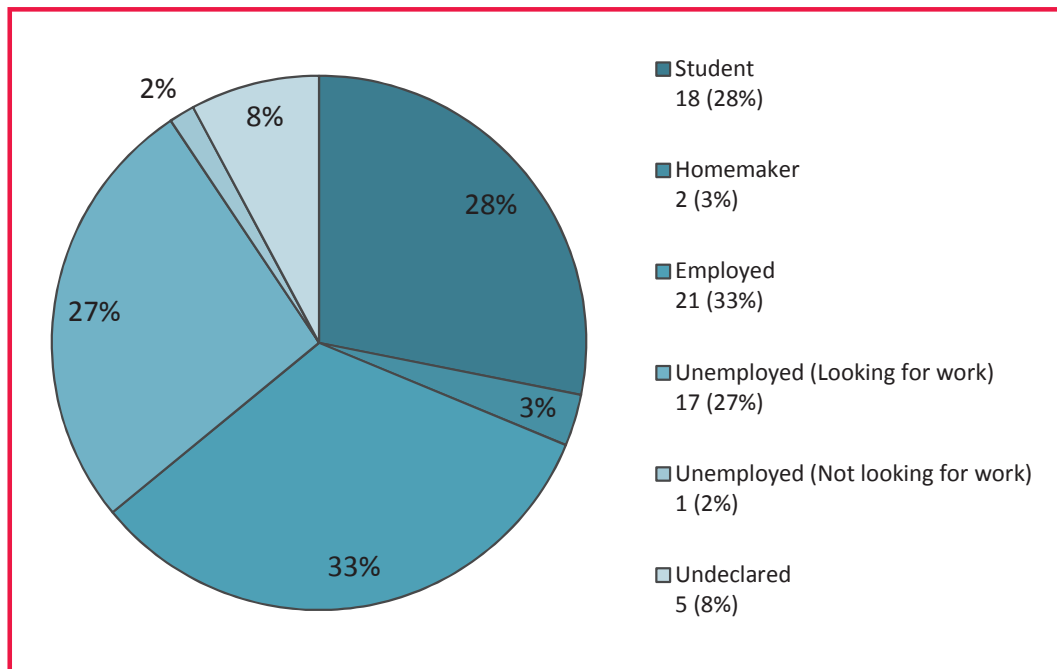
Aboriginal Language Specialist
Aboriginal Self-Government Administration

ACCESS Aircraft Maintenance & Manufacturing
Introduction to Trades

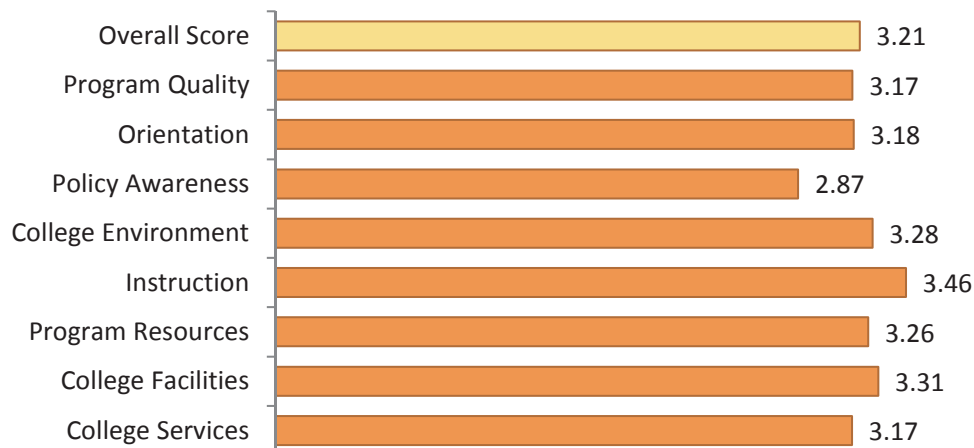
Programs with less than 5 respondents are not illustrated in this report, but are included in the School statistics.

Primary Prior Activity

(Before entering program)

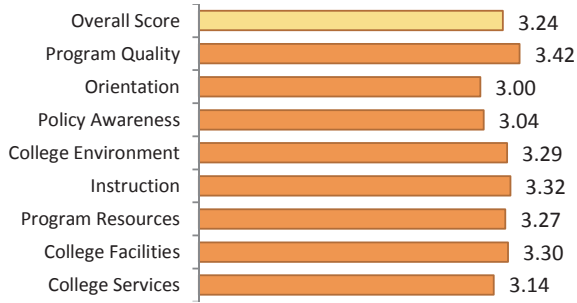


Summary of Student School Ratings



Aboriginal Language Specialist

Two-Year Diploma Program
Respondents: 7



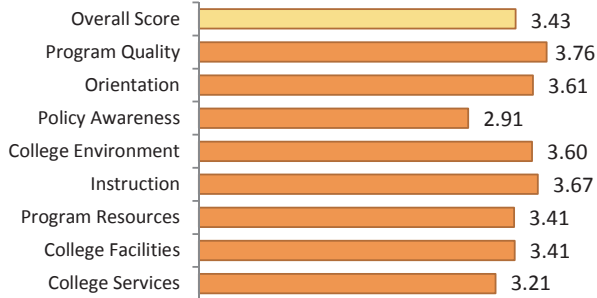
Aboriginal Self-Government Administration

Two-Year Diploma Program
Respondents: 5



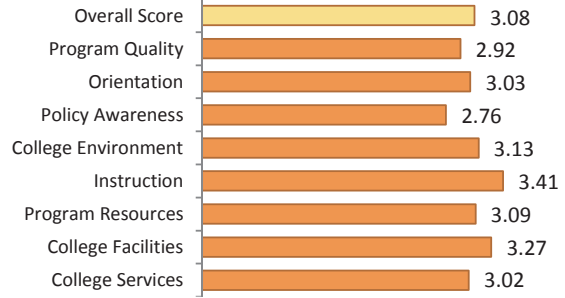
ACCESS Aircraft Maintenance & Manufacturing

One-Year ACCESS Program
Respondents: 9



Introduction to Trades

Five-Month Certificate Program
Respondents: 31



School of Transportation, Aviation & Manufacturing

Programs in this report

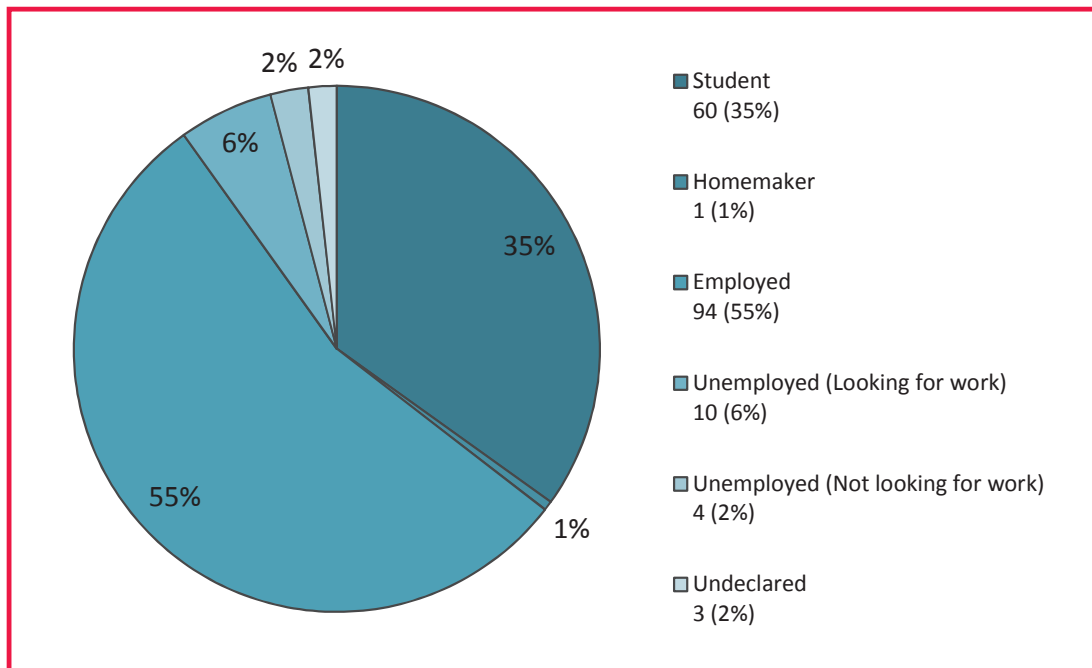
Aircraft Maintenance Engineer
 Heavy Duty Equipment Mechanic
 Intro to Aircraft Maintenance
 Manufacturing Technician
 Mechanical Engineering Technology

Outdoor Power Equipment Technician
 Power Engineering Technology
 Technology Management
 Welding

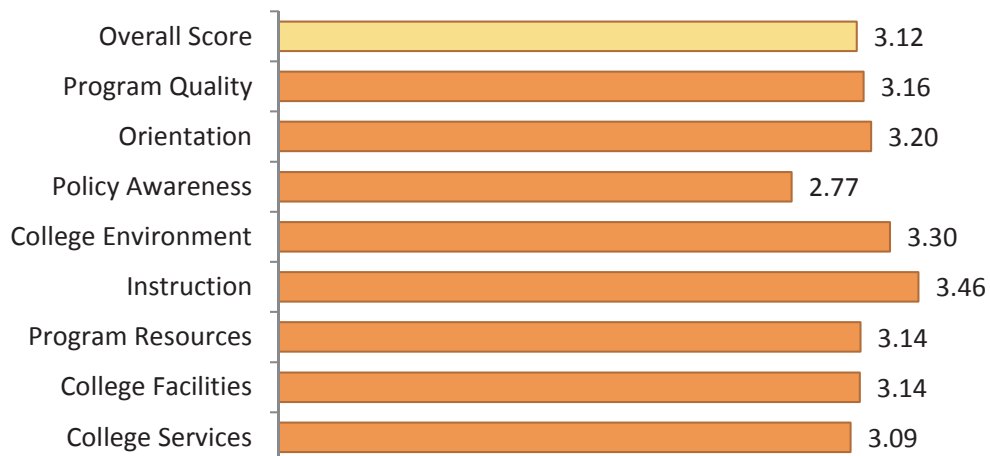
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Primary Prior Activity

(Before entering program)



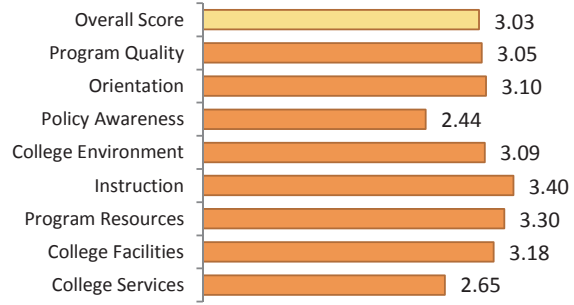
Summary of Student School Ratings



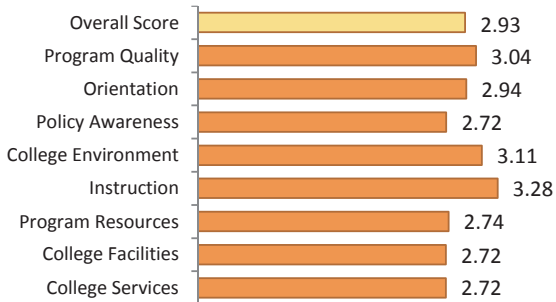
Aircraft Maintenance Engineer
Fifteen-Month Diploma Program
Respondents: 22



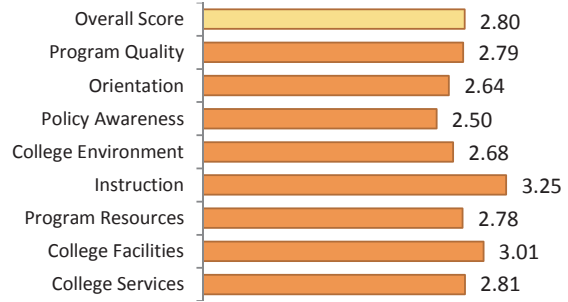
Heavy Duty Equipment Mechanic
One-Year Certificate Program
Respondents: 5



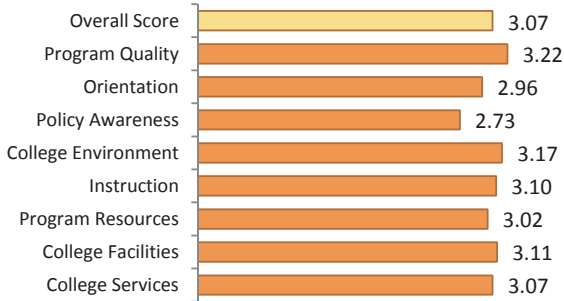
Intro Aircraft Maintenance
Four-Month Certificate Program
Respondents: 17



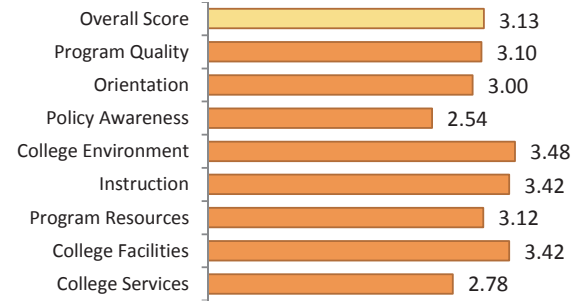
Manufacturing Technician
Two-Year Diploma Program
Respondents: 11



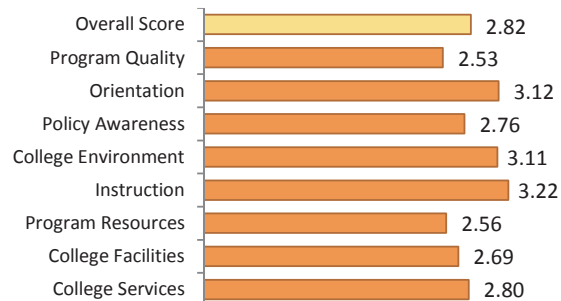
Mechanical Engineering Technology
28-Month Diploma Program
Respondents: 12



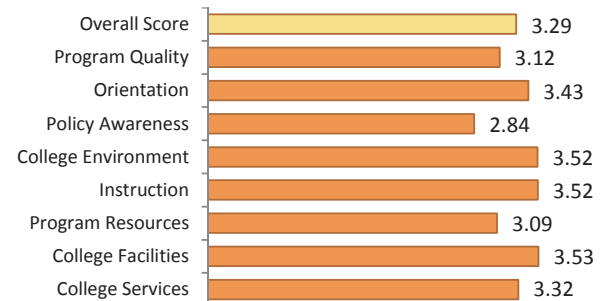
Outdoor Power Equipment Technician
One-Year Certificate Program
Respondents: 12

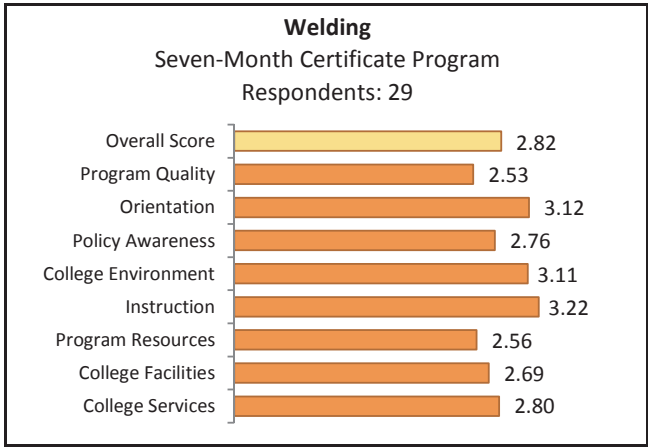


Power Engineering Technology
Two-Year Diploma Program
Respondents: 17



Technology Management
One-Year Advanced Diploma
Respondents: 21





Centre for Teaching Excellence, Innovation & Research

Programs in this report

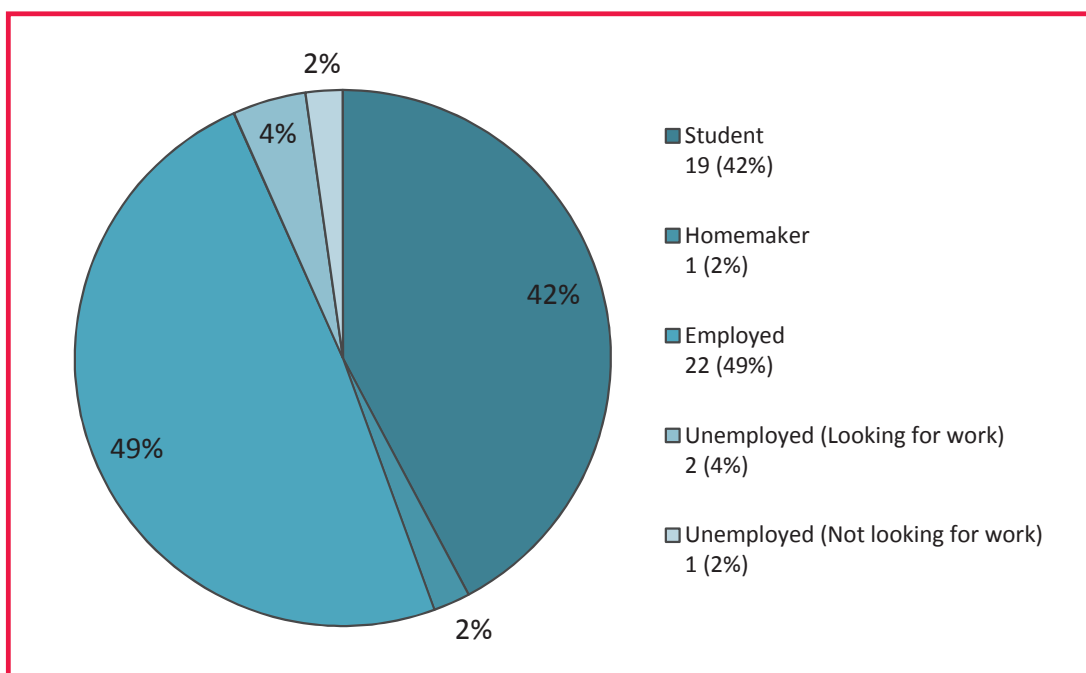
Business Teacher Education After Degree
Business/Technology Teacher Education
Industrial Arts Teacher Education After Degree

Industrial Arts/Technology Teacher Education
Technical Vocational Teacher Education

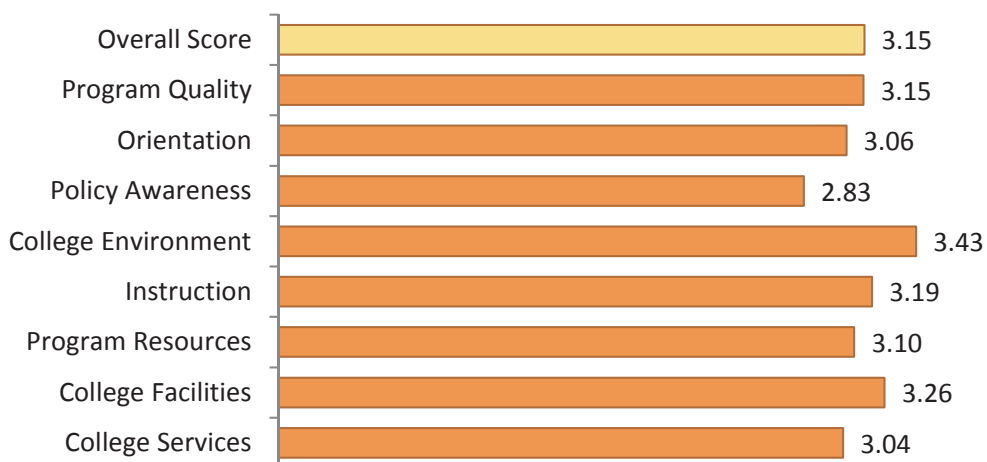
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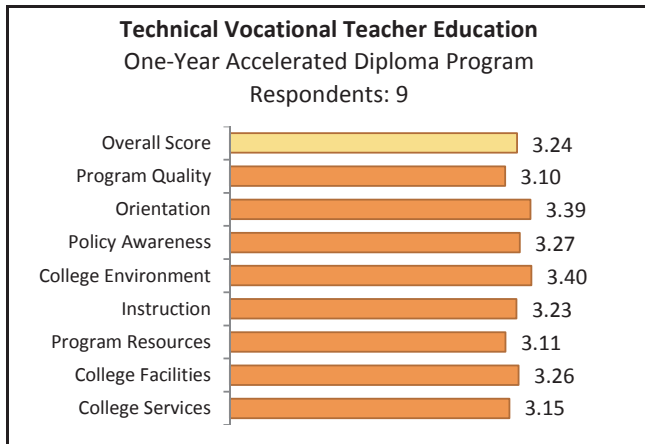
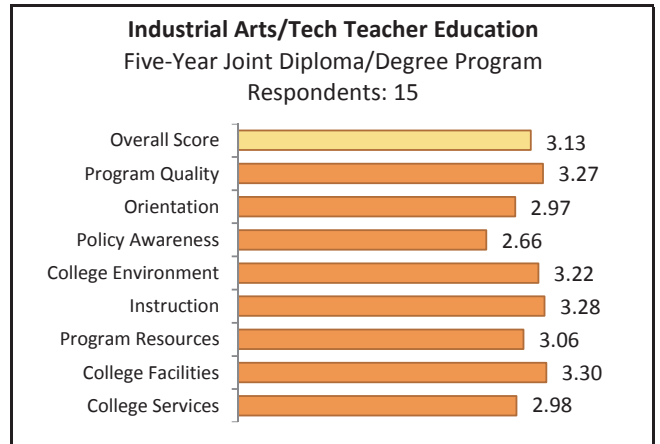
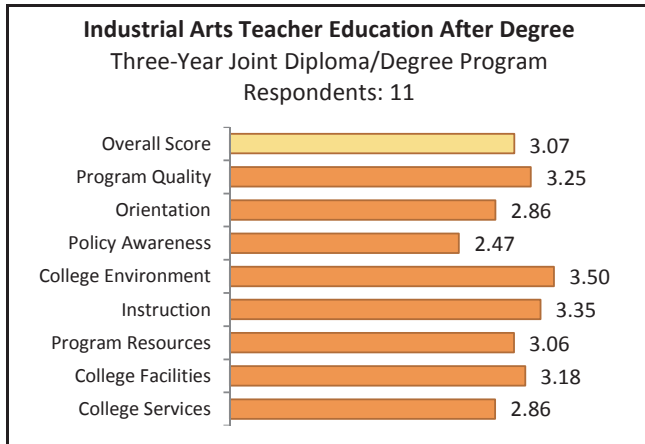
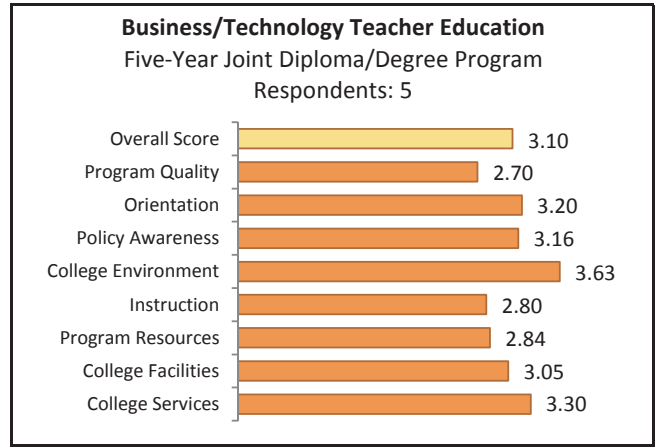
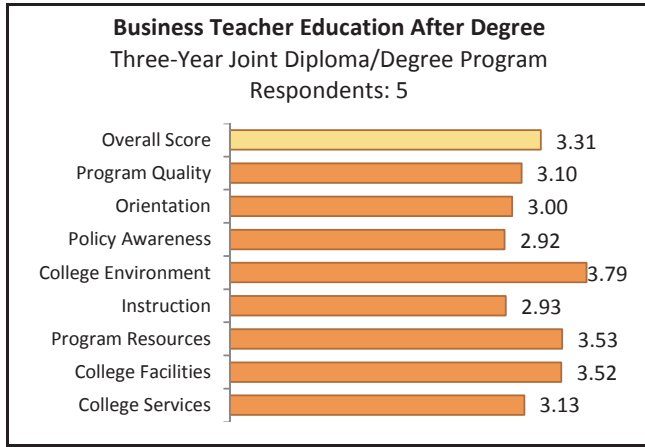
Primary Prior Activity

(Before entering program)



Summary of Student School Ratings





Language Training Centre

Programs in this report

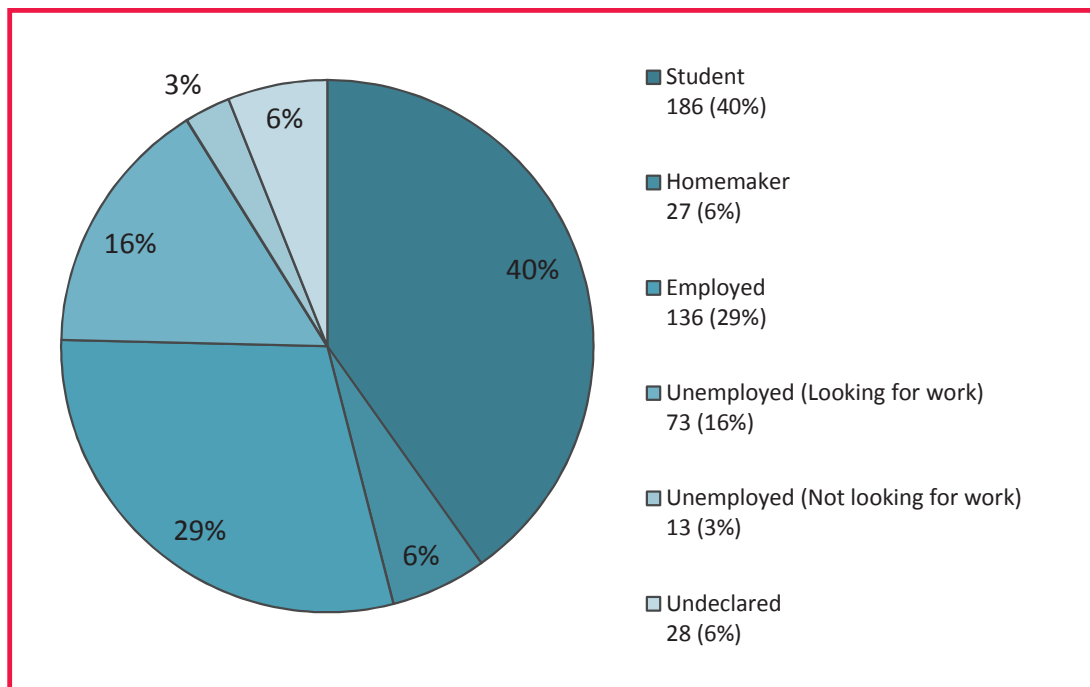
Academic English Prep Univ & College
English for Apprenticeship and Trades
English for Business Purposes
English for Health Care Aides

English for Nursing Purposes
English for Professional Purposes
Intensive English as a Second Language
Intensive English for International Students

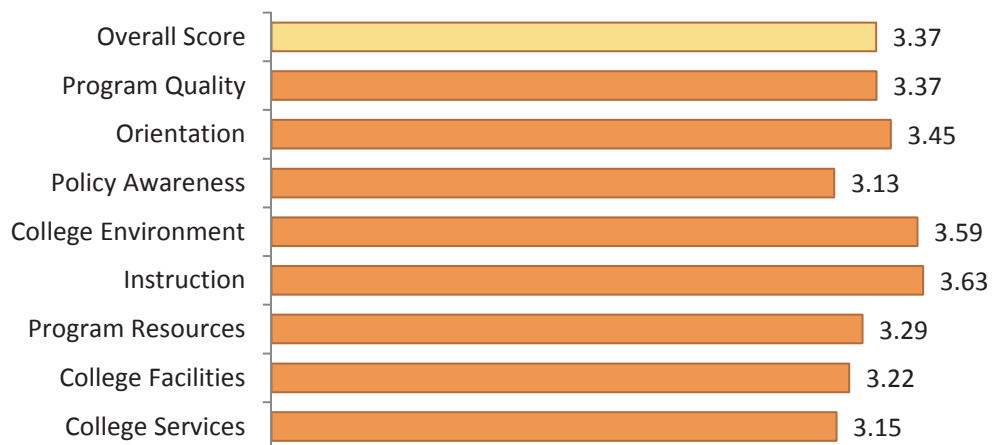
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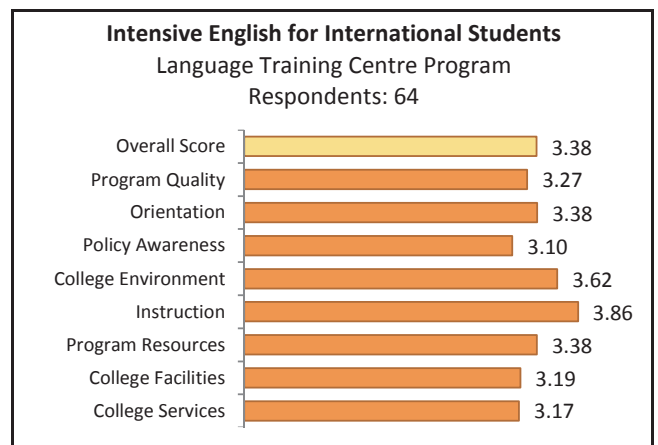
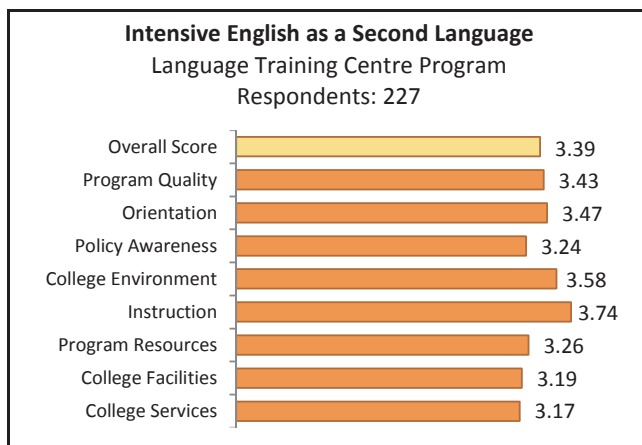
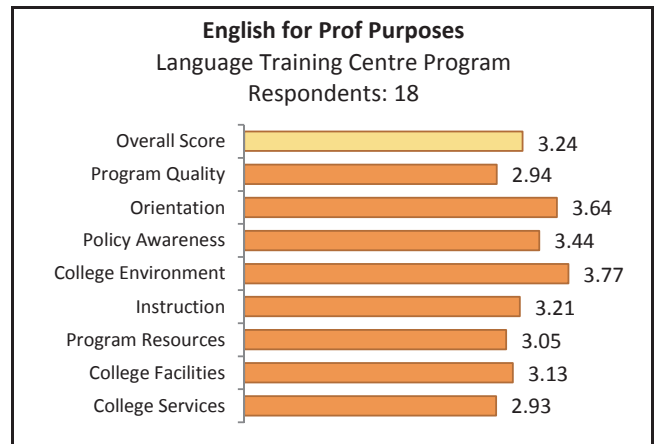
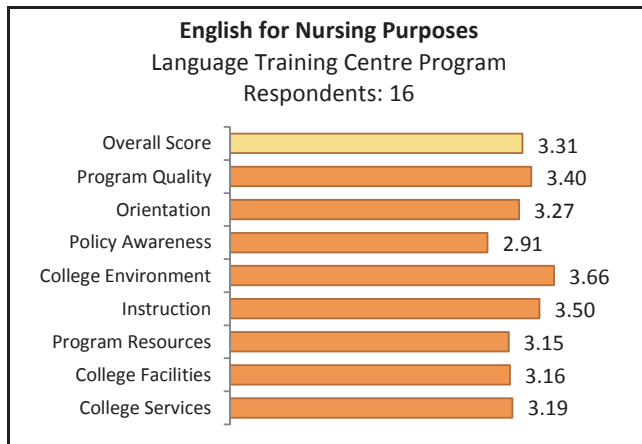
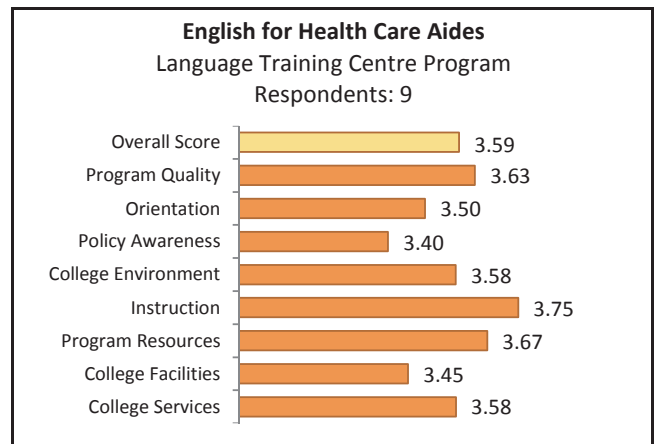
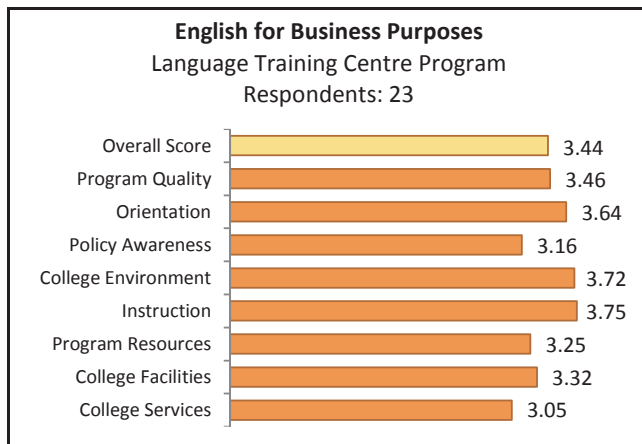
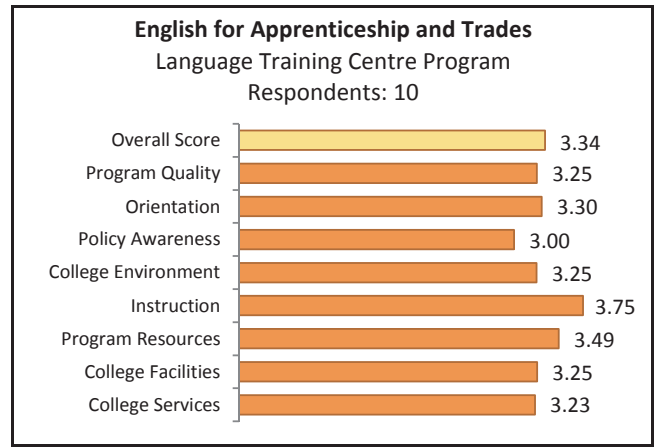
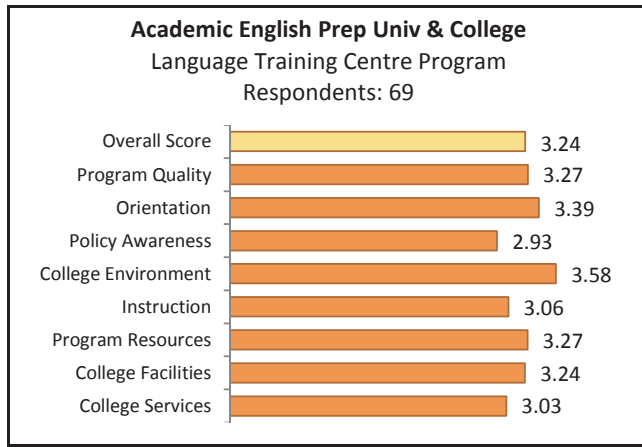
Primary Prior Activity

(Before entering program)



Summary of Student School Ratings





Appendices

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Appendix A - Programs with less than 5 respondents

Construction and Engineering Technologies

- Electronic and Network Technician
- Instrumentation Engineering Technology
- Network Technology (CCNA) - Diploma

Indigenous Education

- ACCESS Civil Engineering Technology
- Biindigen College Studies
- Computer Applications for Business

Transportation, Aviation & Manufacturing

- Precision Metal Machining

Other programs not illustrated (No Award, Contract, etc.)

- Bridging Program for Internationally Educated Nurses
- Canadian Communication for Physicians
- Co-op Vocational Education
- Introduction to Business
- Non-Destructive Testing
- Plumbing Cross Connection Control

Appendix B - Quality Categories

Quality Category (Dimension)	Chart Category	Survey Question #
Overall Program Quality	Program Quality	12 to 17
Quality of Orientation	Orientation	18 to 19
Quality of familiarization with College policies	Policy Awareness	20 to 24
Quality of the welcoming, inclusive college environment	College Environment	25 to 31
Quality of Instruction	Instruction	32 to 35
Quality of program resources	Program Resources	36 to 41
Quality of College facilities	College Facilities	42 to 47
Quality of College services	College Services	48 to 55

Appendix C - Quality Category Questions

Note: Question 1 - 11 ask for demographic information. Question numbers refer to the numbering used in the survey questionnaire, not the numbering used in the survey results reports (which exclude question 1 from the questionnaire.)

Overall Program Quality (Program Quality)

12. Before I applied, I had a good understanding of the program's purpose.
13. The training I have received in this program has met my expectations.
14. The program content is relevant to my career goals.
15. The tuition fee for this program is reasonable for the education provided.
16. Overall, I am satisfied with this program.
17. I would recommend this program to others.

Quality of Orientation (Orientation)

18. The orientation to the program provided by the Department was effective in explaining the requirements of the program.
19. Upon admission to the program, I was made aware of my role and responsibilities as a student.

Quality of familiarization with College policies (Policy Awareness)

20. I am familiar with the College's challenge for credit policy.
21. I am familiar with the College's transfer of credit policy.
22. I am familiar with the College's appeals procedure as it relates to academic and/or discipline issues.
23. I am familiar with the College's harassment policy.
24. I am familiar with Prior Learning Assessment at the College.

Quality of the welcoming, inclusive college environment (College Environment)

25. My gender does not limit my success in the program.
26. My race or ethnic origin does not limit my success in the program.
27. My physical ability does not limit my success in the program.
28. My financial situation does not limit my success in the program.
29. My English language skills do not limit my success in the program.
30. My Mathematical skills do not limit my success in the program.
31. My experience in the program has increased my awareness of values and cultures that are different from my own.

Quality of Instruction (Instruction)

32. The instructors treat students with respect.
33. The instructors are effective in delivering the program.
34. The instructors are knowledgeable in the areas they teach.
35. Overall, I am satisfied with the quality of instruction within the program.

Appendix C - Quality Category Questions continued

Quality of program resources (Program Resources)

36. The training materials (texts, workbooks, handouts, etc.) used in the program are current.
37. I am satisfied with the quality of the training materials used in this program.
38. The equipment used in this program is appropriate for learning the required skills.
39. The equipment used in this program is current with industry.
40. There is a sufficient quantity of equipment provided for the program.
41. There is a sufficient quantity of CURRENT library resource materials for use by students in the program. (Books, video tapes, audio tapes, periodicals, pamphlets, etc.).

Quality of College facilities (College Facilities)

42. The classroom facilities are appropriate.
43. The shop/lab facilities are appropriate.
44. Adequate study space is available to students.
45. Student lounge space is adequate.
46. The gymnasium/fitness facilities are satisfactory.
47. Overall, the College facilities meet my needs as a student.

Quality of College services (College Services)

48. I am satisfied with the service provided from the Academic Support Services (Tutorial Centre).
49. I am satisfied with the service I received from the Counselling Centre.
50. I am satisfied with the service I received from the Job Centre.
51. I am satisfied with the service I received from the Library.
52. I am satisfied with the service I received from the Bookstore.
53. I am satisfied with the service I received from the Enrolment Services Department.
54. I am satisfied with the service I received from the Print and Graphic Centre/Copy Centre.
55. Overall, I am satisfied with the quality of service provided by the College.

Appendix D - Technical Overview of Analytic Techniques¹

Surveys include many questions about one or more topics. Typically, how respondents answer these different questions tends to form patterns, that is, many of the responses are correlated. The RRC Student Evaluation of Program (SEPS) has 44 attitude questions on a variety of matters about the College.

Factor analysis is a statistical approach used to analyze interrelationships among a large number of variables and to explain these variables in terms of their common underlying dimensions or factors (Fisher & van Belle, 1993; Green & Salkind, 2003; Pedhazur & Schmelkin, 1991). This statistical technique allows the information contained in a large number of survey questions to be summarized in a smaller set of factors. The analysis compresses the original variables into a smaller set of dimensions. There are two main types of factor analysis, confirmatory and exploratory.

The analysis in the first annual SEPS report (2003-04 survey) was exploratory. Exploratory factor analysis is used to discover the factor structure of a set of observed variables. Observed variables are the measured variables and are sometimes called indicator variables or manifest variables or reference variables, such as items in a survey instrument. It is often used when researchers have no hypotheses about the nature of the underlying factor structure of their measures.

Factor analysis generates a correlation matrix for all the observed variables. A correlation matrix is a rectangular array of the correlation coefficients of the variables with each other. Factors (dimensions) are extracted from the correlation matrix based on the correlation coefficients of the variables. Then, the factors are rotated in order to maximize the relationship between the variables and some of the factors. In general, the number of dimensions or factors is much smaller than the number of original variables. Factors or dimensions are also sometimes referred to as latent variables to distinguish them from the observed variables.

Additionally, it is possible to compute factor or dimension scores for use in subsequent analyses. As well, the reliability of dimensions, which generally include a number of items, can be tested. The results of the initial exploratory factor analysis are included as Appendix D1.

The first year, 2003-04, established the factor structure; this year we wanted to establish its consistency. In factor analysis, confirmatory analysis is used to test the consistency of the structure. The 2003-04 factor structure included eight dimensions arising from the original set of variables. Confirmatory factor analysis (Coughlin, 2005; Pedhazur & Schmelkin, 1991) was applied to the 2004-05 data set using the 2003-04 structure. Confirmatory factor analysis is used when a particular factor structure has been specified, in which the researcher designates the variables to load on each factor – in this case the factor structure arising from the 2003-04 SEPS.

The analysis proceeded through several steps. First a global test of the fit of the original factor model to the new data set was undertaken. The original factor model was re-estimated using the original data set again forcing eight factors, using principal axis factoring with a promax rotation and a maximum likelihood estimation method. The data set had missing data (some of the individual questions had large numbers of non-responses). The chi-square and degrees of freedom were calculated and the model was then applied to the second data set. Table 1 provides the results.

Table 1.

	SEPS 2003-04	SEPS 2004-05	$\Delta\chi^2$
χ^2	1169.7	1275.8	106.1
df	622	622	0

¹ Research and Planning would like to thank Ashley Blackman for his advice and guidance on the statistical procedures.

Appendix D

- Technical Overview of Analytic Techniques continued

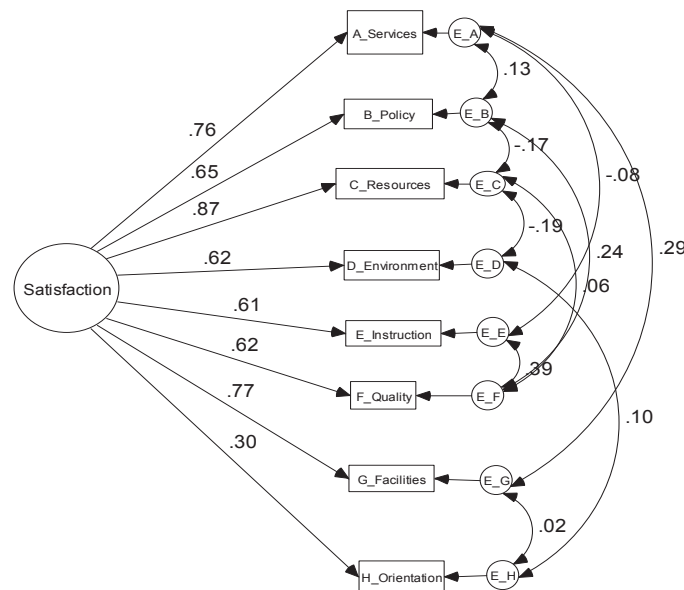
This meant the model was rejected, that is, the original model did not fit the second data set. In order to proceed, the two data sets were explored using multinomial logistic regression to help identify why they are different. Seven questions (or variables) showed a difference. Compared to 2003-04, the responses to questions 25, 28, 32, 38, 41, 45 and 53 were more positive (or less negative) in 2004-05. Combined, these variables have a reliability alpha .72 and this set of variables showed a significant difference from 2003-04 to 2004-05. While the model would still be rejected, removing the variables that changed removed most of the variability.

The last stage of the analysis conducted the confirmatory factor analysis using structural equation modeling (SEM)² with AMOS³. Figures 1 and 2 illustrate the factor structure model for the 2003-04 (2003 in the figure) SEPS and for 2004-05 (2004 in the figure) in its final form, allowing correlated error terms⁴.

This means⁵ that we can have confidence in applying the original factor structure to the 2004-05 survey results. In other words, the original eight dimensions still work with the 2004-05 SEPS findings.

Figure 1. Factor Model for the 2003-04 SEPS.

Satisfaction model based on principal axis factor analysis
2003 GFI .991
Chisq=31.236 df=20 p=.052



² SEM is a multivariate statistical analysis technique that encompasses and extends standard statistical methods such as regression, factor analysis, and simultaneous equations and analysis of variance. It is largely a confirmatory and not an exploratory technique. SEM is used to test hypotheses about the relationships between observed and latent variables. Using SEM it is possible to explore factor models (Coughlin, 2005). The goal of structural equation modeling (SEM) is to compare a covariance matrix generated from a particular sample with a covariance matrix generated by a hypothesized model.

³ AMOS is a structural equation modeling software distributed by SPSS

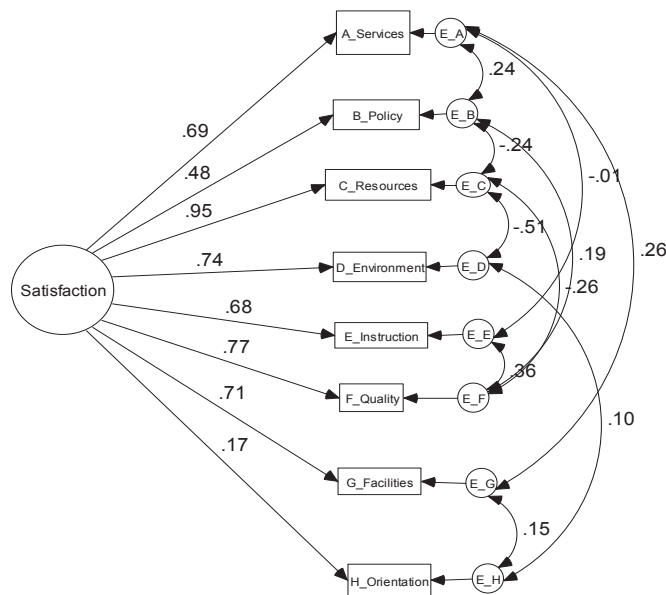
⁴ Correlated error terms refers to situations where knowing the residual of one variable helps in knowing the residual associated with another variable. The correlation of error terms may and should be explicitly modeled in SEM. In SEM, the researcher must model error as well as the variables. It makes particular sense in this instance in that the variables are correlated with each other.

⁵ For example, the goodness-of-fit (GFI) index should be at .90 or greater to have the model considered as adequate (Schumacker & Lomax, 1996).

Appendix D - Technical Overview of Analytic Techniques continued

Figure 2. Factor Model for the 2004-05 SEPS.

Satisfaction model based on principal axis factor analysis
2004 GFI .991
Chisq=31.236 df=20 p=.052



The reliability scores of the eight dimensions for the 2004-05 SEPS data set are illustrated in Table 2.

Table 2. Factors Extracted from the Student Evaluation of Program Survey 2004-05.

Dimension	Reliability ⁶	Number of Items
Overall Program Quality	.839	6
Quality of Orientation	.660	2 ⁷
Quality of familiarization to College policies	.886	5
Quality of the welcoming, inclusive college environment	.802	7
Quality of Instruction	.877	4
Quality of program resources	.852	6
Quality of College Facilities	.842	6
Quality of College Services	.914	7

These reliability scores are very similar to the scores from the 2003-04 SEPS, excepting Orientation, which is somewhat lower.

⁶ Cronbach's alpha measures how well a set of items (or variables) measures a single unidimensional latent construct. When data have a multidimensional structure, Cronbach's alpha will usually be low. Cronbach's alpha is not a statistical test - it is a coefficient of reliability (or consistency). The acceptable range is normally considered to be between .7 and 1.0 (Nunnally, 1978).

⁷ Velicer and Fava (1998) argue that factors should have at least three variables, however, if the original variables are best interpreted as a pair and the intent is to develop the underlying dimensions it makes sense to use only two.

– Exploratory Factor Analysis Results from the 2003-04 SEPS

The first step in exploratory factor analysis is to assess whether or not the data set is appropriate for factor analysis. SPSS 13.0 was used to conduct the analysis. The overall factor analysis was evaluated through the Kaiser-Meyer-Olkin (KMO) and Bartlett's Tests. The KMO measures the sampling adequacy which should be greater than 0.6 for a satisfactory factor analysis to proceed (Tabachnik & Fidell, 2001). The Bartlett's test⁸ of sphericity examines whether there are adequate intercorrelations between the items to use factor analysis and it should be significant ($p \leq .05$).

For the factor analysis of the SEPS, the results (Table 1) indicate a satisfactory analysis:

Table D1. KMO and Bartlett's Test Results for SEPS 2003-04 Factor Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.944
Bartlett's Test of Sphericity	Approx. Chi-Square	11753.541
	df	946
	Sig.	.000

The steps in factor analysis are to select an extraction method for the correlations from the matrix and a rotation method to maximize the loadings of the items into a factor. Examining the correlations among the many survey items in the Student Evaluation of Program Survey (SEPS) for 2003-04 revealed that there was a significant correlation among various subgroups of questions. There are two main extraction methods, principal components analysis or common factor analysis (there are several specific techniques). Two strategies were used in conducting the exploratory factor analysis. First, principal component analysis (PAC)⁹ with a varimax¹⁰ rotation was used for the analysis of the forty-four questions, all of which were attitude-type questions with a four point¹¹ agree – disagree scale. Factors are extracted in order and the first factor accounts for the largest amount of variability and the second factor the second most and so on. The factors were initially selected based on the scree plot¹² (included as Figure 1) and included all factors with an eigenvalue (the variability of a factor)¹³ greater than one. This yielded seven factors. Then the selected factors were rotated through a varimax routine to yield separate uncorrelated factors or dimensions. Factor loading¹⁴ were at a minimum of .30¹⁵. Subsequently, the derived factors were examined in relation to the original set of questions and a further analysis was conducted to achieve eight dimensions, which seemed to be more interpretable for the original question items. The scree test and the eigenvalue-greater-than-one criteria are meant to act as guides in determining factors; what is more important is to have a set of factors that arise from the data and are more meaningful (Fabrigar, et. al., 1999).

⁸ A test statistic used to examine the hypothesis that the variables are uncorrelated. It is used to test the suitability of a correlation matrix for factor analysis by examining if the data contain sufficient correlations to warrant analysis (i.e., whether the correlation matrix (variance/covariance matrix) is an identity matrix). If the obtained chi square value is significant, then the correlation matrix to be analyzed is non-random and is suitable for factor analysis.

⁹ Principal components analysis (PCA) is a form of factor analysis. It involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

¹⁰ A *variance maximizing (varimax) rotation* is a method for rotating axes of a plot such that the eigenvectors remain orthogonal (that is uncorrelated) as they are rotated. These rotations are so that the axes are rotated to a position in which the sum of the variances of the loadings is the maximum possible. This type of rotation is called *variance maximizing* because the purpose of the rotation is to maximize the variance (variability) of the factor (the "new" variable), while minimizing the variance around the new variable. It assumes uncorrelated factors.

¹¹ It may be argued that a four-point scale is not continuous, however, factor analysis is very robust and it is not uncommon to use factor analysis with four point scales.

¹² A scree plot is a plot of the eigenvalue for each factor; generally, a criterion for selection of factors is that all factors are retained with eigenvalues in the sharp descent part of the plot before the values level off.

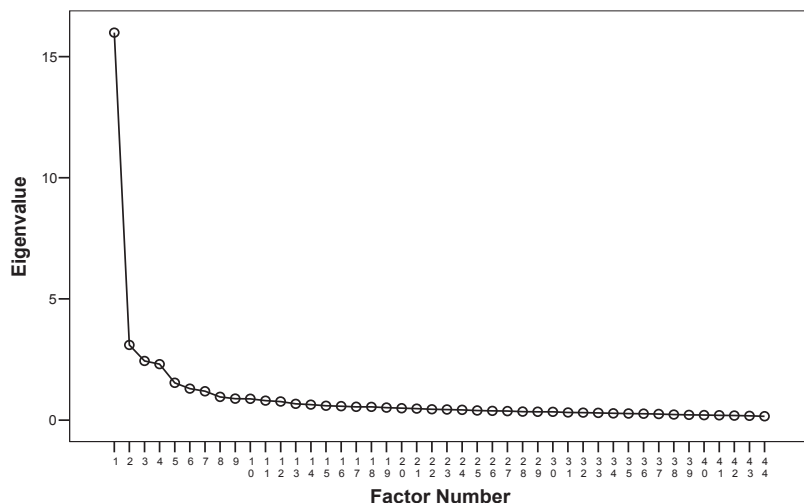
¹³ An eigenvalue is the standardized variance associated with a particular factor.

¹⁴ A factor loading expresses the correlation of an item with a factor.

¹⁵ A general rule of thumb is that factor loadings greater than .30 are considered to be useful. This is just a guideline and may need to be adjusted, for example, as the sample size and the number of variables increase, the criterion may need to be adjusted slightly downward and it may need to be adjusted upward as the number of factors increases (see Hair, et. al., 1998).

Appendix D1 - Exploratory Factor Analysis Results from the 2003-04 SEPS continued

Figure 1. Scree Plot



In addition, a separate analysis was conducted using principal axis factoring (PAF)¹⁶ with a promax¹⁷ rotation. Factor loadings were at a minimum of .40. Initially, seven factors were extracted as with the PCA, but the factors varied very slightly. The analysis was re-run for eight factors, and the results were virtually identical to the PCA. What is reported here derives from the pattern matrix of the principal axis factoring (see Table 3 for the factor loadings). Some researchers (Fabrigar, et. al., 1999; Gorsuch, 1990; Preacher & MacCallum, 2003) suggest that principal axis factoring with an oblique rotation is the preferred method of factor analysis even if principal component analysis is widely used and explained in many texts (for example, Green & Salkind, 2003).

According to the analysis, the forty-four questions can be summarized in eight dimensions, or scales as illustrated in Table 2. The dimensions or scale items were also tested for reliability. Hence, the forty-four items can be summarized in eight dimensions with high reliability.

Table D2. Factors (Dimensions) Extracted from the 2003-04 Student Evaluation of Program Survey.

Dimension	Reliability ¹⁸	Number of Items
Overall Program Quality	.814	6
Quality of Orientation	.721	2 ¹⁹
Quality of familiarization to College policies	.892	5
Quality of the welcoming, inclusive college environment	.794	7
Quality of Instruction	.875	4
Quality of program resources	.856	6
Quality of College Facilities	.869	6
Quality of College Services	.902	7

¹⁶ Principal axis factoring is another common form of factor analysis. It uses squared multiple correlations as the initial estimates of the communalities. The general factor model asserts that there is common factor plus individual idiosyncrasies. Principal component works only with the common factor, whereas principal axis tries to use both. (Principal component treats the individual elements as part of the error term). In theory, developing a model that takes into account more of the sources of variability can be useful. As well, with the SEPS data set, it is likely that the factors are correlated.

¹⁷ Promax is an oblique rotation such that the vertices can have any angle. It allows factors to be correlated. Its name derives from procrustean rotation because it tries to fit a target matrix which has a simple structure. With the SEPS data set, it is likely that the factors are correlated.

¹⁸ Cronbach's alpha measures how well a set of items (or variables) measures a single unidimensional latent construct. When data have a multidimensional structure, Cronbach's alpha will usually be low. Cronbach's alpha is not a statistical test - it is a coefficient of reliability (or consistency). The acceptable range is between .7 and 1.0 (Nunnally, 1978).

¹⁹ Velicer and Fava (1998) argue that factors should have at least three variables, however, if the original variables are best interpreted as a pair and the intent is to develop the underlying dimensions it makes sense to use only two.

Appendix D1 - Exploratory Factor Analysis Results from the 2003-04 SEPS continued

Table D3. Summary of Factor Loadings for Promax, Principal Axis Factoring for the Student Evaluation of Program Survey 2003-04. (Note. Only factor loadings greater than .40 are shown.)

	Factor							
	College Services	Policy Awareness	Program Resources	College Environment	Instruction	Program Quality	College Facilities	Orientation
Q12						.551		
Q13						.574		
Q14						.720		
Q15						.473		
Q16						.672		
Q17						.590		
Q18								.433
Q19								.447
Q20		.756						
Q21		.904						
Q22		.922						
Q23		.722						
Q24		.747						
Q25				.768				
Q26				.767				
Q27				.830				
Q28				.425				
Q29				.612				
Q30				.482				
Q31				.418				
Q32					.779			
Q33					.844			
Q34					.682			
Q35					.828			

Appendix D1 - Exploratory Factor Analysis Results from the 2003-04 SEPS continued

Table D3. continued

	Factor							
	College Services	Policy Awareness	Program Resources	College Environment	Instruction	Program Quality	College Facilities	Orientation
Q36			.677					
Q37			.652					
Q38			.788					
Q39			.821					
Q40			.760					
Q41			.527					
Q42							.658	
Q43							.635	
Q44							.785	
Q45							.723	
Q46							.613	
Q47							.507	
Q48	.571							
Q49	.687							
Q50	.847							
Q51	.729							
Q52	.754							
Q53	.860							
Q54	.818							
Q55	.768							

Appendix D₁ - Exploratory Factor Analysis Results from the 2003-04 SEPS continued

Table D4. Factor Correlation Matrix

Factor Correlations								
	College Services	Policy Awareness	Program Resources	College Environment	Instruction	Program Quality	College Facilities	Orientation
College Services	1.000							
Policy Awareness	.549	1.000						
Program Resources	.659	.500	1.000					
College Environment	.502	.407	.467	1.000				
Instruction	.416	.410	.518	.402	1.000			
Program Quality	.458	.552	.561	.382	.623	1.000		
College Facilities	.706	.486	.692	.443	.469	.494	1.000	
Orientation	.212	.277	.232	.263	.221	.236	.235	1.000

References

- Coughlin, M.A. (2005). Applied multivariate statistics. In M.A. Coughlin (Ed.) *Applications of intermediate/advanced statistics in institutional research*. Tallahassee, FL: The Association for Institutional Research.
- Fabrigar, L.R., Wegener, D.T., MacCallum, R.C. & Strahan, E.J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods, 3*, 272-299.
- Fisher, L.D. & van Belle, G. (1993). *Biostatistics*. New York: Wiley.
- Gorsuch, R.L. (1990). Common factor analysis versus components analysis: Some well and little known facts. *Multivariate Behavioral Research, 25*(1), 33-39.
- Green, S.B. & Salkind, N.J. (2003). *Using SPSS for Windows and Macintosh* (3rd Ed). Upper Saddle River, NJ: Prentice Hall.
- Hair, J.F. Jr., Anderson, R.E., Tatham, R.L., & Black, W.C. (1998). *Multivariate data analysis*, (5th Ed.). Upper Saddle River, NJ: Prentice-Hall.
- Nunnally, J. (1978). *Psychometric theory* (2nd Ed). New York: McGraw-Hill.
- Pedhazur, E.J. & Schmelkin, L.P. (1991). *Measurement, design and analysis: An Integrated approach*. Hillsdale, NJ: Erlbaum.
- Preacher, K.J. & MacCallum, R.C. (2003). Repairing Tom Swift's electric factor analysis machine. *Understanding Statistics, 2*(1), 13-43.
- Schumacker, R. E., & Lomax, R. G. (1996). *A beginner's guide to structural equation modeling*. Mahwah, NJ: Lawrence Erlbaum.
- Tabachnik, B. G., & Fidell, L. S. (2001). *Using multivariate statistics* (4th Ed.). Needham Heights, MA: Allyn and Bacon.
- Velicer, W.F. & Fava, J.L. (1998). Effects of variable and subject sampling on factor pattern recovery. *Psychological Methods, 3*, 231-251.