Jefferson County Public Schools

Comprehensive School Surveys

2007-2008

Technical Report

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Abstract:

This study examined the latent component structure of the JCPS 2007-08 Comprehensive School Survey for 6 populations: elementary, middle, and high school students, parents, classified staff, and certified staff. Exploratory factor analyses were conducted using principle component analysis, identifying an underlying component structure intended to reflect the goals of the surveys. Depending on the survey, between six and nine components were identified, accounting for a maximum of 59% of the model variance. The findings indicate a need to revise the survey for subsequent years by adding and deleting items, re-ordering items by grouping, and adding category headers to reflect the purpose of each group of questions.

The Comprehensive School Surveys are used to assess the opinions of students, parents, staff, and teachers in Jefferson County Public Schools (JCPS) in Louisville, KY using Likert Scale Items and Yes/No questions. The instruments are a collection of six different surveys, adapted to the population of interest: elementary students, middle school students, high school students, parents, classified staff, and certified staff.

Each survey is divided into sections. The three student surveys (elementary, middle, and high) are organized into the following sections: (A) Student Characteristics, (B) School, (C) Home/Community, (D) Personal Development, and (E) School Operation. Both the certified and classified surveys are divided as follows: (A) Background Characteristics, (B) Students, (C) School Operation, and (D) Employee. The Parent Survey layout is similar – (A) Background Characteristics, (B) Students, (C) School Operation, and (D) Parent/Guardian. The purpose of the items is to assess the level of satisfaction of each group of stakeholders within the various categories. Refining these instruments will facilitate enhanced understanding of the needs of JCPS stakeholders and allow the district to focus its continuous improvement program on areas of concern to all stakeholders.

Methodology

The current study is an examination of the structure of the instruments using exploratory factor analysis, identifying the principle components through inter-item correlations (Stevens, 2001). The technical aims of factor analysis and principle components analysis are similar, yet different enough to mention briefly. Principal components analysis aims to reproduce the variance among items (Byrne, 1998; Joreskog & Sorbom, 1979). Once a refined model is developed, confirmatory factor analysis may be used to verify the underlying component structure that emerged in these analyses (Stevens, 2001). These methods, among the oldest and best known, allow for the reduction of items to a few latent constructs, instead of a large number of disparate questions. Principle components analysis fits the purpose of this stage of development better than factor analysis while later stages of the study will benefit more from factor analysis.

Statistical Assumptions

Principle components analysis (PCA), a multivariate statistical procedure, assumes several data characteristics in order to allow meaningful conclusions to emerge: sample size, linearity, multivariate normality, and independence.

Several guidelines have been suggested when determining sample size adequacy. Stevens (2001) suggested a minimum of 5 subjects for variable while noting that others have suggested as many as 20; the primary issue for sample size involves the interpretability of the factor loadings. Because these data sets were so large (minimum N = 2530), we used a random sampling filter to divide the sample into three subsamples. The first subsample was used to conduct the initial principle component extraction. The second subsample was used for calibration of subsample 1 results (throughout this paper, “sample pairs” refers to subsample 1 and subsample 2 for each survey instrument). The third subsample was set aside for later confirmatory analyses, not part of this study. Further, pairwise deletion was chosen to allow subjects with missing data to be considered in items not missing. As a result, the number of observations for each item in each sample differed. Table 1 shows the minimum sample sizes on any single item and the number of items for each survey instrument: every sample except Classified meets the most stringent criterion of 20 subjects per item; it does, however, meet a criterion of 10 subjects per item, a common rule of thumb in PCA (Stevens, 2001).

Table 1: Sample Sizes for each Survey

Survey	Total Sample Size	Minimum Subsample Size on any Single Item	Number of Items
Elementary Students	10609	3119	65
Middle-Grade Students	15299	4701	66
High School Students	16390	5122	72
Parents	21579	4575	67
Classified	2530	751	71
Certified	4154	1220	73

In addition to sample size, the assumption of linearity must also be met in order to make principle components meaningful, measured by the Kaiser-Meyer-Olkin (KMO) test. Table 2 displays the results of the smallest KMO statistic for each survey (none of the sample pairs yielded KMO statistics more than 0.01 difference). Stevens (2001) suggests that a KMO value greater than 0.6 indicates that the linearity condition has been met, with values closer to 1 indicating a tighter linear fit. For every sample, all KMO results were greater than 0.952.

Table 2: KMO Statistics for each Sample/Survey

Survey	Minimum KMO Statistic
Elementary Students	0.954
Middle-Grade Students	0.964
High School Students	0.966
Parents	0.968
Classified	0.952
Certified	0.955

Even with adequate sample sizes and linearity, PCA has meaning only if the items are inter-correlated. Bartlett's Test of Sphericity empirically measures this condition using the null hypothesis that the correlation matrix R is an identity matrix I (no correlation), or R = I. In order to proceed with PCA, Bartlett's Test must indicate rejection of the null hypothesis. Table 3 shows the approximate χ^2 value, the degrees of freedom for each survey, and the corresponding p value. For every survey instrument, high levels of correlation were indicated, giving ample justification to proceed with the analysis.

Table 3: Bartlett's Test of Sphericity

Survey	Approximate χ^2 (df)
Elementary Students	52579.039 (2080)*
Middle-Grade Students	107155.249 (2145)*
High School Students	36044.961 (2556)*
Parents	146893.840 (2211)*
Classified	32146.299 (2485)*
Certified	47631.578 (2628)*

*$p < 0.001$

The multivariate normality assumption is less straightforward than other assumptions for several reasons. First, testing the assumption empirically is difficult. Second, these data mix ordinal variables with dichotomous variables; normality, on the other hand, refers to a continuous distribution – not applicable for these data. So, the ordinal data might be distributed in a binomial pattern (the discrete analog to the continuous normal distribution); the dichotomous data certainly will not be. Fortunately, factor analysis is robust against non-normality. As the sample size increases, the observed statistics will ever more accurately depict the estimated population parameter (Bollen, 1989).

Criteria Used

Any statistical methodology requires decisions to be made by the researchers; PCA demands special consideration for the critical values of factor loadings, extraction criteria for the principle components, and the type of rotation. Historically, factor loadings were interpreted only if their magnitude was greater than 0.3 (Stevens, 2001). Stevens suggests using sample size as a criterion instead, setting critical values at the 0.01 alpha level. For this study, both criteria permitted many weaker factor loadings that were un-interpretable; instead, a more stringent critical value was set at 0.4.

Several methods for determining the number of components to extract have been set forth. The Kaiser Criterion, the most widely used and accepted method, suggests interpreting any component with an eigenvalue greater than one (meaning that the component accounts for more variance than any single item in the instrument). Because this method sometimes allows a number of components that are less meaningful, this method was used as a starting point (Stevens, 2001). To continue the analysis, the Scree plots were examined; however, this method can be too stringent. In addition, parallel analyses with random data (see O'Connor, 2000) were conducted with 1000 random data sets and a criteria level of 95%. This procedure is more restrictive than the traditional eigenvalue threshold criteria, and it is recommended as an additional method for determining how many factors to keep (O'Conner, 2000). It should be noted that many methods call for extracting the number of components that account for at least 70% of the variance; any solution found under this method yielded many factors that were un-interpretable and had eigenvalues less than one, indicating a lack of meaningfulness.

The third special consideration for PCA involves the decision regarding the rotation of the components to render a more meaningful solution. By the mathematical definitions governing PCA, all components extracted are defined to be un-correlated, or orthogonal. Varimax rotation, an orthogonal rotation, operates under the supposition that the rotated components are also orthogonal. Promax rotation, an oblique rotation, allows for the possibility that the rotated components could be correlated. Stevens (2001) suggests using both rotations and comparing the results as a method of calibration, describing the two paradigms in terms of looking at a picture from two different perspectives – each gives a different flavor on the data. In this study, the nature of the extracted components favored the allowance of correlation, so the

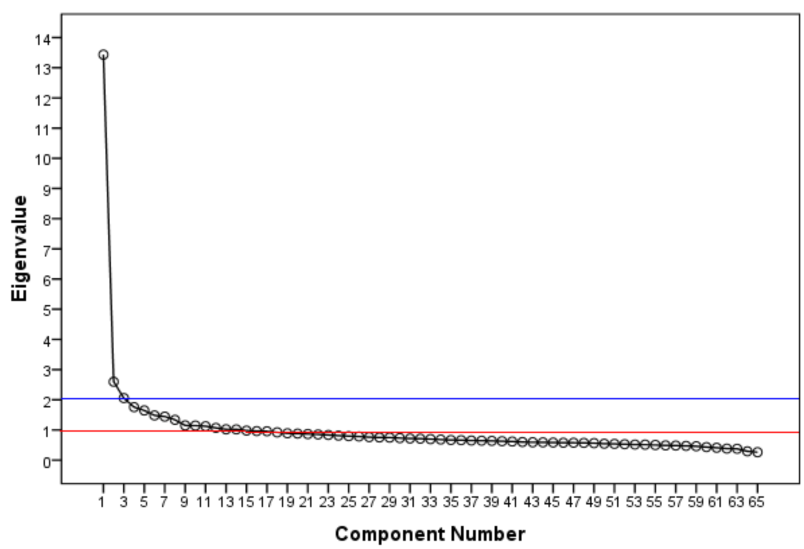
Promax rotated solution was given priority with the Varimax solution given a subordinate, calibrating role. In any case, the solutions to each rotation yielded similar results.

Results

For each sample, three analyses were used to determine the most meaningful number of principle components: the Kaiser Criterion (retain all eigenvalues > 1), the Scree plot (retain components accounting for the most variance, usually cut off when the component eigenvalues level off), and the parallel analysis (examine multiple solutions simultaneously on 1000 random samples of the data). The solutions for each subsample never varied by more than one component, so in the interest of brevity, the Scree plots for only subsample 1 were reported for each sample.

For the elementary student survey, the Kaiser Criterion yielded a 14-component solution (lower line in Figure 1) while the Scree plot indicated approximately 3 principle components (upper line in Figure 1).

Figure 1: Scree Plot for Elementary Student Survey



Parallel analysis suggested a maximum of 9 components. Thus, PCA was conducted with 3, 4, 5, 6, 7, 8, and 9 components. The 6-component solution emerged as the most meaningful. Table 4 shows the items that loaded for each component.

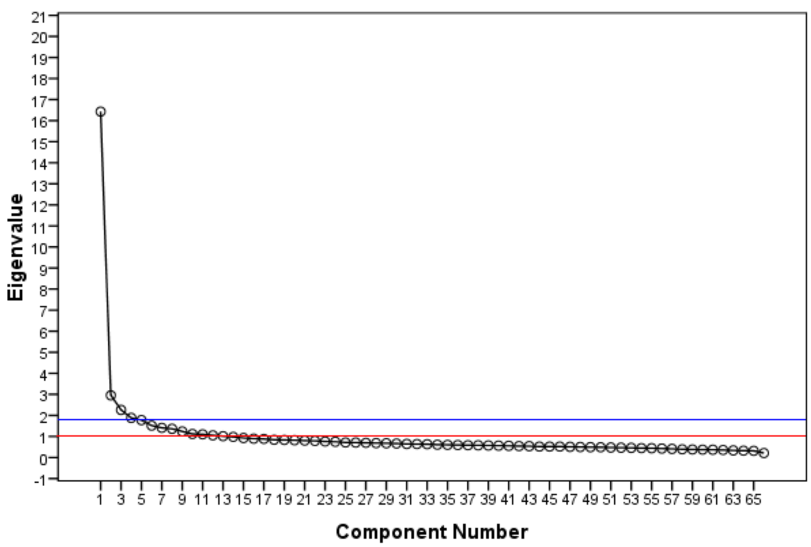
Table 4

Elementary Student Surveys : Six-component Solution

Component	Items
View of School	B01, B02, B03, B04, B06, B08, B11-B13, B16, B19-21, E01, E02,E03, E04, E05, E06, E07, E08, E10-E12, E14, E16-E21, E23, E24
Prosocial behavior	C10-C11, D03-D08
School Climate	B07, B08, B09, B10, C05-C06, E07
Student Activities	C03-C04, C07-C08,
Safety	B14-B15, E22
Home technology	C01-C02

For the middle-grade student survey, the Kaiser Criterion yielded a 13-component solution (lower line in Figure 2) while the Scree plot indicated approximately 4 principle components (upper line in Figure 2).

Figure 2: Scree Plot for Middle-Grade Student Survey



Parallel analysis suggested a maximum of 9 components. Thus, PCA was conducted with 4, 5, 6, 7, 8, and 9 components. The 7-component solution emerged as the most meaningful. Table 5 shows the items that loaded for each component.

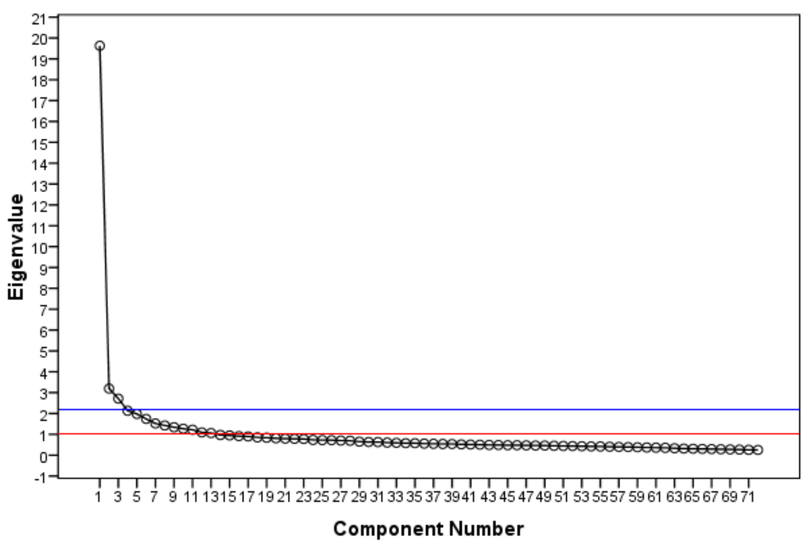
Table 5

Middle School Surveys: Seven-component solution

Component	Items
School operations	E01, E02, E03, E04, E05, E06, E07, E08, E09, E10, E11, E12, E13, E14, E15, E16, E17, E18, E19, E20, E21, E22, E23, E24
School Support	B01, B02, B03, B06, B08, B11, B12, B13, B17, B18, B19
Prosocial behavior	C11, C12, C13, D03, D04, D05, D06, D07, D08
Student Activities	B20, B21, C03, C04, C07, C08
Political Discussion	B09, B10, C05, C06,
Safety	B07, B09, B14, B15, B16,
Home technology	C01, C02

For the high school student survey, the Kaiser Criterion yielded a 13-component solution (lower line in Figure 3) while the Scree plot indicated approximately 3 principle components (upper line in Figure 3).

Figure 3: Scree Plot for High School Student Survey



Parallel analysis suggested a maximum of 10 components. Thus, PCA was conducted with 3, 4, 5, 6, 7, 8, 9, and 10 components. The 8-component solution emerged as the most meaningful. Table 6 shows the items that loaded for each component.

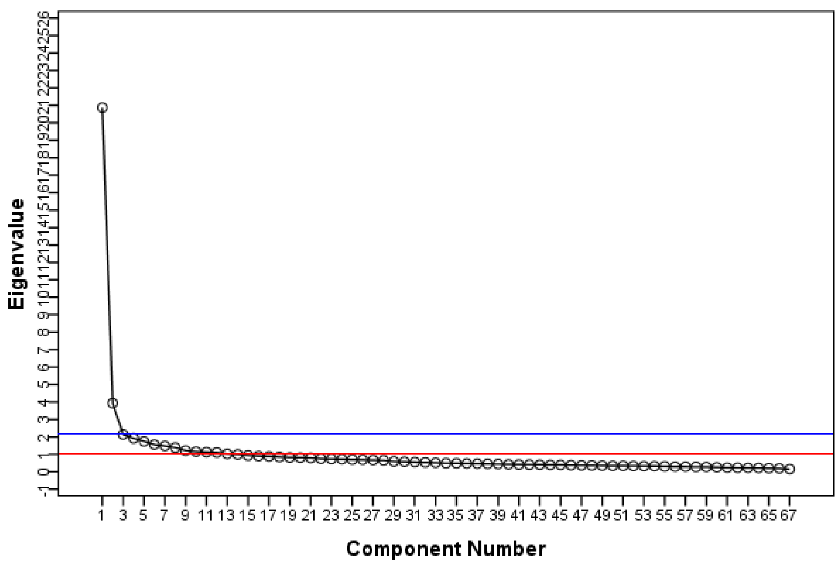
Table 6

High School Surveys: Eight-component solution

Component	Items
School Operations	E01, E02, E03, E04, E05, E06, E07, E08, E09, E10, E11, E12, E13, E14, E15, E16, E17, E18, E19, E20, E21, E22, E23, E24, E25
School Support	B01, B02, B03, B06, B11, B19, B20, B21, B22, B23, B24, B25
Prosocial behavior	C13, C14, D02, D03, D04, D05, D06, D07, D08
Student Activities	B18, C04, C05, C06, C07, C08, C09, C11, C12, C13
Political Discussion	B07, B08, B09, B10, C06, C07
Safety	B14, B15, B16,
Home technology	C01, C02
Athletics	B17, C03, D02

For the parent survey, the Kaiser Criterion yielded a 14-component solution (lower line in Figure 4) while the Scree plot indicated approximately 3 principle components (upper line in Figure 4).

Figure 4: Scree Plot for Parent Survey



Parallel analysis suggested a maximum of 12 components. Thus, PCA was conducted with 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12 components. The 8-component solution emerged as the most meaningful. Table 7 shows the items that loaded for each component.

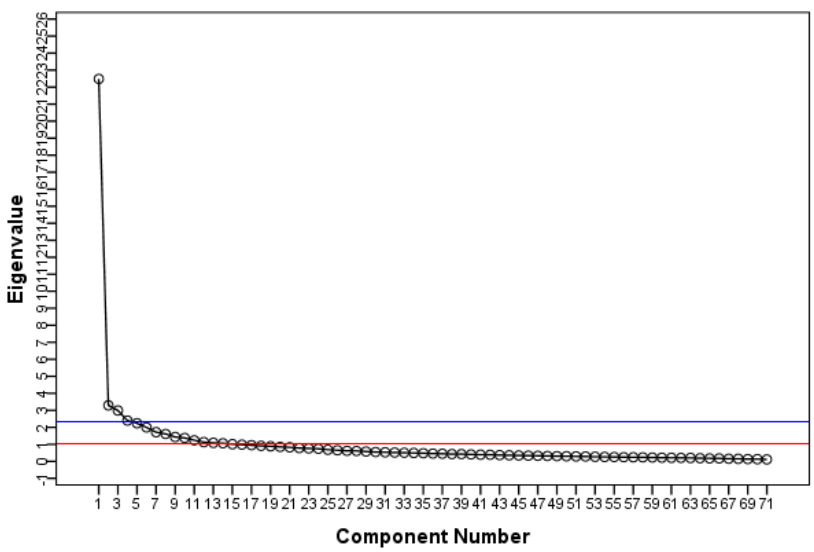
Table 7

Parent Surveys: Eight-component solution

Component	Items
Supportive Environment	B4, B5, B6, B9, C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, C21, C22, C23, C24, C25, C26, C28, C29, D02, D03, D04, D09, D10, D11,
Preparation for Future	D05, D06, D07, D08
Community Service	B13, B14, B15, D14, D15
Child Performance	C13, C14, C15, C16, C17, C18, C19, C20
Belonging	B01, B02, B03, B07, B08, B09,
Environmental Behavior	D18, D19, D20
Safety	C17, C18, C27
Home Technology	C01, C02
Child Activities	B17, C03, D02

For the classified employee survey, the Kaiser Criterion yielded a 14-component solution (lower line in Figure 5) while the Scree plot indicated approximately 3 principle components (upper line in Figure 5).

Figure 5: Scree Plot for Classified Employee Survey



Parallel analysis suggested a maximum of 10 components. Thus, PCA was conducted with 3, 4, 5, 6, 7, 8, 9, and 10 components. The 9-component solution emerged as the most meaningful. Table 8 shows the items that loaded for each component.

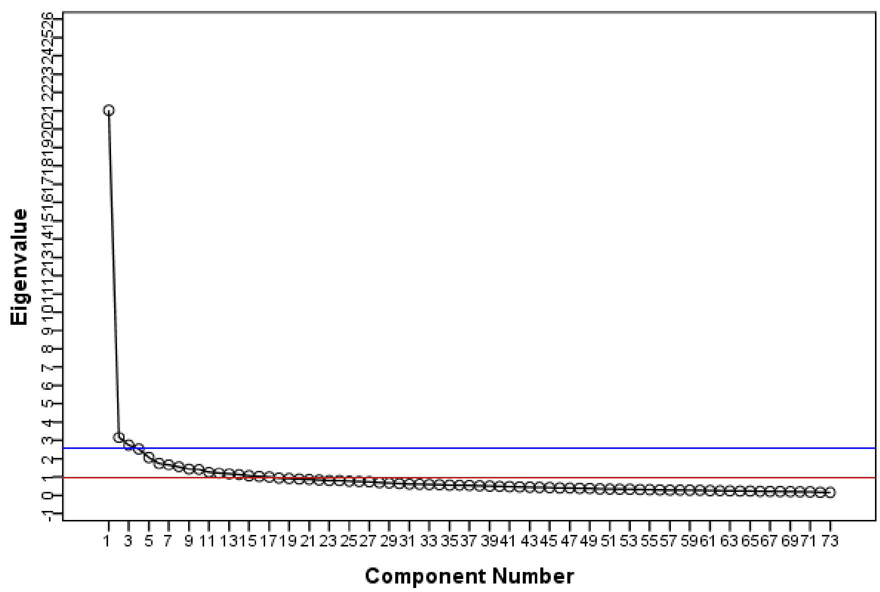
Table 8

Classified Staff Surveys: Nine-component solution

Component	Items
School Operations	E01, E02, E03, E04, E05, E06, E07, E08, E09, E10, E11, E12, E13, E14, E15, E16, E17, E18, E19, E20, E21, E22, E23, E24, E25
Job Quality	B01, B02, B03, B06, B11, B19, B20, B21, B22, B23, B24, B25
Safety	B05, C25, D02, D03, D04, D05, D06
Prosocial Behavior	D29, D30, D31
School Climate	B01, B02, B03, B04
Environmental Behavior	D25, D26, D27, D28
Community Service	D21, D22, D23, D24
Student Activities	B07, B08, B09, B10
Home Technology	D19, D20

For the certified employee survey, the Kaiser Criterion yielded a 16-component solution (lower line in Figure 6) while the Scree plot indicated approximately 4 principle components (upper line in Figure 6).

Figure 6: Scree Plot for Certified Employee Survey



Parallel analysis suggested a maximum of 12 components. Thus, PCA was conducted with 4, 5, 6, 7, 8, 9, 10, 11, and 12 components. The 9-component solution emerged as the most meaningful. Table 9 shows the items that loaded for each component.

Table 9

Certified Staff Surveys: Nine-component solution

Component	Items
School Operations	C06, C07, C08, C09, C10, C11, C12, C13, C14, C15, C16, C17, C18, C19, C20, C21, C22, C23
Job Quality	B05, C01, C02, C04, C05, C224, C25, C26, C27, C28, C29, C31, D09, D10, D11, D12, D13, D14, D15
Belonging	D01, D02, D03
Prosocial Behavior	D22, D23, D24, D25, D26, D27, D28
Safety	C30, D04, D05, D06
School Climate	B01, B02, B03
Student Activities	B07, B08, B09, B10
Community Service	D18, D19
Home Technology	D16, D17

Conclusions and Recommendations

Meaningless Factor Loadings

In every survey sample (and subsample), items were correlated with conceptually unrelated items. In the interest of brevity, the classified sample will serve as an example. Items D32 (“I am aware that JCPS has an Adult and Continuing Education program”) and D33 (“I attended a JCPS Adult Education program during 2006-2007”) were expected to correlate, but did not ($r = 0.031$, $p = 0.193$): this result may indicate that awareness of adult education is not an indicator of usage of program.

Items C25 (“At my school, I feel bullying is a big problem”) & D33 (“I attended a JCPS Adult Education program during 2006-2007”) correlated ($r = 0.543$, $p = 0.000$), but no plausible reason for these items to correlate could be constructed. Perhaps the purpose of the questions is unclear to the audience; re-think the wording to more directly reflect purpose may alleviate these types of issues.

Items D25 (“I routinely reuse and recycle everything that I can”), D26 (“I try to save energy every day”), & D28 (“I exercise frequently”) loaded with different constructs in every iteration: conceptually, they seem unrelated to the rest of the survey and to each other. It may be desirable to ask the purpose of the questions and re-think the wording to more directly reflect the purpose.

Seven items addressed perceptions of safety (D04, D05, D06, C25, C26, C27, C28) were highly correlated (see Table 10) but did not load together on a factor. Item C25 (“At my school, I feel bullying is a big problem”) correlated less than the other safety items. Re-wording the question to enhance the purpose of the question may improve correlation; regrouping conceptually-related items into categories that define the purpose of the question may strengthen the relationships.

Table 10: Correlation matrix for Safety Items (Classified Subsample 1)

Item	D04	D05	D06	C25	C26	C27
D05	0.857*	---				
D06	0.787*	0.825*	---			
C25	0.441*	0.420*	0.417*	---		
C26	0.606*	0.606*	0.589*	0.566*	---	
C27	0.612*	0.612*	0.606*	0.563*	0.741*	---
C28	0.590*	0.606*	0.601*	0.611*	0.716*	0.780*

*$p < 0.001$

Inadequacy of Final Solutions: Next Steps

The final solutions account for an average of 50% of the variance in each data set. Generally, explaining at least 70% of the variance is desired: the inability to achieve that benchmark indicates less-than-desirable levels of inter-item correlation. We have already recommended rewording several questions to increase response rates: we also recommend that each question be re-worded as needed to align with an overall purpose, clearly stated as category headers. Additionally, single-item constructs should either be discarded or enhanced with follow up questions; the purpose for including single question categories should be addressed: generally, a stable component should have at least three items in order to meet the requirements of model identification (creating a meaningful model). In a similar fashion, components with many items should be reduced to a few purposeful items. Finally, enhancing the organizational structure of the survey should yield data that are more meaningful conceptually and will provide the district with more useful information as district improvement plans are developed and implemented.

References

Bollen, K. A. (1989). *Structural equations with latent variables*. New York: John Wiley & Sons.

Byrne, B. M. (1998). *Structural Equation Modeling with LISREL, PRELIS, and SIMPLIS*. Mahwah, NJ: Lawrence Erlbaum Associates.

Joreskog, K. G. & Sorbom, D. (1979). *Advances in factor analysis and structural equation models*. Cambridge, MA: Abt Books.

O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods, Instrumentation, and Computers, 32,* 396-402.

Stevens, J. (2001). *Applied Multivariate Statistics for the Social Sciences*. (4th ed.) Mahwah, New Jersey: Lawrence Erlbaum Associates.