A Comparison of Principal Components Analysis and Factor Analysis for Uncovering the Early Development Instrument (EDI) Domains

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Abstract

Principal Components Analysis (PCA) and Factor Analysis (FA) are often employed in identifying structures that underlie complex psychometric tools. Although the two strategies differ in terms of their applications, it is important to compare structures that may emerge when they are performed on such tools as the Early Development Instrument (EDI). The purpose of such an analysis is to simplify reported findings by using a reduced set of correlated EDI measurements. We compared the underlying components and factors based on different extraction and rotation methods on EDI data from Alberta, Canada, using a two-part strategy: to report on the component and factor structures without imposing any restrictions on the number of components and factors, and then to report on multiple tests to arrive at a clean structure by retaining only a restricted number of factors. Regardless of the chosen method of extraction and rotation, some items were found redundant in both PCA and FA. The analysis revealed that PCA summarized the structure better than FA (ML), eliminating some redundancy in the number of items while retaining a comparatively better overall variance. The results indicate that items that load on more than one component or factor substantially decrease the ability of PCA and FA to detect an underlying construct, and dropping such items could reduce the amount of complexity in EDI when formulating and testing an explanatory model of child development, especially at a community level. The paper concluded that an important task in analyzing the well-regarded EDI domains involves the identification of items that do not contribute to our understanding of child development, either theoretically or methodologically.

Keywords Principal Components Analysis (PCA); Maximum Likelihood (ML); Early Development Instrument (EDI); Canada

Introduction

Over the past two decades, a number of global initiatives−the UN Convention on the Rights of the Child (UNCRC), the World Conference on Education for All (EFA), the UN Millennium Declaration and Millennium Development Goals (MDG)−have pointed out the need to invest in Early Childhood Development (ECD) for meeting the needs of young children and enhancing their readiness for school.[1] Investing in ECD has been cited as crucial not only for economic reasons but also as a means of achieving an environment that improves children's life chances and realizes their rights. The UNCRC incorporated child development into its agenda in 2005[2] and provided a normative framework for the understanding of children's well-being, based upon four general principles: non-discrimination, best interest of the child, survival and development, and respect for the views of the child (See UNICEF, 2006).

Child development is a complex concept with no single definitive set of indicators. There is no universally accepted method of aggregating individual indicators of development in a manner that accurately reflects reality. This may stem from the very nature of the concept itself as a continuous and cumulative process. As an inherently multidimensional concept, it takes into account the complexity of children's lives and their relationships with different systems that are dynamic and interdependent. Bronfenbrenner's bioecological model of child development (Bronfenbrenner, 1979; Bronfenbrenner & Morris, 1998) conceptualized development in terms of four concentric circles of macro and micro environmental influences, recognizing individual changes with the passage of time. The implication is that conceptualization of child development needs to be holistic, multidimensional, and ecological. Therefore, any discourse on children's well-being should not only include their present life and development but also future life opportunities, the conditions that foster their development as well as developmental outcomes in a range of domains.

One increasingly popular approach used to understand children's development at pre-school ages involves the use of a rating system known globally as the Early Development Instrument (EDI). It is based on an inventory of questions (initially 103, but a simple version of the EDI includes only 18 items[3]) that a teacher can use to rate a child's behavior in five domains of development:

[1] The UN Convention on the Rights of the Child (CRC) established a definition of early childhood to include all young children at birth and throughout infancy (0 to 1 year); during the pre-school years (the years may vary by regions and countries); as well as during the transition to school (UNESCO, 1990).

[2] The Convention on the Rights of the Child (CRC), as part of the office of the UN High Commissioner on Human Rights, is responsible for monitoring the implementation of the rights of children.

[3] UNICEF developed this simple version that asks parents to rate their children's behavior in the five developmental domains (Fernald, Kariger, Engle, & Raikes, 2009).

physical health and well-being, emotional maturity, social competence, language and cognitive development, and communication and general knowledge.[4] The five domains are useful in making comparisons between groups of children (within a school, school system, or community) and/or identifying inequities in terms of development. They can also be used in tracking overall developmental progress of children in a community. The ratings, as reported by kindergarten teachers, were found to have associations with other teacher-rated measures (e.g., direct achievement tests) in Canada and Australia, thereby confirming the construct validity of the tool (Brinkman, Silburn, Lawrence, Goldfield, Sayers, & Oberklaid, 2007; Janus & Offord, 2007). However, many statistical issues remain unaddressed by EDI researchers. Several questions need to be answered:

- To what extent are the EDI items independent of one another?
- To what extent are the domains independent of one another?
- Which EDI items are responsible for the greatest variation in a domain?
- Which items are redundant and which items contribute to overlapping domains, if any?

Multivariate analyses can help answer these questions. In this paper, the discussion will focus on Principal Components Analysis (PCA) and Factor Analysis (FA). As a continuation of this exercise, the resulting factors will be utilized to construct a composite index to serve as a useful framework for assessing the severity of developmental problems in the population of pre-school children, in a forthcoming paper. However, before we turn to the analysis, it is important to provide a brief overview of the instrument with reference to some of the statistical and methodological issues involved in conceptualizing the domains.

The Basic Tenet of EDI for Measuring Developmental Appropriateness in Kindergarten Children

The EDI is a measure of children's school readiness in five developmental areas or "domains", and was developed in the late 1990s at the Offord Centre of Child Studies, McMaster University in Canada (Janus & Offord, 2007). It consists of 104 questions, 103 of which are related to the five domains. The five domains consist of 16 sub-domains (Janus & Duku, 2007). Two types of measures, interval and categorical, are derived from the EDI: (1) an interval-level measure for each domain, which varies from 0 (low skill/ability) to 10 (high skill/ability), treating the mean of the items contributing to each domain as a domain score; and (2) a categorical measure, the

[4] CARE employs a simplified version of developmental domains with only three domains, physical, cognitive, and socio-emotional. The version, however, included motor, sensory, language, psychological and emotional aspects (CARE, USAID, Hope for African Children Initiative (2006)).

vulnerability score, which is calculated based on a comparison of children's scores with the lowest 10^{th} percentile boundary for each domain. Thus, if a child's score falls below the lowest 10^{th} percentile in one or more of the five domains, a score of 1 (vulnerable) is given, otherwise, a score of 0 is given (not vulnerable). To put it differently, vulnerable are children who score low (below the 10^{th} percentile cut-off of a comparison population, province or nation) in one or more of the five domains. Janus & Duku (2007) provided their rationale for computing a dichotomous measure of vulnerability based on the 10^{th} percentile cut-off:

> First, it was a way to provide a single EDI-based score without the necessity of averaging among the five domains of school readiness. Averaging or summing the scores to come up with a single total score could potentially lead to diminishing the variance and underestimation of problems, as a child scoring well in one domain but poorly in another would receive an average total score. Because one of the strengths of the EDI is inclusion of a wide range of developmental domains, the dichotomous vulnerability score ensured that even children who have many overall strengths, yet also have weaknesses, were not overlooked. Second, for most behavior and health issues, children with diagnosable conditions represent about 3% to 5% of the population (e.g., Achenbach, Howell, Quay, & Corners, 1991). The EDI's mandate is to identify areas of weakness in groups of children, not to diagnose a serious problem. Therefore, a margin of the 10^{th} percentile was chosen as close enough to capture children who were struggling, but not only those who were doing so visibly as to have already been identified (pp. 384-5).

The intent of this paper is to understand what constructs underlie the EDI data, rather than to present a critical review of the tool itself. In practice, no tool is capable of offering a perfect evaluation of the degree of delay or progress in development of children.[5] The EDI is no exception; it has its limitations. If our goal is to improve the match between developmental issues and intervention efforts, it is important to address some of the challenges associated with it so that we can better understand the meaning and discriminative power of particular items.

As currently conceived, EDI is a multidimensional construct composed of five quantitative domains, used alone or in combination (as in the vulnerability measure). Regardless of Janus and Duku's rationale for using a vulnerability measure instead of a single total score, in practice, all or most domains tend to translate a child's developmental problem/progress into a single entity or feature, mainly because of its conceptualization as a norm-referenced aggregate measure. Further, it is limited in its capacity to provide a measure of the *big picture*. A single index may capture community variations better, especially when they have fewer developmental issues, in contrast to measures of single domains. In addition, there is complexity involved in interpreting domains, subdomains, and vulnerability. A certain initiative may work well in *Community A* with

[5] Readers may refer to, Fernald et al., 2009, for a review of the pros and cons of EDI and also other individual and population-based measures.

low levels of vulnerability, but the same initiative may not work in *Community B* with high levels of vulnerability. *Community B* with a large proportion of children with high levels of vulnerability (a large proportion falling below the 10^{th} percentile) may require intervention efforts quite different from its counterpart(s) with issues in just one or two domains or low overall levels of vulnerability.

Although related to a point just made, the dynamics and interrelationships between the five domains make benchmarking exercises difficult, especially when communities wish to measure their performance relative to others or track their own performances and expectations over time. More importantly, of the five domains, some domains measure progress well and are useful for targeting intervention efforts at a community level. The assumption that those items that are related in some way can be organized into themes by assigning equal weights can be quite subjective; the domains that may be comprised of varying numbers of items (and sometimes varying scales) when grouped together tend to show that they all have the same impact on children's development. Ideally, the relative impact of items, domains and subdomains could be determined by theory and empirical analyses, particularly by using correlations among the items. Empirical procedures such as regression analysis and/or PCA/FA can be employed to examine the interrelationships among the base items or the constructs that are derived from the items. Such techniques can minimize, if not completely eliminate, the risk of a domain or an item receiving undue importance. It is against this background that the results from this study need to be interpreted. However, we hope that the identification of factors and elucidation of their basis should contribute to a better understanding of domains and sub-domains, and possibly the construction of a reliable composite to advance the knowledge base and intervention efforts at the community level.

In the analyses that follow, PCA and FA were used to uncover the latent structure (domains) of all items without imposing a preconceived structure on the EDI (items) scores.[6] Our belief is that the loadings on the factor model can vary to a greater extent with the use of different diagnostic tools and/or methods available in PCA/FA. Whatever the geopolitical unit at which the domain scores are presented, it is essential that factor scores have the optimal capacity to differentiate between children with differing levels of item scores. Consequently, we will explore how well items group under each domain when they are subjected to PCA and FA. Readers are cautioned, however, that items chosen for one context might not be appropriate for assessing the domain structure, and consequently the vulnerability levels and/or overall performance levels in other circumstances, for reasons such as representation, sample size, and ethnic composition of the

[6] By employing PCA/FA to group the EDI questions, it is assumed that there is a child with a different combinations of underlying components/factors, analogous to the idea of differentiating the sexes in terms of whether or not they possess the XX or the XY chromosome pair or the idea of head-tail combinations when a coin is tossed.

population. Analytic procedures, such as FA benefit tremendously from large subject to item ratios if reliable, stable, and consistent estimates are required.

Methods

Data

The primary data set for this study came from the EDI Wave 1 (2009) data, covering the developmental aspects of 9641 children in Alberta. We restricted our study population to only those children who were in class more than one month, had no special needs, and had scores missing in not more than one domain. This restriction makes it easy to compare the structures to those of the original published Offord's domains. The restriction brought the sample size to 7938. Of the 7938 children, 6690 (84%) were from either Edmonton Public or Catholic schools. The reader is cautioned about this limitation in generalizing the findings from this study to other jurisdictions, due to an over-representation of children of urban background.[7]

Statistical Procedures: PCA and FA

Factor Analysis (FA) is a widely used statistical procedure in the social sciences. There is a general consensus that the technique is preferable to the Principal Components Analysis (PCA) mainly because FA seeks the least number of factors which can account for the common variance shared by a set of variables. Factors reflect the common variance of the variables, excluding unique (variable-specific) variance. That is, it does not differentiate between unique variance and error variance to reveal the underlying factor structure (e.g., Bentler & Kano, 1990; Costello & Osborne, 2005).[8] In contrast, PCA accounts for the total variance of variables. Components reflect the common variance of variables plus the unique variance (Garson, 2010). The variance of a single variable can be decomposed into common variance that is shared by other variables in the model, and variance that is unique to the variable including the error

[7] Although we report on the results of Wave 1 (2009) data here, by the time we finished the writing of this paper, Wave 2 (2010) data became available. Thus, we were able to assess the factor structure using the 2010 data (N=16,179) and observed a structure similar to that from the 2009 data. Therefore, we decided to report the results from the 2009 data. Results will be made available to those interested.

[8] PCA is not a model based technique and involves no hypothesis or assumed relationships between components. FA, on the other hand, is a model based technique, takes into account the relationships between indicators, latent factors, and error. The technique is believed to yield consistent results mainly because of its recognition of error. FA has the ability to show unique item variance, whereas PCA identifies all variance equally without regard to types of variance (shared, unique, and error).

component.[9] Figure 1 gives a graphic representation of the two procedures presented with five items and two components/factors.

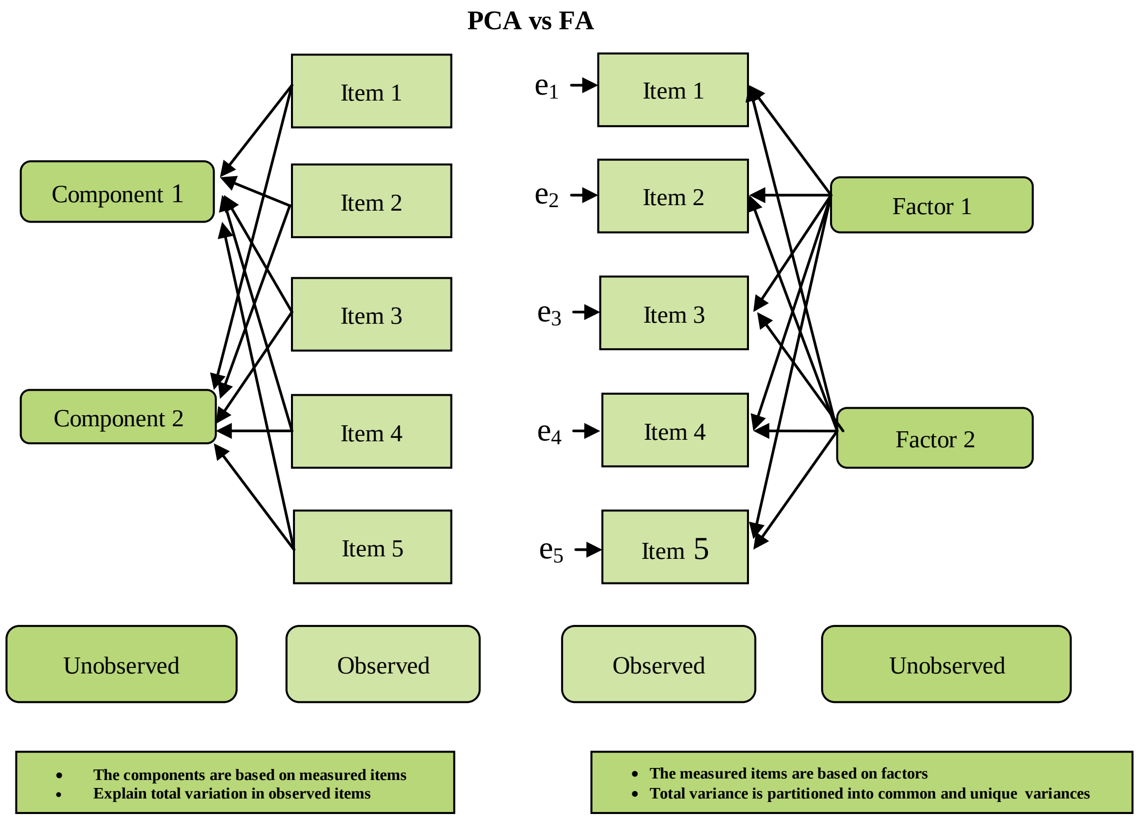

Figure 1: PCA and FA, Two Components/Factors with Five Items (e=Error)

FA, however, is a complex procedure with very few guidelines a researcher can use in terms of extraction of factors, number of factors to retain, rotation methods, or sample size requirements. A common concern is that the task of arriving at decisions on these areas is particularly difficult because there are plenty of options to choose from. There is, however, a general consensus that the following strategies produce optimal results from FA; they can be

[9] PCA is not a model based technique and involves no hypothesis or assumed relationships between components. FA, on the other hand, is a model based technique, takes into account the relationships between indicators, latent factors, and error. The technique is believed to yield consistent results mainly because of its recognition of error. FA has the ability to show unique item variance, whereas PCA identifies all variance equally without regard to types of variance (shared, unique, and error). FA is useful in the following situations: (1) to reduce a large number of variables to a smaller number of factors for modeling purposes (FA is integrated in Structural Equation Modeling (SEM)); (2) to establish that multiple tests have one underlying factor; (3) to identify clusters of cases; and (4) to develop or validate a scale or index (See Garson (2010) for a more general description of FA).

replicable and generalizable to other populations (e.g., Costello & Osborne, 2005; Fabrigar, Wegener, MacCallum, & Strahan, 1999):

- Maximum Likelihood (ML) extraction that allows the computation of a wide range of goodness-of-fit indices;
- Oblique rotation (Direct Oblimin) that yields a theoretically more accurate and reproducible solution; and
- Screeplot that helps to detect the number of factors to be retained.[10]

The key differences between the two procedures are further summarized in Table 1. Based on the literature, ML with Oblique rotation may produce a more reliable and reproducible solution. Nevertheless, PCA is thought to be ideal in the development of composite indicators (Nardo, Saisana, Saltelli, & Tarantola, 2005a; Nardo, Saisana, Saltelli, Tarantola, Hoffman, & Giovannini, 2005b; Nicoletti, Scarpetta, & Boylaud, 2000). PCA is easy to use and allows the imputation of weights according to the importance of sub-components or indicators. However, in some circumstances, different extraction methods within PCA and FA could produce different factor loadings, and thus, influence the value of the composite and consequently the rankings on a composite index. Further, there are important decisions to be made in choosing indicators, including whether or not to drop items in order to have a clean component (factor) structure. It is also important to note that if relevant items are excluded and irrelevant ones are included, the correlation matrix and subsequently the factor structure can be affected.

Table 1: Key Differences between PCA and FA

PCA	FA
• Observed variables are relatively error-free.	• Error represents a portion of the total variance.
• Unobserved latent component is a perfect linear combination of its variables.	• The observed variables are only indicators of the latent factors.
• Ideal if data reduction and composite- construction are the goals.	• Ideal in well-specified theoretical applications.

Since it is important to stimulate research and dialogue on several theoretical (e.g., whether to keep or drop a particular item) and methodological issues (e.g., consistency in factor structure)

[10] Although Velicer's MAP criteria and parallel analysis (Velicer & Jackson, 1990) are highly recommended and are easy to use, they are not the defaults for FA in the most frequently used statistical software, and manual computation is the only alternative.

when presenting the domain and vulnerability statistics from EDI, we decided to test the factor loadings and factor structures based on different extraction and rotation methods. The ability of the two extraction and rotation methods to form underlying components/factors from 103 items was consequently assessed. Initially, we conducted a series of both PCA and ML extraction methods in combination with Varimax (Orthogonal) and Oblique (Direct Oblimin) rotations: (1) without choosing the number of components/factors to be retained; and (2) with restrictions on the number of components/factors to be retained.

Results

No Restrictions on the Number of Components/Factors Extracted

The results of these analyses were based on all 103 items, and are presented in Tables 2, 3, 4, and 5. An assessment of the factor structure was made in terms of: (a) "cross-loading items" (an item that loads at 0.32 or higher on two or more components/factors)[11]; and (b) items with no loadings on any of the factors.[12]

[Tables 2, 3, 4, & 5 here]

Components from PCA: PCA with Varimax rotation produced 17 components from 103 items; 23 items had cross-loadings and one item had no loading on any of the components (Table 2). PCA with Oblique rotation produced 17 components with six items loading on more than one component and six items with no loadings on any of the components (Table 3). For Oblique rotation, however, one component (#12) had only two items loading on it, and as such may be considered a weak and unstable component.[13] With a Kaiser-Meyer-Olkin (KMO) index of 0.97, PCA produced a variance of 62.3% with the same number of components, regardless of the rotation method.[14]

[11] According to Tabachnick & Fidell (2001), 0.32 is a good rule of thumb for the minimum loading of an item, which translates into approximately 10% of overlapping variance with the other items in that factor (See also, Costello & Osborne, 2005)

[12] The component loadings are the correlation coefficients between the items and the principal components. Even when the items are uncorrelated to one another, the loadings can serve as weights. The squared loadings are the percent of variance in that item explained by the corresponding principal component. The component score for a given case (child) is that case's standardized value on each of the item multiplied by the corresponding loading of the item for the given principal component, and then adding the products.

[13] Costello & Osborne (2005) see a solid factor as one with 5 or more strongly loaded (0.5 or higher) items.

[14] Total variance explained in Oblique rotations refers to *extraction sums of squared loadings*. This differs from that obtained by Varimax rotations because in Oblique rotations, the underlying assumption is that the factors are correlated.

Factors from FA: When ML was employed on the same data, Varimax rotation produced 16 factors, with 17 items having cross-loadings and seven items having no loadings at all (Table 4). On the other hand, ML with Oblique rotation produced 16 factors, with two items having cross-loadings and 14 items having no loadings on any of the factors (Table 5). In this instance, however, there were some factors with less than five items loading on them. Therefore, the replicability of these factors in other samples can be questionable. With a KMO of 0.97, ML produced a variance of 55%, 7% less than that from the PCA solution. This is because PCA does not partition unique variance from shared variance, and sets the item communalities at 1.0. In contrast, ML estimates shared variance (communalities) for the items (less than 1, but mostly within the range of 0.39 to 0.70) (Costello & Osborne, 2005).

To sum up, both PCA and ML produced different structures when all the 103 items in EDI were considered. Further, the magnitudes of the item loadings were different. The reasons for this are unknown but the differences cannot be an artifact of sample size. That is, if the observation- to-item ratio is small, the error can be greater. A sample size of 7938 with 103 items (77 cases for every one item) is unlikely to produce incorrect solutions unless the data have severe problems. The fit of the ML (FA) model (Varimax) comprising 16 component yielded a chi-square value of 29677.25 ($df = 3638$, $p < 0.000$), reflecting an excellent fit that is indicative of sample adequacy as well. Poor correspondence between the items and the underlying structures posed a cause for concern. By restricting the number of components and the elimination of both the cross-loading and no-loading items might resolve the problem of messy structures. However, this requires multiple test runs, and some compromise between theory and rotated components/factors.

Several tools in PCA/FA are available for determining how many components to retain. The Kaiser (1960) criterion suggests dropping components/factors with eigenvalues less than 1; values less than 1 might produce negative values of Kuder Richardson or internal consistency. Another is a graphical method, Cattell’s (1966) Scree plot. The practice is to ignore components/factors where the eigenvalues level off to the right of the plot. For our purpose, we used the graphic method. An examination of Cattell’s Scree plot of the eigenvalues suggested retaining five or six structures. That is, the Screeplot revealed a clear break point in the data after six (the curve almost flattened out after this point). Since the predicted number of factors (domains) is five (as suggested by the EDI developers) and the Screeplot suggested five or six, we ran the data setting the numbers to be retained first at five and later at six.

Restrictions on the Number of Components/Factors Extracted: Five

Components from PCA: Table 6 presents the final run of the five component loadings, derived from PCA Varimax rotation, starting with 103 items. When the number of components to be retained was set at five inputing all 103 items, 18 items had cross-loadings and eight had no loadings. The total variance explained by the five rotated principal components without eliminating any of these items was 44.44%. A test of the 77 items after dropping the 26 items resulted in three items with cross-loadings and one with no loading. The 77 items produced a variance of 46.96%. The test with 73 items (after dropping the four items), produced a variance of 47.53% and two cross-loading items. Finally, a clean solution emerged with 71 items. With a KMO of 0.96, the variance accounted for by the 71 items was 47.88%, almost 4% more than the variance accounted for by all the 103 items.[15]

[Table 6 here]

In contrast, the five component Oblique rotation of the 103 items produced a variance of 44.44% with 4 items having cross-loadings and 10 having no loadings. This model was re-estimated after dropping the 14 items. The total variance explained by the five rotated components with 89 items was 47.95%. There were three items that had either cross-loadings or no loadings at all. The three items were dropped to produce five principal components with a total variance of 48.27%. This resulted in two items with no loadings. The analysis was repeated dropping the two items to produce a clean factor structure, with 84 items in total (Table 7). With a KMO of 0.97, the 84 items produced five rotated components with a total variance of 48.92%.

[Table 7 here]

Factors from FA: When analyzed using the ML extraction with Varimax rotation, the five factor solution produced a variance of 40.73% from a total of 103 items with 42 items having either cross-loadings or no loadings (24 and 18 items, respectively). After dropping the 42 items, the five factor solution with 61 items produced an explained variance of 45.60% with three cross-loading items and two with no loadings on any of the factors. A re-run of the model after removing the five items produced an explained variance of 46.27%. There were four items with cross loadings and two with no loadings on any of the factors. The 50 item analysis produced a variance of 48.66% with five cross-loading items and none without a loading. A clean solution

[15] As one would expect, when the restrictions on the number of components/factors were imposed, even when all 103 items were used, the variance accounted for after rotation was lower than that with no restrictions (e.g., 44.44% vs. 62.3%, in PCA Varimax).

emerged after three more analyses involving 45 (49.06%), 42 (50.08%), and 41 (50.34%) items. The cleanest solution with 41 items had a variance of 50.34% (Table 8), up from 40.73% with all 103 items. Factor five, however, had only two items loading on it. With a KMO of 0.95, the overall fit of the model was found excellent ((χ^2 =10692.03, df = 625, p < .000).

[Table 8 here]

The ML extraction with Oblique rotation of 103 items and the five factor solution produced a variance of 40.73%. There were 24 items with no loadings and five with cross-loadings. The 74 item analysis (after dropping the 29 items) produced a variance of 47.55% and led to a 68 item analysis and later to a clean solution with 66 items (Table 9). The variance accounted for by the five factors was 48.91% (KMO=0.96). The model fit was excellent (χ^2 = 56799, df = 1825, p <.000).

[Table 9 here]

To sum up, orthogonal rotations that produce uncorrelated factors emerged with clean structures and reasonably good explained variance using PCA. The five principal components after Oblique rotation produced the cleanest solution with more number of items, compared to Varimax rotation (84 vs. 71): all item loadings were above 0.32, no items had cross-loadings, all items had loadings, and there were no components with fewer than three items. ML, on the other hand, required fewer items than PCA to produce clean solutions (66 vs. 41). With orthogonal rotations however, the interpretation of factor structures may be slightly more straightforward.[16] If we anticipate some correlation among factors, Oblique rotation should produce a conceptually more accurate solution, and perhaps a more reliable one. However, as Costello & Osborne (2005) noted, in the absence of a true correlation, both rotation methods could produce identical results.

Restrictions on the Number of Components/Factors Extracted: Six

A series of PCA and ML with Varimax and Oblique rotations were performed restricting the number of components/factors to be extracted at six, starting with all items and then dropping those items that failed to load or had cross-loadings on a factor. Thus, as in the five factor situation, the number of items incorrectly loading on a factor was recorded, along with no loading items, in each of these analyses.

[16] Whereas the rotated factor matrix is examined in the case of an orthogonal rotation, the pattern matrix and the factor correlation matrix are examined when using an Oblique rotation.

Components from PCA: First, PCA with Varimax rotation was performed on the data with 103 items. Multiple runs starting with 103 items, and later with 76, 67, 62, and 60 items (after dropping the cross-loading and no-loading items) led to a clean solution. The numbers of cross-loadings were 18, 9, 4, and 1 respectively, and the numbers of items with no loadings were 9, 0, 1, and 1, respectively. The variances accounted for after rotations were: 46.84%, 50.03%, 50.12%, and 51.85% for 103, 76, 67, and 62 item analyses, respectively. With a KMO of 0.95, the final 60 item analysis produced an explained variance of 52.71%. However, the 6th component was composed of only two items, and as such may not be reproducible (Table 10).

[Table 10 here]

Second, PCA with Oblique rotations were performed on 103 items, 88 items, and 87 items, successively dropping 15 items first and then one item that either had no loadings or loadings on a unique component. The variances accounted for after rotations were 46.84% (103) and 50.82% (88). With a KMO of 0.97, the variance explained by the clean six factor solution was 51.25%. One factor barely met the minimum required number of items to be reliable and reproducible, with four items loading on the component (Table 11).

[Table 11 here]

Factors from FA: First, ML with Varimax rotations were performed on the data with 103, 64, 57, 50, 44, 41, 39, and 35 items. With a KMO of 0.95, the 35 items produced a four factor solution with an explained variance of 50.28%, up from 42.70% with all the 103 items (Table 12).

Next, ML with Oblique rotations were performed on the data with all 103 items, 75, 71, 70, and 69 items, after dropping the problematic ones, no loading and cross-loading items, in each run. The 69 item analysis produced a KMO of 0.97 and a variance of 51.54% (Table 13). The χ^2 value of the model was statistically significant (χ^2 = 45887.75, df = 1947, p <.000).

[Tables 12 & 13 here]

To sum up, when ML with Oblique rotation was used, the 69 items produced a clean six factor solution with an overall variance (assuming correlations among factors) of 51.54%. The model fit was excellent, as indicated by the goodness-of-fit index. Whereas ML produced a variance of 55% with all the 103 items (without restrictions on the number of factors), the same procedure produced a variance of almost 52% with just 69 items when the extraction was limited to six factors. This means that one-third of the items in the EDI are misclassified or had failed to produce a clear solution. It is likely that both PCA and ML produced inflated item loadings and unreliable structures when all the 103 items were used, including some problematic items in the data.

The analysis revealed that PCA summarized the structure better than ML, eliminating some redundancy in the number of items while retaining a comparatively better overall variance. After a decision on how many components to be retained was made, the next decision dealt with the type of rotation method to be chosen. There are arguments that dimensions of interest to psychologists are not often dimensions we would expect to be uncorrelated or orthogonal (Fabrigar et al., 1999). Therefore, the use of orthogonal factors can result in loss of valuable information. Nevertheless, researchers generally favor conceptually distinct factors produced by Varimax (orthogonal) rotations in factor analyses, based on the expectation that they produce cleaner and independent factors.[17] PCA produced five components with eigenvalues greater than 1, accounting for 47.9% of the item variance which, when rotated orthogonally, yielded item loadings ranging from 0.33 to 0.86, with no overlapping.

A comparison of component loadings based on Varimax and Oblique rotations from PCA suggests that the number of items loading on a component and also the magnitude of the loadings differ based on rotation methods.[18] In five-component PCA, Component #1 from Varimax rotation, for example, had 23 items with loadings ranging from 0.47 to 0.77, whereas from Oblique rotation, Component #2 (Components #1 and #2 are interchanged in Varimax and Oblique; Component #1 in Varimax loaded on Component #2 in Oblique) had 29 items with loadings ranging from 0.35 to 0.79. Using the Varimax rotation, 11% of all items had loadings below 0.5. In contrast, when using the Oblique rotation, 19% had loadings below 0.5. The correlation matrix from the Oblique rotation was checked in order to detect whether or not the components are independent of one another. None of the correlations were large enough to favor the use of an Oblique rotation; they were correlated in the 0.15-0.50 range, with Components #1 and #4 having the highest correlation.

In terms of internal consistency of items in the model, the Cronbach's alpha was examined for each component. In many research situations, the alpha value is widely interpreted as a measure

[17] Tabachnick and Fidell (1983) pointed out that in situations where two items are highly correlated with each other ($r>0.7$) but uncorrelated with others, it suggests the reliability of a factor.
[18] Comparisons of loadings across factors from a PCA and ML cannot be meaningful because they are likely to produce different patterns and loadings, even if they are conducted on the same data; PCA loadings tend to be generally higher.

indicating unidimensionality in items or indicators. However, a set of indicators can have a high coefficient value and still be multidimensional (See, Nardo et al., 2005a). According to Nardo et al., (2005a), this occurs when there are separate clusters of correlated items, but the clusters themselves are not highly correlated. Note that PCA with Oblique rotation (five components) indicated some ambiguity in Component #4 as it shared some items that were conceptually different. High levels of internal consistency were obtained for items comprising five components. Overall, the reliability coefficients were slightly better for PCA with Oblique rotation than those with Varimax rotation (0.958 vs. 0.951; 0.909 vs. 0.905; 0.946 vs. 0.928; 0.933 vs. 0.882; 0.819 vs. 0.797) (Table 14). There are reasons to believe that the items are measuring the same underlying construct in both instances. In future analyses, in composite construction, we will be using the five factor structure from PCA with Varimax rotation. This will enable us to draw clear structures, without inflating the variance estimates, and in particular, take care of the independence between Components #1 and #4.

[Table 14 here]

The Five Components from PCA (Varimax) vs. Offord's Five Domains

The widely accepted domains, developed by the Offord Centre and the five component solution from PCA Varimax were compared for their structures (Table 15). Offord's *physical* domain with 13 items emerged as a six item component (#4) in our analysis. The 26-item *social competence* had only 10 items in common with Component #1 of PCA, although the component itself had 23 items in total. The 30 item *emotional maturity* turned out to be a 10 item component (#3) with only eight items that were common. The *language and cognitive* domain came closer to PCA's Component #2; the domain had 26 items with 24 items matching with that of the PCA. The two items, Qb8 and Qb16 from this domain did not load on any of the components in the PCA). Finally, the *communication and general knowledge* domain with eight items had no matching component in the PCA; none of the items loaded on any of the components. Component #5, however, turned out to be the sub-domain, labeled as *anxious and fearful behavior* by the Offord. Based on comparisons of our results with that of the Offord's, we may label the five components from the PCA as: *physical* (Component #4), *social* (Component #1), *emotional* (Component #3), *language and cognition* (Component #2), and *anxiety and fearfulness* (Component #5).

[Table 15 here]

The five domains are quantified by different metrics.[19] The criteria involved in the selection of items that make up the domains depend on creative and thoughtful processes, which often demand value judgments. As noted earlier, ideally, the items in the aggregated domains need to be weighted relative to each other to account for the tradeoffs of improving one aspect at the expense of another. For example, by reducing hunger (Qa5), an increase in the level of energy (Qa12) might be achieved, at least to some extent, among children who are disadvantaged.[20] A great deal of basic research, addressing varying perceptions of the societal importance of what is more important for children's overall development, will be necessary to create consistent aggregate indicators or domains. Therefore, the methodological challenges can sometime outweigh the challenges associated with theory or expert opinions.

Conclusion

Overall, our results show that there is an obvious performance edge to PCA with five components, based on its ability to capture components with higher variance and fewer items, but it definitely needs further evaluation. In terms of the structure of the EDI domains, the present study showed meaningful, although different from the Offord's domains. Although the patterns are less complex compared to the existing and commonly adopted ones (mainly due to lesser number of items), it cannot be easily summarized because of differing extraction and rotation methods. The patterns differ, to a great extent, for the social and emotional domains. For example, whereas the social domain emerged with almost the same number of items, the items themselves were varied. It may be that the instrument was developed primarily with a focus on behavioral indicators of early child development that were based on theory and/or expert opinions, and in the process, the inter-correlations and the redundancy of certain items were overlooked.

[19] When we analyzed the 2010 data (N=16,179), some changes were noted, the overall pattern, however, remained the same. Of 103 items, a clean five factor solution required only 69 items in order to produce a variance of 48.27% from PCA Varimax in 2010. The two domains, *physical health and wellbeing* and *social competence* retained the same number of items (6 and 23, respectively) in both 2009 and 2010. However, the item, *well coordinated* did not load on the physical domain in 2010, instead *imaginative play* was loaded on the domain. The item *cooperative* did not load on the *social competence* domain in 2010, instead *temper tantrum* loaded on the domain. The *emotional maturity* domain had 10 items in 2009, but the two items, *eager new toy* and *eager new game*, did not load in 2010. To our surprise, exactly the same structures emerged for *language and cognitive development* and *anxiety and fearlfulness* in 2009 and 2010.

[20] There is, perhaps, the necessity of a geographic weighting for different communities within a province or different parts of the country based on the emphasis put on services and programs, especially in a multicultural setting, as is the case here.

Caution should be taken when interpreting the components comprising social and emotional domains. Though we eliminated items that had cross-loadings or no loadings, the items that were removed may represent important aspects of development. Further research will obviously be required in order to establish the usefulness of those removed items. Further, we do not rule out the possibility of inter-correlations among domains in a different setting. For example, one could expect the socio-emotional domains to correlate or have no clear break between the two, in some instances, demographic or cultural. Our analysis points to the fact that the assessment of social and emotional domains may be particularly challenging from the point of view of their stability across populations. The results suggest shortcomings in the measurement of the EDI domains. The PCA procedure provides a valid means of statistically reducing a large number of items to a smaller set of meaningful component items. Reductions in the number of items not only serve to increase the subject to item ratio, but also allows researchers to build models for smaller areas and subgroups of populations. It has an additional benefit of reducing the time, cost, and energy involved in gathering data on young children. Large data sets for other settings whose main goal is to identify clear factor structures, using transparent and clear methodologies, will ultimately be necessary to shed light on major domains in terms of their patterns and structures.

We believe the present exercise raises a number of issues and directions for future research. First, we believe that one-third of the items in the EDI may prove theoretically useful in understanding early child development, but not empirically useful. Second, it is important that future studies investigate combinations of items in the social and emotional domains, rather than items in isolation. That is, if different configurations are assumed, it is important to include items that are conceptually different, than those developed originally. Third, some items in the EDI may be valid in all settings. However, more research is needed to clarify the items particularly within the communication and general knowledge domain. Finally, the pattern observed here may be considered robust in assessing development, in general. However, our belief is that global measures such as the EDI include considerations of diverse factors (e.g., similarity/dissimilarity of classrooms within schools and teaching strategies) to assess the degree of importance of developmentally appropriate behaviors, which is important when planning for system level changes.

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References

Bentler, P. M. & Kano, Y. (1990). On the equivalence of factors and components. *Multivariate Behavioral Research, 25(1)*, 67-74.

Brinkman, S., Silburn, S., Lawrence, D., Goldfield, S., Sayers, M., & Oberklaid, F. (2007). Investigating the validity of the Australian Early Development Index. *Early Education and Development, 18(3)*, 427-451.

Bronfenbrenner, U. (1979). *The Ecology of Human Development: Experiments by Nature and Design*. Cambridge, MA: Harvard University Press.

Bronfenbrenner, U. & Morris, P. A. (1998). The ecology of developmental process. In W. Damon & R. M. Lerner (Eds.), *Handbook of Child Psychology, Vol. 1: Theoretical Models of Human Development* (5th ed., pp. 992-1028). New York: Wiley.

CARE, USAID, Hope for African Children Initiative (2006). Promising Practices: Promoting Early Childhood Development for OVC in Resource Constrained Settings (The 5x5 Model). Retrieved from www.crin.org/docs/promisingpractices.pdf

Costello, A. B. & Osborne, J. W. (2005). Best practices in explanatory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation, 10(7)*, 1-8.

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, 4(3)*, 272-299.

Fernald, L. C. H., Kariger, P., Engle, P., & Raikes, A. (2009). *Examining Early Child Development in Low Income Countries: A Toolkit for the Assessment of Children in the First Five Years of Life.* Washington, DC: The World Bank.

Garson, G. D. (2010). Factor analysis. Retrieved from http://faculty.chass.ncsu.edu/garson/PA765/factor.htm

Janus, M. & Offord, D. (2007). Development and psychometric properties of the Early Development Inventory (EDI): A measure of children's school readiness. *Canadian Journal of Behavioral Science, 39(1)*, 1-22.

Janus, M. & Duku, E. (2007). The school entry gap: Socioeconomic, family, and health factors associated with children's school readiness to learn. *Early Education and Development, 18(3)*, 375-403.

Nardo, M., Saisana, M., Saltelli, A., & Tarantola, S. (2005a). *Tools for Composite Indicators Building* (EUR 21682 EN). Italy: European Commission-JRC.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2005b). *Handbook on Constructing Composite Indicators: Methodology and User Guide* (OECD Statistics Working Papers, 2005/3). Italy: European Commission-JRC, OECD Publishing.

Nicoletti, G., Scarpetta, S., & Boylaud, O. (2000). *Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation* (Economic department working papers NO. 226, ECO/WKP (99)18). Retrieved from http://www.oecd.org/eco/eco

Ott, W. R. (1978). *Environmental Indices: Theory and Practice*. Ann Arbor: Ann Arbor Science.

Tabachnick, B. G. & Fidell, L. S. (1983). *Using Multivariate Statistics.* New York: Harper & Row.

Tabachnick, B. G. & Fidell, L. S. (2001). *Using Multivariate Statistics (4^{th} Ed.).* Needham Heights, MA: Allyn & Bacon.

UNESCO (United Nations Educational, Scientific and Cultural Organization) (1990). *The World Declaration on Education for All: Meeting Basic Learning Needs.* Retrieved from www.unesco.org/education/efa/ed_for_all/background/jomtien_declaration.shtml

UNICEF (2006). Child Protection from Violence, Exploitation and Abuse. Retrieved from http://www.unicef.org/protection/index_orphans.html

Velicer, W. F. & Jackson, D. N. (1990). Component Analysis Versus Common Factor Analysis-Some Further Observation. *Multivariate Behavioral Research, 25(1),* 97-114.

Table 2: PCA Varimax (Rotated Component Matrix) all 103 Items (Loadings >.32), Alberta, 2009 (N=7938)						
Component	Item	Loading	Cross-			
			Component	Loading	Component	Loading
1	Qc01: overall soc/emotional	0.526	3	0.329		
	Qc02: gets along with peers	0.654				
	Qc03: cooperative	0.747				
	Qc04: plays with various children	0.652				
	Qc05: follows rules	0.707				
	Qc06: respects property	0.702				
	Qc07: self-control	0.715				
	Qc09: respect for adults	0.722				
	Qc10: respect for children	0.784				
	Qc11: accept responsibility	0.728				
	Qc12: listens	0.469	5	0.448		
	Qc13: follows directions	0.524	5	0.354	11	0.392
	Qc16: takes care of materials	0.532			11	0.381
	Qc22: independent solve problems	0.405				
	Qc24: follow class routines	0.524	5	0.321	11	0.379
	Qc25: adjust to change	0.47	11	0.403		
	Qc27: tolerance for mistake	0.589				
	Qc45: disobedient	0.501	5	0.401	10	0.419
2	Qc28: help hurt	0.767				
	Qc29: clear up mess	0.77				
	Qc30: stop quarrel	0.787				
	Qc31: offers help	0.796				
	Qc32: comforts upset	0.862				
	Qc33: spontaneously helps	0.801				
	Qc34: invite bystanders	0.775				
	Qc35: helps sick	0.854				
3	Qb01: effective use - English	0.835				
	Qb02: listens - English	0.742				
	Qb03: tells a story	0.784				
	Qb04: imaginative play	0.646				
	Qb05: communicates needs	0.816				
	Qb06: understands	0.759				
	Qb07: articulates clearly	0.74				
	Qc26: knowledge about world	0.455	4	0.353		
4	Qb11: identify letters	0.68				
	Qb12: sounds to letters	0.627				
	Qb13: rhyming awareness	0.516				
	Qb14: group reading	0.42				
	Qb24: remembers things	0.401				
	Qb27: sorts and classifies	0.468				
	Qb28: 1 to 1 correspondence	0.62				

	Qb29: counts to 20	0.663				
	Qb30: recognizes 1-10	0.76				
	Qb31: compares numbers	0.695				
	Qb32: recognizes shapes	0.518				
	Qb33: time concepts	0.41				
5	Qc42: restless	0.802				
	Qc43: distractible	0.759				
	Qc44: fidgets	0.801				
	Qc47: impulsive	0.586	1	0.458		
	Qc48: difficulty awaiting turns	0.529	1	0.483		
	Qc49: can't settle	0.694				
	Qc50: inattentive	0.697				
6	Qa09: proficient at holding pen	0.732				
	Qa10: manipulates objects	0.784				
	Qa11: climbs stairs	0.765				
	Qa12: level of energy	0.656				
	Qa13: overall physical	0.77				
7	Qc08: self-confidence	0.487				
	Qc51: seems unhappy	0.578				
	Qc52: fearful	0.805				
	Qc53: worried	0.808				
	Qc55: nervous	0.639				
	Qc56: indecisive	0.53				
	Qc57: shy	0.544				
8	Qb15: reads simple words	0.552	4	0.471		
	Qb16: reads complex words	0.617				
	Qb17: reads sentences	0.706				
	Qb20: writing voluntarily	0.38				
	Qb22: write simple words	0.514	16	0.448		
	Qb23: write simple sentences	0.655				
9	Qc18: curious	0.593				
	Qc19: eager new toy	0.87				
	Qc20: eager new game	0.863				
	Qc21: eager new book	0.658				
10	Qc37: gets into fights	0.705	1	0.327		
	Qc38: bullies or mean	0.636	1	0.459		
	Qc39: kicks etc.	0.725				
	Qc40: takes things	0.602				
	Qc41: laughs at others	0.509	1	0.375		
11	Qc14: completes work on time	0.508				
	Qc15: independent	0.496	1	0.351		
	Qc17: works neatly	0.388	1	0.349	6	0.332
	Qc23: follow simple instructions	0.481	1	0.376		
12	Qa02:dressed inappropriately	0.677				
	Qa03: too tired	0.663				

	Qa04:late	0.493				
	Qa05:hungry	0.7				
13	Qb25: interested in maths	0.788				
	Qb26: interested in number games	0.806				
14	Qb09: interested in books	0.791				
	Qb10: interested in reading	0.658				
15	Qc36: upset when left	0.568				
	Qc46: temper tantrums	0.53	1	0.361		
	Qc54: cries a lot	0.648	7	0.393		
16	Qb08: handles a book	0.439	14	0.33		
	Qb18: experiments writing	0.349				
	Qb19: writing directions	0.391	4	0.352		
	Qb21: write own name	0.467	4	0.366		
17	Qa06: washroom	0.718				
	Qa07: hand preference	0.619				
	Qa08: well coordinated	0.457	6	0.349		
No Loading Item	Qc58: sucks thumb					
Variance accounted for after rotation: 62.30%						

Table 3: PCA Oblique (Pattern Matrix) all 103 Items (Loadings >.32), Alberta, 2009 (N=7938)				
Component	**Item**	**Loading**	**Cross-**	
			Component	**Loading**
1	Qc13: follows directions	0.437		
	Qc14: completes work on time	0.525		
	Qc15: independent	0.513		
	Qc16: takes care of materials	0.434		
	Qc17: works neatly	0.393		
	Qc23: follow simple instructions	0.517		
	Qc24: follow class routines	0.427		
	Qc25: adjust to change	0.452		
2	Qc37: gets into fights	-0.789		
	Qc38: bullies or mean	-0.71		
	Qc39: kicks etc.	-0.817		
	Qc40: takes things	-0.672		
	Qc41: laughs at others	-0.56		
	Qc45: disobedient	-0.413	11	0.344
3	Qc28: help hurt	-0.811		
	Qc29: clear up mess	-0.828		
	Qc30: stop quarrel	-0.848		
	Qc31: offers help	-0.841		
	Qc32: comforts upset	-0.936		
	Qc33: spontaneously helps	-0.867		
	Qc34: invite bystanders	-0.824		
	Qc35: helps sick	-0.931		
4	Qc08: self-confidence	0.429		
	Qc51: seems unhappy	0.504		
	Qc52: fearful	0.792		
	Qc53: worried	0.796		
	Qc55: nervous	0.614		
	Qc56: indecisive	0.503		
	Qc57: shy	0.535		
5	Qb11: identify letters	0.644		
	Qb12: sounds to letters	0.559		
	Qb13: rhyming awareness	0.393		
	Qb28: 1 to 1 correspondence	0.482		
	Qb29: counts to 20	0.659		

	Qb30: recognizes 1-10	0.774		
	Qb31: compares numbers	0.632		
	Qb32: recognizes shapes	0.405		
6	Qc18: curious	-0.617		
	Qc19: eager new toy	-0.978		
	Qc20: eager new game	-0.962		
	Qc21: eager new book	-0.689		
7	Qb01: effective use - English	0.895		
	Qb02: listens - English	0.773		
	Qb03: tells a story	0.806		
	Qb04: imaginative play	0.636		
	Qb05: communicates needs	0.862		
	Qb06: understands	0.778		
	Qb07: articulates clearly	0.799		
	Qc26: knowledge about world	0.393		
8	Qa09: proficient at holding pen	0.737		
	Qa10: manipulates objects	0.788		
	Qa11: climbs stairs	0.776		
	Qa12: level of energy	0.648		
	Qa13: overall physical	0.772		
9	Qa02:dressed inappropriately	0.71		
	Qa03: too tired	0.68		
	Qa04:late	0.495		
	Qa05:hungry	0.733		
10	Qb15: reads simple words	0.52	5	0.344
	Qb16: reads complex words	0.621		
	Qb17: reads sentences	0.707		
	Qb20: writing voluntarily	0.325		
	Qb22: write simple words	0.533	16	0.419
	Qb23: write simple sentences	0.685		
11	Qc12: listens	0.413		
	Qc42: restless	0.872		
	Qc43: distractible	0.802		
	Qc44: fidgets	0.876		
	Qc47: impulsive	0.581		
	Qc48: difficulty awaiting turns	0.524		
	Qc49: can't settle	0.722		
	Qc50: inattentive	0.732		

12	Qb09: interested in books	0.832		
	Qb10: interested in reading	0.664		
13	Qb25: interested in maths	-0.879		
	Qb26: interested in number games	-0.898		
	Qb27: sorts and classifies	-0.345	16	0.322
14	Qc01: overall soc/emotional	-0.434		
	Qc02: gets along with peers	-0.576		
	Qc03: cooperative	-0.677		
	Qc04: plays with various children	-0.616		
	Qc05: follows rules	-0.486		
	Qc06: respects property	-0.455	2	-0.323
	Qc07: self-control	-0.513		
	Qc09: respect for adults	-0.542		
	Qc10: respect for children	-0.629		
	Qc11: accept responsibility	-0.543		
	Qc27: tolerance for mistake	-0.415		
15	Qa06: washroom	0.746		
	Qa07: hand preference	0.642		
	Qa08: well coordinated	0.452		
16	Qb08: handles a book	0.385	12	0.384
	Qb19: writing directions	0.355		
	Qb21: write own name	0.492		
17	Qc36: upset when left	-0.598		
	Qc46: temper tantrums	-0.525		
	Qc54: cries a lot	-0.672		
No Loading Items	Qb14: group reading			
	Qb18: experiments writing			
	Qb24: remembers things			
	Qb33: time concepts			
	Qc22: independent solve problems			
	Qc58: sucks thumb			
Variance accounted for (Extraction Sums of Squared Loadings, Cumulative): 62.30%				

Table 4: ML Varimax (Rotated Factor Matrix) all 103 Items (Loadings >.32), Alberta, 2009 (N=7938)						
Factor	Item	Loading	Cross-			
			Factor	Loading	Factor	Loading
1	Qc02: gets along with peers	0.563	15	0.501		
	Qc03: cooperative	0.631				
	Qc04: plays with various children	0.502				
	Qc05: follows rules	0.697				
	Qc06: respects property	0.75				
	Qc07: self-control	0.738				
	Qc09: respect for adults	0.753				
	Qc10: respect for children	0.814				
	Qc11: accept responsibility	0.723				
	Qc12: listens	0.466	6	0.36	9	0.361
	Qc13: follows directions	0.496	9	0.457		
	Qc16: takes care of materials	0.565				
	Qc17: works neatly	0.374	9	0.323		
	Qc22: independent solve problems	0.338				
	Qc24: follow class routines	0.507	9	0.403		
	Qc25: adjust to change	0.432	9	0.38		
	Qc27: tolerance for mistake	0.578				
	Qc37: gets into fights	0.573	14	0.539		
	Qc38: bullies or mean	0.656	14	0.348		
	Qc40: takes things	0.518				
	Qc41: laughs at others	0.534				
	Qc45: disobedient	0.668				
	Qc46: temper tantrums	0.464				
	Qc47: impulsive	0.615	6	0.456		
	Qc48: difficulty awaiting turns	0.606	6	0.396		
2	Qb11: identify letters	0.645				
	Qb12: sounds to letters	0.623				
	Qb13: rhyming awareness	0.533				
	Qb14: group reading	0.466				
	Qb19: writing directions	0.425				
	Qb21: write own name	0.381				
	Qb24: remembers things	0.46				
	Qb27: sorts and classifies	0.494				
	Qb28: 1 to 1 correspondence	0.612				
	Qb29: counts to 20	0.592				
	Qb30: recognizes 1-10	0.692				
	Qb31: compares numbers	0.667				
	Qb32: recognizes shapes	0.49				
	Qb33: time concepts	0.464				
	Qc26: knowledge about world	0.446	4	0.399		

3	Qc28: help hurt	0.744				
	Qc29: clear up mess	0.729				
	Qc30: stop quarrel	0.757				
	Qc31: offers help	0.778				
	Qc32: comforts upset	0.86				
	Qc33: spontaneously helps	0.765				
	Qc34: invite bystanders	0.748				
	Qc35: helps sick	0.847				
4	Qb01: effective use - English	0.818				
	Qb02: listens - English	0.709				
	Qb03: tells a story	0.76				
	Qb04: imaginative play	0.597				
	Qb05: communicates needs	0.797				
	Qb06: understands	0.724				
	Qb07: articulates clearly	0.696				
5	Qc08: self-confidence	0.428				
	Qc36: upset when left	0.383				
	Qc51: seems unhappy	0.578				
	Qc52: fearful	0.81				
	Qc53: worried	0.806				
	Qc54: cries a lot	0.497				
	Qc55: nervous	0.609				
	Qc56: indecisive	0.444				
	Qc57: shy	0.416				
6	Qc42: restless	0.744	1	0.435		
	Qc43: distractible	0.686	1	0.385		
	Qc44: fidgets	0.743	1	0.393		
	Qc49: can't settle	0.582	1	0.435		
	Qc50: inattentive	0.596	1	0.379		
7	Qa08: well coordinated	0.322				
	Qa09: proficient at holding pen	0.672	16	0.428		
	Qa10: manipulates objects	0.75				
	Qa11: climbs stairs	0.752				
	Qa12: level of energy	0.638				
	Qa13: overall physical	0.777				
8	Qc18: curious	0.47				
	Qc19: eager new toy	0.86				
	Qc20: eager new game	0.874				
	Qc21: eager new book	0.563	13	0.336		
9	Qc14: completes work on time	0.509				
	Qc15: independent	0.5			2	0.34
	Qc23: follow simple instructions	0.449	1	0.325	2	0.341
10	Qb15: reads simple words	0.519	2	0.501		
	Qb16: reads complex words	0.485				

	Qb17: reads sentences	0.657				
	Qb22: write simple words	0.407	2	0.356		
	Qb23: write simple sentences	0.51				
11	Qa02:dressed inappropriately	0.402				
	Qa03: too tired	0.562				
	Qa05:hungry	0.489				
12	Qb25: interested in maths	0.697	2	0.408		
	Qb26: interested in number games	0.808	2	0.374		
13	Qb09: interested in books	0.623				
	Qb10: interested in reading	0.602	2	0.382		
14	Qc39: kicks etc.	0.569	1	0.559		
15	Qc01: overall soc/emotional	0.442	1	0.419	4	0.321
No Loading Items	Qa04:late					
	Qa06: washroom					
	Qa07: hand preference					
	Qb08: handles a book					
	Qb18: experiments writing					
	Qb20: writing voluntarily					
	Qc58: sucks thumb					
Variance accounted for after rotation: 55%						

Table 5: ML Oblique (Pattern Matrix) all 103 Items (Loadings >.32), Alberta, 2009 (N=7938)				
Factor	Item	Loading	Cross-	
			Factor	Loading
1	Qc13: follows directions	0.473		
	Qc14: completes work on time	0.501		
	Qc15: independent	0.495		
	Qc23: follow simple instructions	0.496		
	Qc24: follow class routines	0.441		
	Qc25: adjust to change	0.429		
2	Qc37: gets into fights	0.836		
	Qc38: bullies or mean	0.631		
	Qc39: kicks etc.	0.876		
	Qc40: takes things	0.492		
	Qc41: laughs at others	0.377		
	Qc45: disobedient	0.373		
	Qc46: temper tantrums	0.325		
3	Qc28: help hurt	-0.782		
	Qc29: clear up mess	-0.771		
	Qc30: stop quarrel	-0.808		
	Qc31: offers help	-0.81		
	Qc32: comforts upset	-0.933		
	Qc33: spontaneously helps	-0.816		
	Qc34: invite bystanders	-0.781		
	Qc35: helps sick	-0.925		
4	Qb25: interested in maths	0.85		
	Qb26: interested in number games	0.984		
5	Qc18: curious	-0.456		
	Qc19: eager new toy	-0.969		
	Qc20: eager new game	-0.978		
	Qc21: eager new book	-0.563		
6	Qa11: climbs stairs	-0.754		
	Qa12: level of energy	-0.763		
	Qa13: overall physical	-0.846		
7	Qc08: self-confidence	0.343		
	Qc36: upset when left	0.332		
	Qc51: seems unhappy	0.485		
	Qc52: fearful	0.869		
	Qc53: worried	0.856		
	Qc54: cries a lot	0.431		
	Qc55: nervous	0.613		
	Qc56: indecisive	0.362		
	Qc57: shy	0.372		

8	Qc12: listens	-0.343	1	0.34
	Qc42: restless	-0.867		
	Qc43: distractible	-0.751		
	Qc44: fidgets	-0.86		
	Qc47: impulsive	-0.509		
	Qc48: difficulty awaiting turns	-0.45		
	Qc49: can't settle	-0.641		
	Qc50: inattentive	-0.639		
9	Qb01: effective use - English	-0.882		
	Qb02: listens - English	-0.713		
	Qb03: tells a story	-0.784		
	Qb04: imaginative play	-0.569		
	Qb05: communicates needs	-0.844		
	Qb06: understands	-0.723		
	Qb07: articulates clearly	-0.763		
	Qc26: knowledge about world	-0.329		
10	Qb11: identify letters	0.576		
	Qb12: sounds to letters	0.491		
	Qb13: rhyming awareness	0.355		
	Qb27: sorts and classifies	0.356		
	Qb28: 1 to 1 correspondence	0.519		
	Qb29: counts to 20	0.565		
	Qb30: recognizes 1-10	0.714		
	Qb31: compares numbers	0.63		
	Qb32: recognizes shapes	0.419		
11	Qc01: overall soc/emotional	-0.657		
	Qc02: gets along with peers	-0.771		
	Qc03: cooperative	-0.573		
	Qc04: plays with various children	-0.538		
12	Qa09: proficient at holding pen	-0.685		
	Qa10: manipulates objects	-0.562	6	-0.427
	Qc17: works neatly	-0.356		
13	Qb15: reads simple words	-0.56		
	Qb16: reads complex words	-0.516		
	Qb17: reads sentences	-0.722		
	Qb22: write simple words	-0.45		
	Qb23: write simple sentences	-0.563		
14	Qb09: interested in books	0.711		
	Qb10: interested in reading	0.678		
15	Qc05: follows rules	0.36		
	Qc06: respects property	0.473		
	Qc07: self-control	0.384		
	Qc09: respect for adults	0.558		
	Qc10: respect for children	0.566		

	Qc11: accept responsibility	0.431		
	Qc27: tolerance for mistake	0.384		
16	Qa02:dressed inappropriately	0.421		
	Qa03: too tired	0.577		
	Qa05:hungry	0.52		
No Loading Item	Qa04:late			
	Qa06: washroom			
	Qa07: hand preference			
	Qa08: well coordinated			
	Qb08: handles a book			
	Qb14: group reading			
	Qb18: experiments writing			
	Qb19: writing directions			
	Qb20: writing voluntarily			
	Qb21: write own name			
	Qb24: remembers things			
	Qb33: time concepts			
	Qc16: takes care of materials			
	Qc22: independent solve problems			
	Qc58: sucks thumb			
Variance accounted for after rotation (Extraction Sums of Squared Loadings, Cumulative): 55%				

Table 6: PCA Varimax, 5 Components (Rotated Component Matrix), 71 Items, Alberta, 2009 (N=7938)		
Component	**Item**	**Loadings**
1	Qc03: cooperative	0.58
	Qc05: follows rules	0.707
	Qc06: respects property	0.723
	Qc07: self-control	0.754
	Qc09: respect for adults	0.692
	Qc10: respect for children	0.729
	Qc11: accept responsibility	0.692
	Qc16: takes care of materials	0.598
	Qc24: follow class routines	0.577
	Qc25: adjust to change	0.47
	Qc37: gets into fights	0.655
	Qc38: bullies or mean	0.681
	Qc39: kicks etc.	0.635
	Qc40: takes things	0.602
	Qc41: laughs at others	0.585
	Qc42: restless	0.691
	Qc43: distractible	0.643
	Qc44: fidgets	0.651
	Qc45: disobedient	0.765
	Qc47: impulsive	0.773
	Qc48: difficulty awaiting turns	0.74
	Qc49: can't settle	0.661
	Qc50: inattentive	0.601
2	Qb09: interested in books	0.369
	Qb10: interested in reading	0.55
	Qb11: identify letters	0.673
	Qb12: sounds to letters	0.697
	Qb13: rhyming awareness	0.645
	Qb14: group reading	0.585
	Qb15: reads simple words	0.667
	Qb17: reads sentences	0.505
	Qb18: experiments writing	0.346
	Qb19: writing directions	0.501
	Qb20: writing voluntarily	0.429
	Qb21: write own name	0.426

	Qb22: write simple words	0.511
	Qb23: write simple sentences	0.41
	Qb24: remembers things	0.589
	Qb25: interested in maths	0.582
	Qb26: interested in number games	0.554
	Qb27: sorts and classifies	0.545
	Qb28: 1 to 1 correspondence	0.617
	Qb29: counts to 20	0.601
	Qb30: recognizes 1-10	0.662
	Qb31: compares numbers	0.653
	Qb32: recognizes shapes	0.525
	Qb33: time concepts	0.513
3	Qc19: eager new toy	0.33
	Qc20: eager new game	0.335
	Qc28: help hurt	0.784
	Qc29: clear up mess	0.771
	Qc30: stop quarrel	0.776
	Qc31: offers help	0.793
	Qc32: comforts upset	0.855
	Qc33: spontaneously helps	0.795
	Qc34: invite bystanders	0.784
	Qc35: helps sick	0.839
4	Qa08: well coordinated	0.437
	Qa09: proficient at holding pen	0.747
	Qa10: manipulates objects	0.81
	Qa11: climbs stairs	0.803
	Qa12: level of energy	0.687
	Qa13: overall physical	0.805
5	Qc36: upset when left	0.49
	Qc51: seems unhappy	0.648
	Qc52: fearful	0.799
	Qc53: worried	0.801
	Qc54: cries a lot	0.574
	Qc55: nervous	0.65
	Qc56: indecisive	0.507
	Qc57: shy	0.517
Variance accounted for after rotation: 47.88%		

Table 7: PCA Oblique, 5 Components (Pattern Matrix), 84 Items, Alberta, 2009 (N=7938)		
Component	**Item**	**Loading**
1	Qb09: interested in books	0.394
	Qb10: interested in reading	0.567
	Qb11: identify letters	0.709
	Qb12: sounds to letters	0.702
	Qb13: rhyming awareness	0.607
	Qb14: group reading	0.595
	Qb15: reads simple words	0.673
	Qb17: reads sentences	0.462
	Qb18: experiments writing	0.34
	Qb19: writing directions	0.52
	Qb20: writing voluntarily	0.341
	Qb21: write own name	0.445
	Qb22: write simple words	0.473
	Qb23: write simple sentences	0.347
	Qb24: remembers things	0.543
	Qb25: interested in maths	0.625
	Qb26: interested in number games	0.59
	Qb27: sorts and classifies	0.57
	Qb28: 1 to 1 correspondence	0.655
	Qb29: counts to 20	0.601
	Qb30: recognizes 1-10	0.7
	Qb31: compares numbers	0.676
	Qb32: recognizes shapes	0.526
	Qb33: time concepts	0.483
	Qc26: knowledge about world	0.411
2	Qc03: cooperative	-0.524
	Qc04: plays with various children	-0.359
	Qc05: follows rules	-0.718
	Qc06: respects property	-0.736
	Qc07: self-control	-0.765
	Qc09: respect for adults	-0.695
	Qc10: respect for children	-0.732
	Qc11: accept responsibility	-0.679
	Qc12: listens	-0.574
	Qc13: follows directions	-0.559

	Qc14: completes work on time	-0.353
	Qc16: takes care of materials	-0.612
	Qc17: works neatly	-0.473
	Qc24: follow class routines	-0.563
	Qc25: adjust to change	-0.394
	Qc27: tolerance for mistake	-0.504
	Qc37: gets into fights	-0.646
	Qc38: bullies or mean	-0.682
	Qc39: kicks etc.	-0.622
	Qc40: takes things	-0.599
	Qc41: laughs at others	-0.591
	Qc42: restless	-0.724
	Qc43: distractible	-0.65
	Qc44: fidgets	-0.672
	Qc45: disobedient	-0.773
	Qc47: impulsive	-0.793
	Qc48: difficulty awaiting turns	-0.757
	Qc49: can't settle	-0.664
	Qc50: inattentive	-0.595
3	Qc28: help hurt	-0.805
	Qc29: clear up mess	-0.786
	Qc30: stop quarrel	-0.792
	Qc31: offers help	-0.791
	Qc32: comforts upset	-0.89
	Qc33: spontaneously helps	-0.813
	Qc34: invite bystanders	-0.804
	Qc35: helps sick	-0.87
4	Qa08: well coordinated	-0.322
	Qa09: proficient at holding pen	-0.675
	Qa10: manipulates objects	-0.762
	Qa11: climbs stairs	-0.788
	Qa12: level of energy	-0.676
	Qa13: overall physical	-0.781
	Qb01: effective use - English	-0.743
	Qb02: listens - English	-0.704
	Qb03: tells a story	-0.681
	Qb04: imaginative play	-0.618
	Qb05: communicates needs	-0.756
	Qb06: understands	-0.702

	Qb07: articulates clearly	-0.703
	Qc01: overall soc/emotional	-0.442
5	Qc08: self-confidence	0.412
	Qc36: upset when left	0.515
	Qc51: seems unhappy	0.658
	Qc52: fearful	0.828
	Qc53: worried	0.828
	Qc54: cries a lot	0.612
	Qc55: nervous	0.675
	Qc56: indecisive	0.463
Variance accounted for (Extraction sums of squared loadings, Cumulative): 48.92%		

Table 8: ML Varimax, 5 Factors (Rotated Factor Matrix), 41 Items, Alberta, 2009 (N=7938)		
Factor	**Item**	**Loading**
1	Qc03:cooperative	0.649
	Qc05: follows rules	0.735
	Qc06: respects property	0.767
	Qc07: self-control	0.774
	Qc09: respect for adults	0.778
	Qc10: respect for children	0.811
	Qc11: accept responsibility	0.754
	Qc16: takes care of materials	0.612
	Qc27: tolerance for mistake	0.576
	Qc41: laughs at others	0.513
	Qc45:disobedient	0.677
	Qc46: temper tantrums	0.479
2	Qb11: identify letters	0.681
	Qb12: sounds to letters	0.693
	Qb13: rhyming awareness	0.619
	Qb14: group reading	0.516
	Qb19: writing directions	0.452
	Qb20: writing voluntarily	0.381
	Qb21: write own name	0.393
	Qb23: write simple sentences	0.354
	Qb24: remembers things	0.550
	Qb27: sorts and classifies	0.502
	Qb28: 1 to 1 correspondence	0.611
	Qb29: counts to 20	0.626
	Qb30: recognizes 1-10	0.700
	Qb31: compares numbers	0.670
	Qb32: recognizes shapes	0.503
	Qb33: time concepts	0.484
3	Qc28: help hurt	0.753
	Qc29: clear up mess	0.732
	Qc30: stop quarrel	0.769
	Qc31: offers help	0.792
	Qc32: comforts upset	0.869
	Qc33: spontaneously helps	0.769
	Qc34: invite bystanders	0.757

	Qc35: helps sick	0.859
4	Qa11: climbs stairs	0.751
	Qa12: level of energy	0.737
	Qa13: overall physical	0.889
5	Qc18: curious	0.621
	Qc21: eager new book	0.593
Variance accounted for after rotation: 50.34%		

Table 9: ML Oblique, 5 Factors (Pattern Matrix), 66 Items, Alberta, 2009 (N=7938)		
Factor	**Item**	**Loading**
1	Qc03: cooperative	0.597
	Qc04: plays with various children	0.457
	Qc05: follows rules	0.709
	Qc06: respects property	0.756
	Qc07: self-control	0.765
	Qc09: respect for adults	0.745
	Qc10: respect for children	0.773
	Qc11: accept responsibility	0.704
	Qc16: takes care of materials	0.587
	Qc24: follow class routines	0.543
	Qc25: adjust to change	0.461
	Qc27: tolerance for mistake	0.522
	Qc37: gets into fights	0.648
	Qc38: bullies or mean	0.691
	Qc39: kicks etc.	0.63
	Qc40: takes things	0.604
	Qc41: laughs at others	0.573
	Qc42: restless	0.62
	Qc43: distractible	0.563
	Qc44: fidgets	0.577
	Qc45: disobedient	0.771
	Qc46: temper tantrums	0.534
	Qc49: can't settle	0.597
	Qc50: inattentive	0.513
2	Qb01: effective use - English	-0.877
	Qb02: listens - English	-0.707
	Qb03: tells a story	-0.787
	Qb04: imaginative play	-0.592
	Qb05: communicates needs	-0.845
	Qb06: understands	-0.729
	Qb07: articulates clearly	-0.729
3	Qc28: help hurt	-0.776
	Qc29: clear up mess	-0.76
	Qc30: stop quarrel	-0.788
	Qc31: offers help	-0.798

	Qc32: comforts upset	-0.912
	Qc33: spontaneously helps	-0.8
	Qc34: invite bystanders	-0.781
	Qc35: helps sick	-0.895
4	Qb09: interested in books	0.337
	Qb10: interested in reading	0.509
	Qb11: identify letters	0.696
	Qb12: sounds to letters	0.69
	Qb13: rhyming awareness	0.574
	Qb14: group reading	0.54
	Qb15: reads simple words	0.65
	Qb17: reads sentences	0.434
	Qb19: writing directions	0.469
	Qb20: writing voluntarily	0.329
	Qb21: write own name	0.401
	Qb22: write simple words	0.424
	Qb24: remembers things	0.523
	Qb25: interested in maths	0.559
	Qb26: interested in number games	0.527
	Qb27: sorts and classifies	0.504
	Qb28: 1 to 1 correspondence	0.609
	Qb29: counts to 20	0.589
	Qb30: recognizes 1-10	0.696
	Qb31: compares numbers	0.649
	Qb32: recognizes shapes	0.465
	Qb33: time concepts	0.42
5	Qa09: proficient at holding pen	0.763
	Qa10: manipulates objects	0.843
	Qa11: climbs stairs	0.817
	Qa12: level of energy	0.666
	Qa13: overall physical	0.817
Variance accounted for (Extraction Sums of Squared Loadings, Cumulative): 48.91%		

Table 10: PCA Varimax, 6 Components (Rotated Component Matrix), 60 Items, Alberta, 2009 (N=7938)		
Component	**Item**	**Loading**
1	Qc05: follows rules	0.706
	Qc06: respects property	0.761
	Qc07: self-control	0.751
	Qc09: respect for adults	0.737
	Qc10: respect for children	0.776
	Qc11: accept responsibility	0.716
	Qc16: takes care of materials	0.609
	Qc24: follow class routines	0.556
	Qc25: adjust to change	0.463
	Qc27: tolerance for mistake	0.577
	Qc37: gets into fights	0.671
	Qc38: bullies or mean	0.717
	Qc39: kicks etc.	0.653
	Qc40: takes things	0.618
	Qc41: laughs at others	0.61
	Qc45: disobedient	0.746
	Qc48: difficulty awaiting turns	0.685
2	Qb11: identify letters	0.695
	Qb12: sounds to letters	0.721
	Qb13: rhyming awareness	0.661
	Qb14: group reading	0.572
	Qb15: reads simple words	0.687
	Qb17: reads sentences	0.533
	Qb19: writing directions	0.49
	Qb20: writing voluntarily	0.416
	Qb21: write own name	0.431
	Qb22: write simple words	0.536
	Qb23: write simple sentences	0.442
	Qb24: remembers things	0.58
	Qb27: sorts and classifies	0.529
	Qb28: 1 to 1 correspondence	0.616
	Qb29: counts to 20	0.629
	Qb30: recognizes 1-10	0.685
	Qb31: compares numbers	0.666
	Qb32: recognizes shapes	0.528

	Qb33: time concepts	0.52
3	Qc28: help hurt	0.779
	Qc29: clear up mess	0.775
	Qc30: stop quarrel	0.794
	Qc31: offers help	0.808
	Qc32: comforts upset	0.866
	Qc33: spontaneously helps	0.804
	Qc34: invite bystanders	0.786
	Qc35: helps sick	0.857
4	Qa08: well coordinated	0.444
	Qa09: proficient at holding pen	0.76
	Qa10: manipulates objects	0.83
	Qa11: climbs stairs	0.825
	Qa12: level of energy	0.707
	Qa13: overall physical	0.826
5	Qc36: upset when left	0.501
	Qc51: seems unhappy	0.654
	Qc52: fearful	0.802
	Qc53: worried	0.804
	Qc54: cries a lot	0.596
	Qc55: nervous	0.663
	Qc56: indecisive	0.506
	Qc57: shy	0.498
6	Qc19: eager new toy	0.793
	Qc20: eager new game	0.777
Variance accounted for after rotation: 52.71%.		

Table 11: PCA Oblique, 6 Components (Pattern Matrix), 87 Items, Alberta, 2009 (N=7938)		
Component	**Item**	**Loading**
1	Qb09: interested in books	0.355
	Qb10: interested in reading	0.525
	Qb11: identify letters	0.708
	Qb12: sounds to letters	0.702
	Qb13: rhyming awareness	0.599
	Qb14: group reading	0.571
	Qb15: reads simple words	0.675
	Qb17: reads sentences	0.469
	Qb19: writing directions	0.508
	Qb20: writing voluntarily	0.332
	Qb21: write own name	0.442
	Qb22: write simple words	0.478
	Qb23: write simple sentences	0.362
	Qb24: remembers things	0.533
	Qb25: interested in maths	0.582
	Qb26: interested in number games	0.546
	Qb27: sorts and classifies	0.55
	Qb28: 1 to 1 correspondence	0.647
	Qb29: counts to 20	0.606
	Qb30: recognizes 1-10	0.708
	Qb31: compares numbers	0.669
	Qb32: recognizes shapes	0.51
	Qb33: time concepts	0.464
	Qc26: knowledge about world	0.357
2	Qc03: cooperative	-0.528
	Qc05: follows rules	-0.718
	Qc06: respects property	-0.743
	Qc07: self-control	-0.762
	Qc09: respect for adults	-0.704
	Qc10: respect for children	-0.738
	Qc11: accept responsibility	-0.683
	Qc12: listens	-0.563
	Qc13: follows directions	-0.557
	Qc14: completes work on time	-0.352
	Qc15: independent	-0.365

	Qc16: takes care of materials	-0.616
	Qc17: works neatly	-0.466
	Qc24: follow class routines	-0.562
	Qc25: adjust to change	-0.4
	Qc27: tolerance for mistake	-0.509
	Qc37: gets into fights	-0.636
	Qc38: bullies or mean	-0.676
	Qc39: kicks etc.	-0.613
	Qc40: takes things	-0.594
	Qc41: laughs at others	-0.584
	Qc42: restless	-0.687
	Qc43: distractible	-0.618
	Qc44: fidgets	-0.635
	Qc45: disobedient	-0.759
	Qc47: impulsive	-0.769
	Qc48: difficulty awaiting turns	-0.737
	Qc49: can't settle	-0.635
	Qc50: inattentive	-0.566
3	Qc28: help hurt	-0.812
	Qc29: clear up mess	-0.814
	Qc30: stop quarrel	-0.839
	Qc31: offers help	-0.834
	Qc32: comforts upset	-0.928
	Qc33: spontaneously helps	-0.853
	Qc34: invite bystanders	-0.824
	Qc35: helps sick	-0.922
4	Qa09: proficient at holding pen	-0.68
	Qa10: manipulates objects	-0.766
	Qa11: climbs stairs	-0.791
	Qa12: level of energy	-0.674
	Qa13: overall physical	-0.781
	Qa8: well coordinated	-0.324
	Qb01: effective use - English	-0.745
	Qb02: listens - English	-0.709
	Qb03: tells a story	-0.68
	Qb04: imaginative play	-0.611
	Qb05: communicates needs	-0.758
	Qb06: understands	-0.706

	Qb07: articulates clearly	-0.706
	Qc01: overall soc/emotional	-0.445
5	Qc08: self-confidence	0.391
	Qc36: upset when left	0.512
	Qc51: seems unhappy	0.655
	Qc52: fearful	0.825
	Qc53: worried	0.825
	Qc54: cries a lot	0.613
	Qc55: nervous	0.681
	Qc56: indecisive	0.468
6	Qc19: eager new toy	-0.748
	Qc20: eager new game	-0.736
	Qc21: eager new book	-0.584
	Qc18: curious	-0.535
Variance accounted for (Extraction Sums of Squared Loadings, Cumulative): 51.25%		

Table 12: ML Varimax, 6 Factors (Rotated Factor Matrix), 36 Items, Alberta, 2009 (N=7938)		
Factor	**Item**	**Loading**
1	Qc05: follows rules	0.722
	Qc06: respects property	0.81
	Qc07: self-control	0.752
	Qc09: respect for adults	0.768
	Qc10: respect for children	0.819
	Qc11: accept responsibility	0.737
	Qc16: takes care of materials	0.633
	Qc27: tolerance for mistake	0.573
	Qc40: takes things	0.519
	Qc41: laughs at others	0.512
2	Qc28: help hurt	0.752
	Qc30: stop quarrel	0.771
	Qc31: offers help	0.793
	Qc32: comforts upset	0.883
	Qc33: spontaneously helps	0.75
	Qc34: invite bystanders	0.761
	Qc35: helps sick	0.871
3	Qb11: identify letters	0.617
	Qb13: rhyming awareness	0.576
	Qb14: group reading	0.524
	Qb19: writing directions	0.479
	Qb20: writing voluntarily	0.349
	Qb21: write own name	0.425
	Qb23: write simple sentences	0.328
	Qb24: remembers things	0.529
	Qb27: sorts and classifies	0.579
	Qb28: 1 to 1 correspondence	0.654
	Qb31: compares numbers	0.633
	Qb32: recognizes shapes	0.539
	Qb33: time concepts	0.519
	Qc18: curious	0.33
4	Qa08: well coordinated	0.338
	Qa11: climbs stairs	0.763
	Qa12: level of energy	0.75
	Qa13: overall physical	0.909
Variance accounted for after rotation: 50.28%		

Table 13: ML Oblique, 6 Factors (Pattern Matrix), 69 Items, Alberta, 2009 (N=7938)		
Factor	**Item**	**Loading**
1	Qc01: overall soc/emotional	0.443
	Qc02: gets along with peers	0.608
	Qc03: cooperative	0.71
	Qc04: plays with various children	0.589
	Qc05: follows rules	0.649
	Qc06: respects property	0.788
	Qc07: self-control	0.698
	Qc09: respect for adults	0.809
	Qc10: respect for children	0.868
	Qc11: accept responsibility	0.733
	Qc16: takes care of materials	0.541
	Qc24: follow class routines	0.412
	Qc25: adjust to change	0.404
	Qc27: tolerance for mistake	0.562
	Qc37: gets into fights	0.555
	Qc38: bullies or mean	0.669
	Qc39: kicks etc.	0.551
	Qc40: takes things	0.516
	Qc41: laughs at others	0.5
	Qc45: disobedient	0.596
	Qc46: temper tantrums	0.484
2	Qb1: effective use - English	-0.892
	Qb2: listens - English	-0.725
	Qb3: tells a story	-0.807
	Qb4: imaginative play	-0.596
	Qb5: communicates needs	-0.858
	Qb6: understands	-0.743
	Qb7: articulates clearly	-0.748
3	Qc28: help hurt	-0.771
	Qc29: clear up mess	-0.763
	Qc30: stop quarrel	-0.801
	Qc31: offers help	-0.81
	Qc32: comforts upset	-0.92
	Qc33: spontaneously helps	-0.805
	Qc34: invite bystanders	-0.783

	Qc35: helps sick	-0.908
4	Qb09: interested in books	0.345
	Qb10: interested in reading	0.509
	Qb11: identify letters	0.696
	Qb12: sounds to letters	0.685
	Qb13: rhyming awareness	0.564
	Qb14: group reading	0.54
	Qb15: reads simple words	0.628
	Qb17: reads sentences	0.405
	Qb19: writing directions	0.468
	Qb21: write own name	0.411
	Qb22: write simple words	0.416
	Qb24: remembers things	0.506
	Qb25: interested in maths	0.562
	Qb26: interested in number games	0.531
	Qb27: sorts and classifies	0.523
	Qb28: 1 to 1 correspondence	0.622
	Qb29: counts to 20	0.587
	Qb30: recognizes 1-10	0.694
	Qb31: compares numbers	0.65
	Qb32: recognizes shapes	0.479
	Qb33: time concepts	0.427
	Qc15: independent	0.323
5	Qa08: well coordinated	-0.365
	Qa09: proficient at holding pen	-0.722
	Qa10: manipulates objects	-0.809
	Qa11: climbs stairs	-0.835
	Qa12: level of energy	-0.7
	Qa13: overall physical	-0.85
6	Qc42: restless	-0.837
	Qc43: distractible	-0.752
	Qc44: fidgets	-0.836
	Qc49: can't settle	-0.618
	Qc50: inattentive	-0.623
Variance accounted for (Extraction Sums of Squared Loadings, Cumulative) after rotation: 51.54%		

Table 14: Internal Consistency (Cronbach's alpha) for the PCA Varimax and Oblique Rotation Methods (N=7938)

PCA Varimax					PCA Oblique				
Component					Component				
1	2	3	4	5	1	2	3	4	5
23Items	24Items	10Items	6Items	8Items	25Items	29Items	8Items	14Items	8Items
Qc03	Qb09	Qc28	Qa08	Qc36	Qb09	Qc03	Qc28	Qa08	Qc36
Qc05	Qb10	Qc29	Qa09	Qc51	Qb10	Qc05	Qc29	Qa09	Qc51
Qc06	Qb11	Qc30	Qa10	Qc52	Qb11	Qc06	Qc30	Qa10	Qc52
Qc07	Qb12	Qc31	Qa11	Qc53	Qb12	Qc07	Qc31	Qa11	Qc53
Qc09	Qb13	Qc32	Qa12	Qc54	Qb13	Qc09	Qc32	Qa12	Qc54
Qc10	Qb14	Qc33	Qa13	Qc55	Qb14	Qc10	Qc33	Qa13	Qc55
Qc11	Qb15	Qc34		Qc56	Qb15	Qc11	Qc34	Qb01	Qc56
Qc16	Qb17	Qc35		Qc57	Qb17	Qc16	Qc35	Qb02	Qc08
Qc24	Qb18	Qc19			Qb18	Qc24		Qb03	
Qc25	Qb19	Qc20			Qb19	Qc25		Qb04	
Qc37	Qb20				Qb20	Qc37		Qb05	
Qc38	Qb21				Qb21	Qc38		Qb06	
Qc39	Qb22				Qb22	Qc39		Qb07	
Qc40	Qb23				Qb23	Qc40		Qc01	
Qc41	Qb24				Qb24	Qc41			
Qc42	Qb25				Qb25	Qc42			
Qc43	Qb26				Qb26	Qc43			
Qc44	Qb27				Qb27	Qc44			
Qc45	Qb28				Qb28	Qc45			
Qc47	Qb29				Qb29	Qc47			
Qc48	Qb30				Qb30	Qc48			
Qc49	Qb31				Qb31	Qc49			
Qc50	Qb32				Qb32	Qc50			
	Qb33				Qb33	Qc04			
					Qc26	Qc12			
						Qc13			
						Qc14			
						Qc17			
						Qc27			
Cronbach's alpha					**Cronbach's alpha**				
.951	**.905**	**.928**	**.882**	**.797**	**.909**	**.958**	**.946**	**.933**	**.819**

Note: The items that match are shaded with the same color. For example, the medium dark grey in column 1 of PCA Varimax should be compared to the medium grey in column 2 of PCA Oblique.

Table 15: Comparing Components and Domains: PCA's Varimax vs. Offord's Domains									
PCA's Components					**Offord's Domains**				
1	**2**	**3**	**4**	**5**	**Social**	**Language**	**Emotional**	**Physical**	**Com. & GK**
23Items	24Items	10Items	6tems	8Items	**26Items**	**26Items**	**30 Items**	**13Items**	**8Items**
Qc03	Qb09	Qc28	Qa08	Qc36	Qc03	Qb09	Qc28	Qa08	Qb01
Qc05	Qb10	Qc29	Qa09	Qc51	Qc05	Qb10	Qc29	Qa09	Qb02
Qc06	Qb11	Qc30	Qa10	Qc52	Qc06	Qb11	Qc30	Qa10	Qb03
Qc07	Qb12	Qc31	Qa11	Qc53	Qc07	Qb12	Qc31	Qa11	Qb04
Qc09	Qb13	Qc32	Qa12	Qc54	Qc09	Qb13	Qc32	Qa12	Qb05
Qc10	Qb14	Qc33	Qa13	Qc55	Qc10	Qb14	Qc33	Qa13	Qb06
Qc11	Qb15	Qc34		Qc56	Qc11	Qb15	Qc34	Qa02	Qb07
Qc16	Qb17	Qc35		Qc57	Qc16	Qb17	Qc35	Qa03	Qc26
Qc24	Qb18	Qc19			Qc24	Qb18	Qc36	Qa04	
Qc25	Qb19	Qc20			Qc25	Qb19	Qc51	Qa05	
Qc37	Qb20				Qc19	Qb20	Qc52	Qa06	
Qc38	Qb21				Qc20	Qb21	Qc53	Qa07	
Qc39	Qb22				Qc21	Qb22	Qc54	Qc58	
Qc40	Qb23				Qc22	Qb23	Qc55		
Qc41	Qb24				Qc23	Qb24	Qc56		
Qc42	Qb25				Qc27	Qb25	Qc57		
Qc43	Qb26				Qc01	Qb26	Qc37		
Qc44	Qb27				Qc02	Qb27	Qc38		
Qc45	Qb28				Qc04	Qb28	Qc39		
Qc47	Qb29				Qc08	Qb29	Qc40		
Qc48	Qb30				Qc12	Qb30	Qc41		
Qc49	Qb31				Qc13	Qb31	Qc42		
Qc50	Qb32				Qc14	Qb32	Qc43		
	Qb33				Qc15	Qb33	Qc44		
					Qc17	Qb08	Qc45		
					Qc18	Qb16	Qc47		
							Qc48		
							Qc49		
							Qc50		
							Qc46		

Note: The items that match are shaded with the same color. For example, the orange in column 1 of PCA should be compared to the Offord's column 3 in orange.