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Improving the Reporting of Student Satisfaction Surveys Through Factor Analysis

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Abstract

A prime role of institutional research is to contextualize institutional or survey data in a clear, accurate, concise, and compelling fashion. The purpose of this paper is to delineate the strategy used by a comprehensive Canadian community college to improve the analysis and reporting of student satisfaction surveys. Although data-rich with many years of student satisfaction surveys, the community college was knowledge-poor as the data were only readily available in unsummarized form. Using exploratory factor analysis, the 44 questions on the surveys were reduced to eight dimensions. The data reduction technique facilitated the testing of relationships of student satisfaction with various institutional characteristics and student characteristics. The new variables were also used to prepare a new, public institutional research report, illustrating in graphic form satisfaction findings by program, department, and the College as a whole. The outcome was the greater use of the survey results by members of the College community, as well as prospective students and external agencies.

Improving the Reporting of Student Satisfaction Surveys Through Factor Analysis

Quality in education is a challenging concept to define, let alone to measure. Vroeijenstijn (1992) suggests that everyone in higher education has an interest or concern about quality, but not everyone has the same

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idea about what it means. Bennett (2001) says quality is fundamentally what is improved about students' capabilities or knowledge as a result of their education. Tam (1999) argues that the assessment of quality in higher education should be measured in terms of impact on students' growth. Tan and Kek (2004) maintain that educational quality is determined by the extent to which students' needs and expectations are met. Indeed, quality in education may be characterized, in part, by the ability of an institution to satisfy students' needs and expectations (Tan & Kek, 2004).

It is clear that higher education institutions are placing greater emphasis on student expectations and becoming increasingly aware of the importance of student satisfaction (Cheng & Tam, 1997; Elliot & Shin, 2002). Harvey (2001) argues student feedback plays an important role in assessing quality and standards. Astin (1993) suggests that student satisfaction is perhaps the key education outcome. This is supported by the finding that student satisfaction seems to have a positive impact on student motivation, student retention, and student recruitment (Elliot & Shin, 2002; Thomas & Galambos, 2004; Tinto, 1993).

In addition, student satisfaction measures are widely used in advanced education with most postsecondary institutions undertaking such research, often through institutional research (Beltyukova & Fox, 2002; Downey, 2003). Nonetheless, there is criticism of the utility and validity of student satisfaction measures (Downey, 2003), especially with instructor ratings (Greenwald, 1997). Admittedly, student satisfaction is a complex concept impacted by multiple characteristics of students and institutions (Thomas & Galambos, 2004). However, it seems clear that student satisfaction is a common measure used to assess educational quality and is beneficial to institutions in understanding student experiences and in assessing overall quality.

For many years, our community college (Red River College or the College) in Western Canada has conducted an annual survey, the Student Evaluation of Program Survey (SEPS), of all students to measure satisfaction. Each year, students in their final term are surveyed to gather information on many aspects of the College. The questionnaire consists of a core of 11 demographic questions, 44 Likert-type attitude questions for all students, and additional questions for unique program features, such as co-operative work placement and clinical placement. A very large quantity of data is collected through the survey and reported for over 100 programs. Traditionally, findings were reported in tables for each question for each program by year. Aggregate tables were also prepared by faculty and for the College as a whole. The data were distributed in large three-ring binders and available in MS Access files to senior academic leaders. However, given the bulk of the binders and the level of detail reported, full information was practically inaccessible to many constituencies such as students and faculty members. For example, the College-wide summary results alone were 12 pages in length, and the overall detailed tables ran for hundreds of pages. Although selected single-question items were used for trend analysis, full information was not used for planning, evaluation, and monitoring, or for accountability to external funders. As the fundamental role of institutional research in post-secondary education is to provide the analytic inputs to facilitate decision-making (Frost, 1993; McLaughlin, Howard, & McLaughlin, 1998), a strategy was initiated to make the findings more accessible.

Methods

The data set for this research is the College's student evaluation of program survey results for 2003–04. A total of 2,561 students from a potential population of 3,442 completed the survey questionnaire and are included in the data set. Like most surveys, this instrument includes 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.

In order to understand the correlations and to summarize the findings in the 2003–04 SEPS, the data were first reduced through factor analysis. This statistical technique allows the information contained in a large number of questions to be summarized in a smaller set of higher-order variables or factors. The main applications of factor analytic techniques are (a) to reduce the number of variables and (b) to detect and confirm structure in the relationships between variables, that is, to classify variables into categories which are relatively independent of each other. 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 (Coughlin, 2005; Fisher & van Belle, 1993; Green & Salkind, 2003; Pedhazur & Schmelkin, 1991). The analysis compresses the original variables into a smaller set of underlying or basic factors. These factors consist of subcategories of the original variables correlated with one another but relatively independent of other subcategories of variables combined into other factors (Tabachnik & Fidell, 2001).

There are two main types of factor analysis, exploratory and confirmatory. Exploratory factor analysis is generally used to discover the structure of a set of variables by grouping variables that are correlated. It is used when researchers have no hypotheses about the nature of the underlying factor structure of their measures. At this stage of research, researchers are primarily interested in data reduction, which is a common issue for institutional research.

Confirmatory factor analysis is a more complicated statistical technique, perhaps best performed through structural equation modeling; it typically involves specialized statistical software, like AMOS. It requires the researcher to specify a factor structure in advance and to identify the variables to load on each factor (Coughlin, 2005; Pedhazur & Schmelkin, 1991). At this level of research, hypotheses about the factor structure are being tested. Confirmatory factor analysis is employed to test the validity of an identified factor structure.

For this study, as there was no predetermined factor structure for the 2003–04 SEPS results, and because the prime interest was in data reduction, exploratory factor analysis was conducted. All of the attitude-type questions are on a four-point *agree – disagree* response scale. It may be argued that a four-point scale is not continuous; strictly speaking, it is ordinal. In practice, ordinal variables are often used in such analyses (Allison, 1999), and the basic requirement for factor analysis is to have variables at the ordinal level (Coughlin, 2005). Such measures are sometimes referred to as "quasi-interval" (see Henkel, 1975; Labovitz, 1975). Moreover, factor analysis is very robust, and it is not uncommon to use factor analysis with four-point scales.

Prior to undertaking exploratory factor analysis, the data set should be assessed to ascertain if it is appropriate for factor analysis. The factorability of a data set is evaluated through the Kaiser-Meyer-Olkin Measure (KMO) and Bartlett's Test of Sphericity. The KMO measures the sampling adequacy, which should be greater than 0.6 for factor analysis to be used (Tabachnik & Fidell, 2001). Sampling adequacy here measures whether the data are likely to factor well. If the data set is factorable, distinct factors will emerge. The KMO is computed as the ratio of the sum of squared correlations to the sum of squared correlations plus the sum of squared partial correlations. Values of the KMO range from 0 to 1.0. The value approaches 1.0 if the partial correlations are small, meaning most variables measure a common factor (Tabachnik & Fidell, 2001). The Bartlett's Test of Sphericity examines whether there are adequate intercorrelations between the items to use factor analysis, and it should be significant ($p \leq .05$). This rejects the hypothesis that the correlations in a correlation matrix are zero (Tabachnik &

Fidell, 2001). These tests are readily available in SPSS and other analytic software. SPSS 13.0 was used to conduct the analysis for this study.

In brief, and with specific details of the study later, the way factor analysis works is that it traditionally starts from a correlation matrix for all the variables from the original data set. A correlation matrix is the rectangular array of the correlation coefficients of the variables with each other. There are three key steps in exploratory factor analysis: (a) extract the factors, (b) select the number of relevant factors, and (c) rotate the factors to maximize some set of relationships. Each of these will be elaborated in turn.

The first step is to extract factors. Factors (dimensions) are extracted from the correlation matrix based on the correlation coefficients of the variables. Most factor analyses use one of the two main extraction methods, either Principal Components Analysis (PCA) or Common Factor Analysis (there are also several other specific techniques). SPSS and other analytic software provide these options for researchers. Both methods were used in conducting the exploratory factor analysis for this research. However, for purposes of reporting, the Common Factor Analysis is detailed in the body of this article while PCA is briefly outlined in an endnote.[1] The Common Factor Analysis method used is Principal Axis Factoring (PAF), which is argued to be the preferred method in recent literature (Coughlin, 2005; Gorsuch, 1990; Preacher & MacCallum, 2003). In PAF, the primary or main diagonal (running from the top left corner to the bottom right corner) of the matrix contains estimates of the communalities (the proportion of item variance that is in common with the other items). It uses squared multiple correlations for each item as the initial estimates of the communalities (Pedhazur & Schmelkin, 1991). PAF analyzes common factor variability, that is, it attempts to account for common variance only. SPSS will provide a table of the communalities. Initially the extraction process in PAF produces an equal number of factors with the initial variables and calculates an eigenvalue. An *eigenvalue* is the variability of a factor or the standardized variance associated with a particular factor (eigenvector). Eigenvalues in PAF are extracted sequentially by the amount of variance they explain, that is, the first factor will have the highest eigenvalue and so on to the last factor explaining the least. SPSS and other statistical software will produce output illustrating the total variance explained. At this point in a PAF, a researcher will have an array of eigenvalues.

The second step is to select the number of relevant factors. In general, the number of dimensions or factors is much smaller than the number of original variables. Sometimes factors or dimensions or constructs are referred to as latent variables, particularly in psychological research, to distinguish them from what are referred to as measured, observed, manifest, or indicator variables. The *latent concepts*

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[1] Principal Components Analysis (PCA) with a Varimax rotation was also computed for these data. PCA is also a mathematical procedure to transform a large number of possibly correlated variables into a reduced number of uncorrelated variables which are referred to as principal components by some to distinguish the procedure from PAF. This is the default procedure in SPSS and is commonly employed (see Green & Salkind, 2003). PCA starts with ones on the principal diagonal. The 1.0 represents the relationship of the item with itself. These replace the communalities used in PAF, and this means that the extracted factors account for all of the variability of each item, both common factor variability and the variance in the item that is idiosyncratic to the item. The steps in PCA are the same as for PAF. Using SPSS, PCA produces output with the eigenvalues of the components and a scree plot. Instead of a Pattern Matrix (in PAF) PCA produces a Component Matrix to use in assigning items to components. The rotation method used in this study was Varimax, an orthogonal technique. Varimax (variance maximizing) rotation is a method for rotating axes of a plot such that the eigenvectors remain orthogonal (that is uncorrelated) as they are rotated. This results in a situation where the sum of the variances of the loadings on a factor is the maximum possible. This rotation helps to simplify the interpretation of the components. Reviewing the Component Matrix resulted in similar components to the factors achieved through PAF.

or *constructs* are inferred from the directly measured variables, in this case, the 44 questions on the survey. Factors may be considered as manifesting the processes that form the correlations among the original variables (Tabachnik & Fidell, 2001). As noted previously, PAF results in an array of eigenvalues from which to select the relevant number of factors. There are several methods to select factors (see Coughlin, 2005; Green & Salkind, 2003; Tabachnik & Fidell, 2001). One is to use the Cattell Scree Test (plot) which may be produced in SPSS. A *scree plot* takes its name from the scree (rubble) at the bottom of a cliff and is a plot of the eigenvalues against their sequence number. It displays the highest eigenvalue, which is for the first factor, and then decreasing eigenvalues for the next factors until factors have small values. Figure 1 shows the scree plot for our data. A criterion for selection of factors is to retain all factors with eigenvalues in the sharp descent part of the plot before the values level off. A second strategy, developed primarily for PCA is called the Kaiser-Guttman rule; it includes all factors with an eigenvalue greater than one. Another strategy to assist in selecting the number of factors is called Thurstone's Simple Structure (Tabachnik & Fidell, 2001). If a simple structure is present, each factor has an adequate number of highly correlated variables (usually at least 3), and only one factor correlates highly with each variable. Thurstone's Simple Structure is used after factors are rotated. The scree test, the eigenvalue-greater-than-one criteria, and the Simple Structure Test are meant to act as guides in determining factors; it is also important to have a set of factors that can be identified from the data and that are meaningful (Fabrigar, Wegener, MacCallum, & Strahan, 1999). Researchers should always consider this before finalizing the number of relevant factors.

The third step is to rotate the selected factors to maximize the relationship between the variables and the factors and to help in the interpretation of the factors. There are two main categories of rotation: orthogonal and oblique. Briefly, orthogonal rotation assumes that there is no association between the factors. *Orthogonal* means at right angles, and when two variables are orthogonal, the correlation between them is zero (Pedhazur & Schmelkin, 1991). Using an orthogonal rotation method in factor analysis retains this restriction. *Oblique* rotation allows the factors to be correlated (see Dillon & Goldstein, 1984). This method takes into account the relationships that may be present between factors. In this study, once the relevant number of factors was decided, the eigenvalues were rotated with a Promax rotation. *Promax* is an oblique rotation that allows factors to be correlated. With the SEPS data set, it is likely that

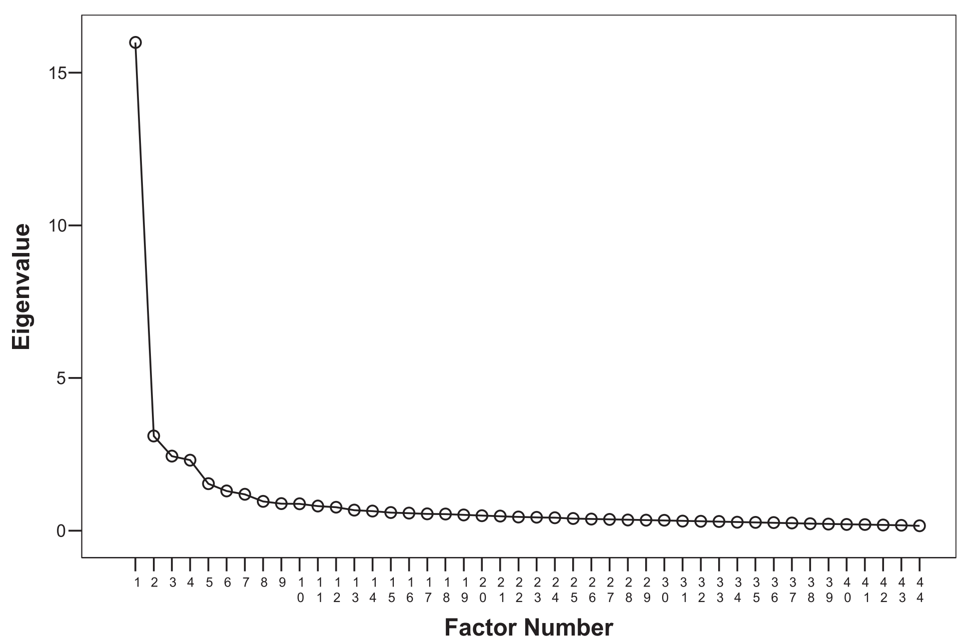

Figure 1. Scree plot for the principal axis factoring with eight factors.

the factors are correlated, as may be the case frequently with the type of surveys undertaken in institutional research. Some researchers (Fabrigar, et al., 1999; Gorsuch, 1990; Preacher & MacCallum, 2003) suggest that PAF with a Promax rotation is the preferred method of factor analysis even if PCA is widely used and explained in many texts (for example, Green & Salkind, 2003).

At this point, PAF will have produced several matrices. A factor correlation matrix displays the correlations among the factors; the structure matrix displays the correlations between factors and items; and the pattern matrix displays the unique contribution each factor makes to the variance of the item. The pattern matrix is the matrix traditionally used by researchers to determine which items fit with each factor. A general guideline is that factor loadings greater than .40 are considered to be useful (Coughlin, 2005). This is just a guideline and may need to be adjusted. For example, as the sample size and the number of variables increase, the guideline may need to be altered downward. It may need to be adjusted higher as the number of factors increases (see Hair, Anderson, Tatham, & Black, 1998). With SPSS, it is possible for researchers to specify that the pattern matrix only lists factor loadings over a certain value (for example .40) to facilitate interpretation.

The researcher now will be able to identify which original items load (or fit best) on which factor. The nature of the original items will help interpret the dimension expressed by the computed factors and in the naming of the factors. The pattern matrix, as produced by SPSS, will only have factor numbers, and knowledge of the subject matter is needed to assign names to the factors. As previously mentioned, factor names should reflect the common element or underlying construct shared by the original items loading highly on the factor.

After these steps, it is possible to compute factor scores for the selected factors. For each survey respondent, factors scores represent the estimates of the scores each respondent would have on each of the factors if the factors had been measured directly (Tabachnik & Fidell, 2001). This allows the factors that represent the underlying or latent dimensions to be used in subsequent analyses. There are several procedures for estimating factor scores. A simple strategy is to sum and average scores on variables that load highly on each factor. This is useful for some relatively straightforward research purposes (Tabachnik & Fidell, 2001) and may be used when the response scales for all items are the same. Other methods include the regression approach and the Anderson Rubin method, which are available in SPSS and other statistical software. These methods produce standardized scores that may be challenging to interpret and use in reporting of results, but they deal with issues of non-consistent scales and are useful if there is a lack of simple structure with items loading on more than one factor.

Finally, the reliability of factors that each summarizes a number of items can be evaluated. In this study, once the factors were identified, new variables were created. The reliability of these new dimension variables was tested through Cronbach's alpha. Cronbach's alpha is not a statistical test; it is a coefficient of reliability (or consistency) that measures how well a set of items (or variables) measures a single unidimensional latent construct. The acceptable range is between .7 and 1.0 (Nunnally, 1978).

Results

Table 1 shows that the data set from the 2003–04 SEPS satisfied the KMO Test at .946, confirming sampling adequacy. As noted, it should be greater than 0.6 (Tabachnik & Fidell, 2001). The Bartlett’s Test Chi square value of 11699.727 was significant; hence, the correlation matrix to be analyzed was non-random and was suitable for factor analysis.

Examining the correlations among the many survey items in the 2003–04 SEPS revealed that there was a systematic pattern

Table 1

KMO and Bartlett's Test Results for 2003–04 SEPS Factor Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.946
Bartlett's Test of Sphericity	Approx. Chi-Square	11699.727
	df	946
	Sig.	.000

of correlations within various subgroups of items. Initially seven factors were extracted with PAF. The extraction was re-run for eight factors, as the original set of questions suggested an additional factor. SPSS and other analytic software allow researchers to select the number of factors to be extracted. As noted already, the scree test and the eigenvalue-greater-than-one criteria are meant to act as guides in determining factors. It is as important for researchers to use knowledge of the data in their assessment of the appropriate number of factors. In the case of this research, it was apparent that a small set of the questions in the survey spoke directly to orientation and, as this is a critical activity, the extraction was re-run to determine if these would separate out—and they did. In addition, in reviewing the full pattern matrix with eight factors, it was clear that the columns (the factors) had some high correlations and many low correlations, the columns had different patterns, and the rows (the items) had only one high value (see Tabachnik & Fidell, 2001). This is the manner in which a factor pattern loading matrix is reviewed to assign items to factors.

Figure 1 provides the scree plot for the PAF with eight factors. Table 2 provides part of the SPSS output for the eigenvalues (the first 15) with PAF. The first column under Initial Eigenvalues is the factor number, the second column is the eigenvalue for each factor; the third column is the percent of variance explained, and the final column is cumulative total of variance explained. The columns under Extraction Sums provide the values of the factor sum of the squared loadings. These values are somewhat different and smaller than the initial values as PAF was used, and these are a function of the item communalities.

Table 3 provides a summary of the items by factor (named based on an understanding of the original items) along with the loading for each item with its factor. The loadings came from the pattern matrix of the PAF factoring produced through SPSS. Our analysis achieved simple structure; each set of items, as illustrated, was a separate factor. Table 4 provides the factor correlations (the correlations of factors with each other), which is a standard requirement to exhibit when using an oblique rotation.

The eight factors were labeled satisfaction with the Program Overall (Program Quality); Orientation; Familiarization to College Policies (Policy Awareness); Welcoming, Inclusive College Environment; Academic Instruction; Program Resources; College Facilities; and College Services. For example, Academic Instruction was the name we gave one of the factors. Academic instruction is, of course, the core mission of educational institutions; hence, the Instruction factor will be examined to illustrate the logical coherence of the items and that the grouping of the items makes sense. There were four items in this factor, and they are grouped under the factor in Table 3. Each of these items speaks directly to instruction, and none of the other items related as directly.

With the factor analysis complete and the factors named, factor scores were computed. As noted previously, factor scores can be computed through SPSS and other softwares; these factor scores compute individual scores for each respondent on each factor. SPSS will also save these scores as new variables for subsequent analysis. These factor scores,

Table 2

Initial and Extracted Eigenvalues for the 2003–04 SEPS Data using Principal Axis Factoring

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.99	36.341	36.341	15.591	35.435	35.435
2	3.100	7.044	43.386	2.698	6.131	41.565
3	2.438	5.542	48.927	2.098	4.767	46.333
4	2.309	5.248	54.175	1.839	4.180	50.512
5	1.539	3.498	57.673	1.140	2.592	53.104
6	1.299	2.953	60.626	.834	1.896	55.000
7	1.188	2.700	63.326	.798	1.814	56.815
8	.957	2.176	65.502	.519	1.179	57.993
9	.885	2.011	67.512			
10	.878	1.995	69.508			
11	.802	1.823	71.331			
12	.766	1.741	73.071			
13	.670	1.522	74.594			
14	.639	1.452	76.046			
15	.592	1.346	77.392			

Note. Table truncated at factor 15.

Table 3

Summary of Items and Factor Loadings

Loading	Factor Name and Items
	Program Quality
.551	Before I applied, I had a good understanding of the program's purpose.
.574	The training I have received in this program has met my expectations.
.720	The program content is relevant to my career goals.
.473	The tuition fee for this program is reasonable for the education provided.
.672	Overall, I am satisfied with this program.
.590	I would recommend this program to others.
	Orientation
.433	The orientation to the program provided by the Department was effective in explaining the requirements of the program.
.447	Upon admission to the program, I was made aware of my role and responsibilities as a student.

Table 3 *(continued)*

	Policy Awareness
.756	I am familiar with the College's challenge for credit policy.
.904	I am familiar with the College's transfer of credit policy.
.922	I am familiar with the College's appeals procedure as it relates to academic and/or discipline issues.
.722	I am familiar with the College's harassment policy.
.747	I am familiar with Prior Learning Assessment at the College.
	College Environment
.768	My gender does not limit my success in the program.
.767	My race or ethnic origin does not limit my success in the program.
.830	My physical ability does not limit my success in the program.
.425	My financial situation does not limit my success in the program.
.612	My English language skills do not limit my success in the program.
.482	My mathematical skills do not limit my success in the program.
.418	My experience in the program has increased my awareness of values and cultures that are different from my own.
	Instruction
.779	The instructors treat students with respect.
.844	The instructors are effective in delivering the program.
.682	The instructors are knowledgeable in the areas they teach.
.828	Overall, I am satisfied with the quality of instruction within the program.
	Program Resources
.677	The training materials (texts, workbooks, handouts, etc.) used in the program are current.
.652	I am satisfied with the quality of the training materials used in this program.
.788	The equipment used in this program is appropriate for learning the required skills.
.821	The equipment used in this program is current with industry.
.760	There is a sufficient quantity of equipment provided for the program.
.527	There is a sufficient quantity of CURRENT library resource materials for use by students in the program.
	College Facilities
.658	The classroom facilities are appropriate.
.635	The shop/lab facilities are appropriate.
.785	Adequate study space is available to students.
.723	Student lounge space is adequate.
.613	The gymnasium/fitness facilities are satisfactory.
.507	Overall, the College facilities meet my needs as a student.
	College Services
.571	I am satisfied with the service provided from the Academic Support Services (Tutorial Centre).
.687	I am satisfied with the service I received from the Counselling Centre.
.847	I am satisfied with the service I received from the Job Centre.
.729	I am satisfied with the service I received from the Library.
.754	I am satisfied with the service I received from the Bookstore.
.860	I am satisfied with the service I received from the Enrolment Services Department.
.818	I am satisfied with the service I received from the Print and Graphic Centre/Copy Centre.
.768	Overall, I am satisfied with the quality of service provided by the College.

Table 4

Summary of Factor Correlations for the 2003–04 SEPS

	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

calculated, for example, through the regression method, are the most precise and capture the statistical relationships in the data. There are some concerns with using these scores. For example, they are not directly comparable with the original scale of the questions on the survey instrument, as they are standardized measures, computed from the factor score coefficient matrix. For the purposes of this study, as the original items all had the same response categories and all of the items loaded on a factor, the factors were calculated as summated mean scales to preserve comparability and for reporting (see Coughlin, 2005; Pedhazur & Schmelkin, 1991).

As illustrated in Table 5, the dimensions or scale items were confirmed for reliability (.72 or higher) with Cronbach's alpha. One of the dimensions, Orientation, had only two variables. Simple structure would suggest, and 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. In addition, the two items were highly correlated (r = .6) and did not correlate nearly as highly with any other item (see Tabachnik & Fidell, 2001).

The new dimensions were used in a new Institutional Research report, illustrating in graphic form satisfaction findings by program, department, and the College as a whole (Red River College, 2005). The first year report was about 55 pages in length, much shorter than the many hundreds of pages in the original set of

Table 5

Reliability of the Factors (Dimensions) Extracted from the 2003–04 SEPS

Dimension	**Reliability**	**Number of Items**
Overall Program Quality	.814	6
Quality of Orientation	.721	2
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

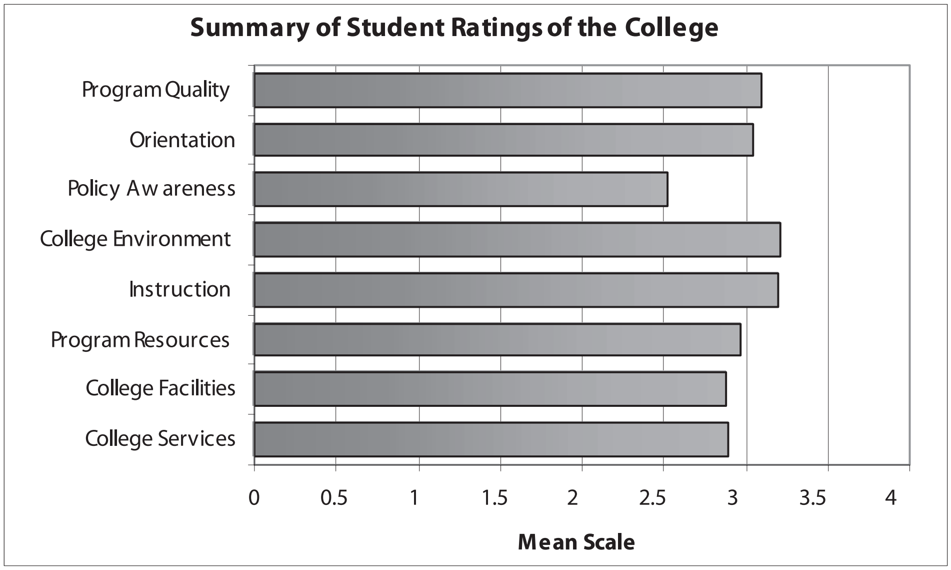

Figure 2. Illustrative graph from the 2003–04 Student Evaluation of Program Report providing the Summary of Student Ratings for the College.

three-ring binders. Figure 2 provides an example of the College-wide results, which in traditional form was in 12 pages of tables and now takes about one third of a page. The report itself is publicly available in electronic form and widely distributed in hard copy. The new variables have also provided the opportunity to conduct more readily detailed analyses, which facilitates understanding and acting on the influence of institutional and individual characteristics on satisfaction with different aspects of students' experiences.

Discussion/Conclusion

Using exploratory factor analysis improved the reporting of the student satisfaction survey. Forty-four original variables were summarized in eight factors reflecting key dimensions of student satisfaction with their college experience. Student satisfaction data are now widely accessible. A public report was prepared summarizing satisfaction using the dimension variables, illustrated in graphic form, at the college, faculty, and program levels. Survey data previously not available in summary form are now readily available and used by the President and other senior academic and administrative leaders of the College for decision-making. In addition, the College is able to demonstrate to students, through a public report, its commitment to listening to students' voices.

The report has been well received and used by a variety of constituents, including the senior executive of the College, the Board of Governors, Senior Academic Committee, College Council, faculty, students, and external funding agencies. It is available at http://www.rrc.mb.ca. The program-level findings in the report are also directly linked to program descriptions on the College's web page, allowing prospective students to see the ratings of former students. The goal of the factor analysis exercise to find a credible, reliable summary of data that was acceptable to the whole college constituency was achieved.

At a program level, it is now feasible to illustrate long-term trends in students' assessments in a form that includes all information but can be produced and reviewed in a manageable format. Furthermore, relationships among various institutional characteristics and student characteristics to different dimensions of satisfaction can now be tested with factors as the dependent variables. For example, differences in student satisfaction with the various dimensions by gender or academic type of program and delivery method can be readily examined through *t*-test or ANOVA. In addition, regression analysis with the overall program quality dimension as the dependent variable will help identify important predictor variables.

Understanding student satisfaction is critical for

institutions of higher education. In a sense, student satisfaction is a key outcome by itself (Astin, 1993; Okun & Weir, 1990); however, it is also related to student performance (Pike, 1991) and to student persistence (Tinto 1993). Upcraft and Schuh (1996) suggest student satisfaction data help measure student outcomes in response to accountability demands and also signal that institutions are serious about responding to students' needs and improving effectiveness. Collecting information on satisfaction is necessary and so is mining that information for knowledge to help direct policies and action. Sanders and Chan (1996) outlined a methodology for conducting surveys and discussed various ways of maximizing the utility of the data. The use of factor analysis with student satisfaction data will enhance the role of institutional research in reporting findings and in identifying more completely the local, within-institution determinants of satisfaction to help identify needed improvements.

The public report has become a staple of the work of the Institutional Research Department. A subsequent 2004–05 Student Evaluation of Program Report has been evaluated using confirmatory factor analysis. As was indicated in the first part of this paper, factor analysis is usually conceived as having two stages: an exploratory stage and a confirmatory stage. The first stage, as discussed in this paper, identified a structure for the data. Some researchers have found it useful to apply further iterations of factor analysis to explore whether the structure can be simplified further. This approach is sometimes known as second-order factor analysis. Other researchers have moved directly to a confirmatory stage. Having identified a basic structure, it might be useful to explore whether a second-order model might add more insight to the results. Confirmatory factor analysis is a more statistically complex procedure used when a particular factor structure has been discovered or specified in advance, that is, the researcher designates the variables to load on each factor. In this situation, the factor structure discovered for the 2003–04 survey data was tested against the 2004–05 survey data. Using AMOS (a structural equation modeling software distributed by SPSS), the 2003–04 factor structure was confirmed, which meant that the original eight factors worked with the 2004–05 survey data.

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