Understanding the Academic Profiles of Students Participating in the Alternate Assessment based on Alternate Achievement Standards (AA-AAS): A Cluster Analysis

Amanda E. Ferster

University of Georgia

Fei Zhao

Arizona Department of Education

Amy K. Clark

University of Kansas

Author Note

The present publication was developed under grant 84.373X100001 from the U.S. Department of Education, Office of Special Education Programs. The views expressed herein are solely those of the author(s), and no official endorsement by the U.S. Department should be inferred.

Abstract

Through the analysis of a large-scale survey, this study reveals the varied academic profiles of students participating in the Alternate Assessment based on Alternate Achievement Standards. The method employed--a two-step cluster analysis using educator ratings of students' academic skills--clarifies that students' skills are relatively distinct from their sensory, mobility, or behavioral characteristics. Primary educators serving across fourteen states participated in the data collection effort. Three clusters separated the cases into homogenous sub-groups. Ultimately, the clusters were defined through ability ratings across academic domains; the cluster profiles remained parallel across all academic variables. Student needs were incorporated as auxiliary information—depicting that the academic profile should be treated separately from students' physical limitations. The results of the study provide stakeholders with insight into the diverse skills and abilities of the student population.

Keywords: Academic profile, Alternate Assessment based on Alternate Achievement Standards, cluster analysis, Dynamic Learning Maps

Understanding the Academic Profiles of Students Participating in the Alternate Assessment based on Alternate Achievement Standards (AA-AAS): A Cluster Analysis

The Alternate Assessment based on Alternate Achievement Standards (AA-AAS) is reserved for students with significant cognitive disabilities. State and local educational officials commonly refer to it as the 'one-percent' assessment. This label does not represent a characteristic of the assessment population. Rather, it corresponds to the cap placed on the percentage of AA-AAS assessment scores that may contribute to proficiency within the accountability system. Unfortunately, as an unintended consequence of the practitioner imposed language, the public may perceive the label as a population attribute. That is, they may over interpret the characterization, inferring that there is little variation in the students' academic abilities.

Since the reauthorization of the Elementary and Secondary Education Act, the No Child Left Behind Act of 2001 (NCLB, 2001), and its subsequent non-regulatory guidance (USDE, 2003; 2005), efforts have been made to better understand the population of students participating in the Alternate Assessment based on Alternate Achievement Standards (AA-AAS). Historically, federal guidance reserved the AA-AAS for those students with 'significant cognitive disabilities,' yet maintained individual state flexibility in defining the criterion that constitutes this label. As a result, the nationwide population of students participating in the assessment was ill defined. Furthermore, due the NCLB accountability calculations, the true purpose of the assessment— understanding the skills and abilities of the students—seemed to take a back seat to the political debates regarding how student performance contribute to agencies' accountability systems.

Currently, there are two consortiums engaged in developing alternate assessments linked to the Common Core State Standards, the Dynamic Learning Maps (DLM) Alternate Assessment Consortium and the National Center and State Collaborative (NCSC) Consortium. Now that states are pooling their assessment development efforts, an opportunity exits to clarify the unique knowledge, skills, and abilities of these students for stakeholders. Clear communication of student characteristics for the public is critical. It is imperative to synthesize numerous descriptive data elements into a digestible format that clearly articulates key findings.

In addition to improving public understanding, a well-defined population further aids test development efforts. With regard to the Dynamic Learning Maps (DLM) project, fine-grained information is necessary with respect to students' access needs. However, test developers also require a gauge of the variability of the students' *current* academic functioning. The DLM assessment system defines routes of student learning; developers need insight into students' current skill set. This will ensure the system accounts for all levels of student achievement within each student 'grade of record' (i.e., grade level). Again, to meet this goal, assessment developers will be best served through a succinct profile based summary of *initial* student ability.

Cluster analysis is an analytic technique that supports both goals; researchers use the approach to summarize copious bits of information into meaningful groups or classes. Specifically, related to special education research, practitioners have used the approach to: define clusters of children based on their neuropsychological, psychoeducational, and sociobehavioral characteristics (Conti-Ramsden, Crutchley, & Botting, 1997; Jorgenson, Jorgenson, & Davis, 1987;Williams, Gridley, & Fitzhugh-Bell, 1992), distinguish children with learning disabilities through cognitive and motivational traits (Pintrich, Anderman, & Klobucar, 1994), and evaluate student career paths and transition services (Baer, Flexer, & Dennis, 2007).

Method

Data Source

The First Contact Survey is a web-based inventory developed by the Dynamic Learning Maps consortium. It is comprised of approximately 65 items. Educators that have extensive knowledge of the students participating in the AA-AAS, student's primary educator, completed the operational instrument. The survey collects information regarding rater and facility characteristics, student demographics, special education placement, sensory perception, motor skills, expressive and receptive language, computer access, use of AAC devices, engagement with and attention to instruction, and academic skills. With regard to the latter, educators rate each student based on the degree, or percentage of time, a student displays a specific skill. The skill areas relate to expressive and receptive communication, reading, mathematics, and writing. Although the survey covers numerous domains, the instrument presents academic items as cross-tabular rating scales.

The operational First Contact Census Survey was administered throughout the 2012-2013 academic year. The survey window closed on May 31, 2013. A total of 44,782 valid student ratings were obtained from educators across 14 states. The majority of students in the sample were classified as a student with Autism, an intellectual disability, or multiple disabilities. While nominal, some classifications were unexpected, such as: specific learning disability, sensory classifications, and emotional disturbance.

To highlight several academic ratings, the figures below present snippets of the students' reading, mathematics, and communication ratings, respectively. As shown in Figure

1, although the percentage of high school students rated as reading ‘at or above the second grade level’ surpasses the percentage of elementary and middle school students, the graphic highlights that students within a grade band possess varied knowledge, skills, and abilities. Figure 2 presents the percentage of students that perform a mathematics skill greater than 80% of the time by grade band. Here, it is evident that the least number of students demonstrate the most complex mathematical skill. Figure 3 presents the percentage of students within each level of ‘expressive communication with speech’, given that the child uses speech. The majority of the students who use speech to meet their expressive needs do so by regularly combining three or more words according to grammatical rules. While the descriptive visuals provide information regarding the population, the graphics highlight that readers must mentally synthesize the summaries to garner an appreciation of the overall population. Individual item responses depict isolated information—cohesive profiles of student ability are needed to describe the population ratings.

This study employs the two-step clustering algorithm within IBM SPSS Statistics version 21. It is well suited to large-scale datasets and permits flexibility in data types (i.e., permits categorical or continuous item types). The technique uses a best-fit strategy to minimize within-cluster variation and maximize between-cluster variation. To increase processing speed, the algorithm first assigns each case to a precluster. Relative to the variables of interest, it computes proximity or “distance” indices across all possible case-pairs. In a subsequent stage, it treats the preclusters as unique units, as raw scores, within a conventional hierarchical clustering algorithm (Norusis, 2010).

Unlike other clustering techniques or discriminant analysis, which require researchers to specify, *a priori*, the number of clusters to include within the solution, the two-step technique includes an automated option based on information indices—Schwarz's Bayesian Criterion(BIC) or Akaike's Information Criterion (AIC). Furthermore, results include indices regarding the importance of each variable within the cluster construction process. That is, the procedure removes unsubstantiated notions from the exploratory analysis—it facilitates an objective solution regarding the number of clusters and interpretation of each group.

According to Punj and Stewart (1983), obtaining a cluster solution is possible even when there are no distinct natural groupings in the data. Therefore, researchers should verify the solution via a cross validation procedure; the authors recommend reliance on a holdout sample analysis to check the stability of results. As described above, the research dataset is of a sufficient *N* to incorporate the stability check into the exploratory analysis.

Analysis

The research dataset was partitioned into two equivalent samples using a 50% random sample selection procedure. Dataset A contained 22, 269 valid cases while the holdout sample, dataset B, contained 22,513 valid cases. While the researchers purposively omitted student demographics, twelve academic variables were selected for inclusion in the initial analysis. Eleven of the variables were standardized and treated as continuous; one variable was categorical. Table 1 presents all items included in the analysis.

The log-likelihood distance measure was selected to evaluate the similarity between clusters. Unlike Euclidean distance, it uses a probability distribution for each variable as opposed to line distance. Therefore, it accepts both categorical and continuous variables. The distance between clusters is defined as the decrease in the log-likelihood when the two clusters are merged into one. This distance measure is used as a similarity index; cases are assigned to a precluster comprised of cases most similar to it. In a subsequent stage, the technique further clusters, or groups, the preclusters using the hierarchical algorithm. Stage-two produces multiple cluster solutions, which are ultimately reduced, via the information criterion and distance ratios, to produce the best exploratory solution. (Okazaki, 2005; SPSS, 2001).

Results

The results of the analysis suggest that three clusters adequately categorize the ratings into homogenous sub-groups. As shown in figure 4, cluster size was reasonable with approximately 40%, 33%, and 27% of students categorized into clusters, 1, 2, and 3, respectively. The quality of the cluster solution was labeled “Fair.” Therefore, the three-cluster solution was evaluated through the hold-out sample analysis. The secondary analysis produced similar results with respect to cluster size and mean centroids of the cluster across the academic variables.

Figures 5 through 7 depict the mean ratings of the students within each cluster on key academic variables. As expected, the ratings within a cluster continuously decreased as the skill set increased in complexity. Interestingly, across all academic domains, the three clusters maintained a parallel profile. That is, based on educator ratings, Cluster 2 is best defined as the highest achieving group across all areas—receptive language, reading, and mathematics. They also maintain this distinction when considering holistic ratings (e.g., “attention to teacher-directed instruction” and “general level of understanding instruction.”) Educators rated 100% of students within Cluster 2 as “generally sustaining attention to teacher-directed instruction”—the highest rating possible. Furthermore, the educators described the majority of students in this cluster, 76%, at least capable of “demonstrating understanding of previously instructed skills with prompting and support.” Alternately stated, educators rated many of the Cluster 2 students as demonstrating understanding without support and noted many apply their knowledge to novel situations.

Cluster 1 is the next highest achieving group. With respect to the least complex skills, mean ratings for Cluster 1 and 2 are quite similar. Students within Cluster 1 primarily diverge from the highly rated Cluster 2 students with respect to the most complex skills. With regard to the overarching items, "level of attention to teacher directed instruction" was an important separating variable during cluster assignment. Here, no students in Cluster 1 were rated as "generally sustaining attention to teacher-directed instruction." Instead, the majority of students were rated as "needing repeated bids or prompts to maintain attention."

Cluster 3 mean academic ratings are discrepant from the other two clusters. The majority of students in this cluster, 73.1%, are reading at or below the pre-primer level. The typical student in this cluster sorts objects by common properties consistently 20-51% of the time. Furthermore, approximately 12% are described as not participating in instructional activities--even with prompting and support. To summarize, the students comprising Cluster 3 are most in need of academic supports.

Discussion

While exploratory, the results of this study have shown that the "one-percent" population is a diverse group with respect to their academic skills. Equally important is the separation of students' academic profile from their physical characteristics or needs. Table 2 depicts the crosstabulation of the cluster solution by specific sensory, mobility, and behavioral characteristics. This basic descriptive information depicts that, although Cluster 3 is characterized with a greater percentage of students with unique needs, in most cases, student characteristics are relatively distinct from a specific academic profile. For instance, the implementation of a behavioral intervention plan is not substantially discrepant across clusters 2 and 3. Furthermore, while students with the most severe disabilities were more likely to be classified in Cluster 3, physical disabilities constitute a substantial percentage of

Clusters 1 and 2 as well. The most noteworthy relationship occurs between cluster and the students' use of speech to meet expressive needs. Here too, greater than 9% of the students within Clusters 1 and 2 do not use speech to meet expressive needs. While important for stakeholders to understand, it is a critical assessment development consideration—developers must plan for unique student needs at all levels of ability.

This study complements the special education literature. Results further our understanding of the population of students participating in the Alternate Assessment based on Alternate Achievement Standards. Results succinctly communicate the diversity of students' academic abilities for stakeholders; they clarify the separation between students' personal needs and their knowledge, skills, and abilities.

References

Anderberg, M. R.(1973).*Cluster analysis for applications.* New York: Academic Press.

Antonenko, P. D., Toy, S., & Niederhauser, D. S. (2012). Using cluster analysis for data mining in educational technology research. *Educational Technology Research and Development*, *60*(3), 383-398.

Baer, R. M., Flexer, R. W., & Dennis, L. (2007). Examining the career paths and transition services of students with disabilities exiting high school. *Education and Training in Developmental Disabilities, 42(3),* 317.

Conti-Ramsden, G., Crutchley, A., & Botting, N. (1997). The extent to which psychometric tests differentiate subgroups of children with SLI. *Journal of Speech, Language and Hearing Research, 40(4)*, 765.

Huberty, C. J., Jordan, E. M., & Brandt, W. C. (2005). Cluster analysis in higher education research. In J. C. Smart (Ed.), Higher Education: Handbook of Theory and Research (Vol. 20, pp. 437-457). Great Britain: Springer.

Jorgenson, C. B., Jorgenson, D. E., & Davis, W. P. (1987). A cluster analysis of learning disabled children. *International journal of neuroscience, 35(1-2)*, 59-63.

Norusis, M. J. (2010). Cluster analysis (chap. 16). *PASW Statistics 18 Statistical Procedures Comparison.* Upper Saddle River, NJ: Prentice-Hall. Retrieved February 16, 2011 from http://www.norusis.com/pdf/SPC_v13.pdf

Pintrich, P. R., Anderman, E. M., & Klobucar, C. (1994). Intraindividual differences in motivation and cognition in students with and without learning disabilities. *Journal of Learning Disabilities, 27(6),* 360-370.

Sharma, S. & Kumar, A. (2006). Cluster Analysis and Factor Analysis, in R. Grover and M. Vriens (Eds.), *The Handbook of Marketing Research*: *Uses,. Misuses, and Future Advances*, pp. 95-109, Thousand Oaks, CA: Sage.

Williams, D. L., Gridley, B. E., & Fitzhugh-Bell, K. (1992). Cluster analysis of children and adolescents with brain damage and learning disabilities using neuropsychological, psychoeducational, and sociobehavioral variables. *Journal of learning disabilities, 25(5),* 290-299.

Table 1

Variables used within the Cluster Analysis

Academic Domain	Item
Receptive Communication	Can point to, look at, or touch things in the immediate vicinity when asked (e.g., pictures, objects, body parts)
	Responds appropriately in any modality (speech, sign, gestures, facial expressions) when offered a favored item that is not present or visible (e.g., "Do you want some ice cream?")
	Follows 2-step directions presented verbally or through sign (e.g., gets a worksheet or journal and begins to work, distributes items needed by peers for a lesson or activity, looks at requested or desired item and then looks at location where it should go)
Reading	Reads words, phrases, or sentences in print or Braille when symbols are provided with the words
	Explains or elaborates on text read in print or Braille
	Reading Level
Mathematics	Sorts objects by common properties (e.g., color, size, shape)
	Adds or subtracts by joining or separating groups of objects
	Forms groups of objects for multiplication or division
	Multiplies and/or divides using numerals
General	General Level of Understanding Instruction
	Level of Attention to Teacher-directed Instruction

Table 2

Student Characteristics within Cluster

Characteristic		Cluster 1	Cluster 2	Cluster 3	Total
No known vision loss	*N*	6238	4975	4078	15291
	% within Cluster	70.0%	68.0%	67.5%	68.7%
Normal vision with glasses or contact lenses	*N*	2388	2102	892	5382
	% within Cluster	26.8%	28.7%	14.8%	24.2%
Blind or low vision	*N*	283	240	1073	1596
	% within Cluster	3.2%	3.3%	17.8%	7.2%
No known hearing loss	*N*	8570	7007	5628	21205
	% within Cluster	96.2%	95.8%	93.1%	95.2%
Deaf or hard of hearing	*N*	339	310	415	1064
	% within Cluster	3.8%	4.2%	6.9%	4.8%
Walks unaided	*N*	8603	7011	3982	19596
	% within Cluster	96.6%	95.8%	65.9%	88.0%
Walks with physical assistance	*N*	189	132	698	1019
	% within Cluster	2.1%	1.8%	11.6%	4.6%
Cannot walk	*N*	117	174	1363	1654
	% within Cluster	1.3%	2.4%	22.6%	7.4%
Student uses speech to meet expressive needs	*N*	7915	6639	2260	16814
	% within Cluster	88.8%	90.7%	37.4%	75.5%
Student does not use speech to meet expressive needs	*N*	994	678	3783	5455
	% within Cluster	11.2%	9.3%	62.6%	24.5%
Student has a behavior intervention plan	*N*	1596	595	923	3114
	% within Cluster	17.9%	8.1%	15.3%	14.0%
Student does not have a behavior intervention plan	*N*	7310	6719	5120	19149
	% within Cluster	82.1%	91.9%	84.7%	86.0%

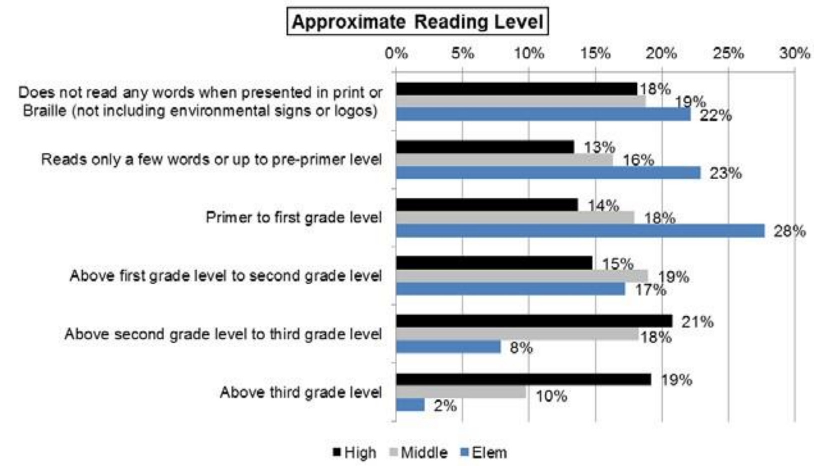

Figure 1: Students' Reading Level by Grade Band

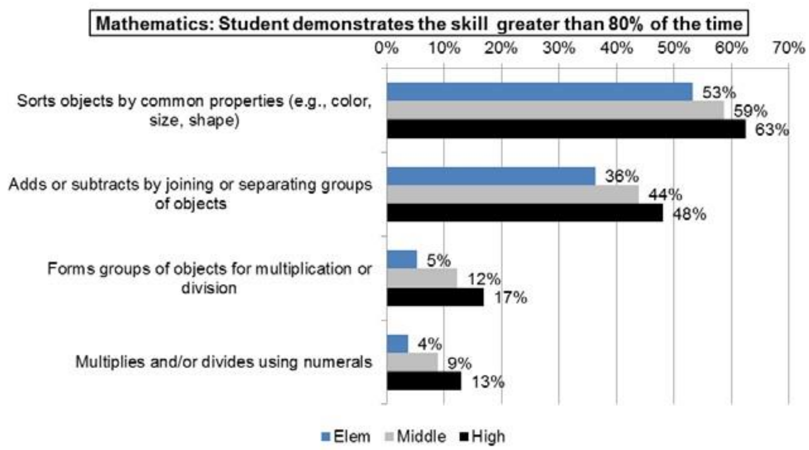

Figure 2: Students' Mathematics Skill by Grade Band

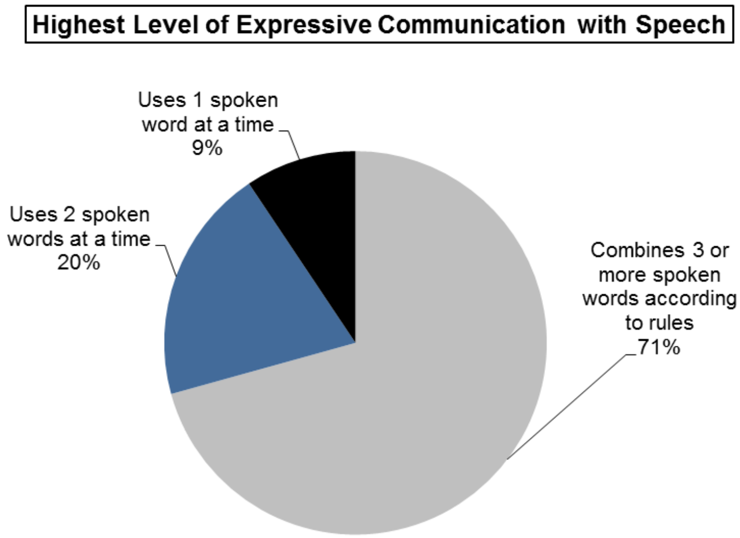

Figure 3. Students' Levels of Expressive Communication with Speech

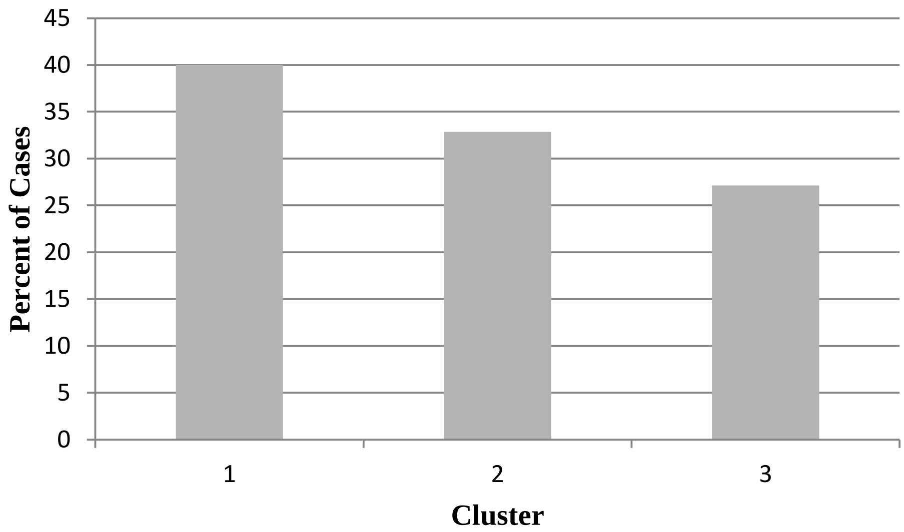

Figure 4. Cluster size

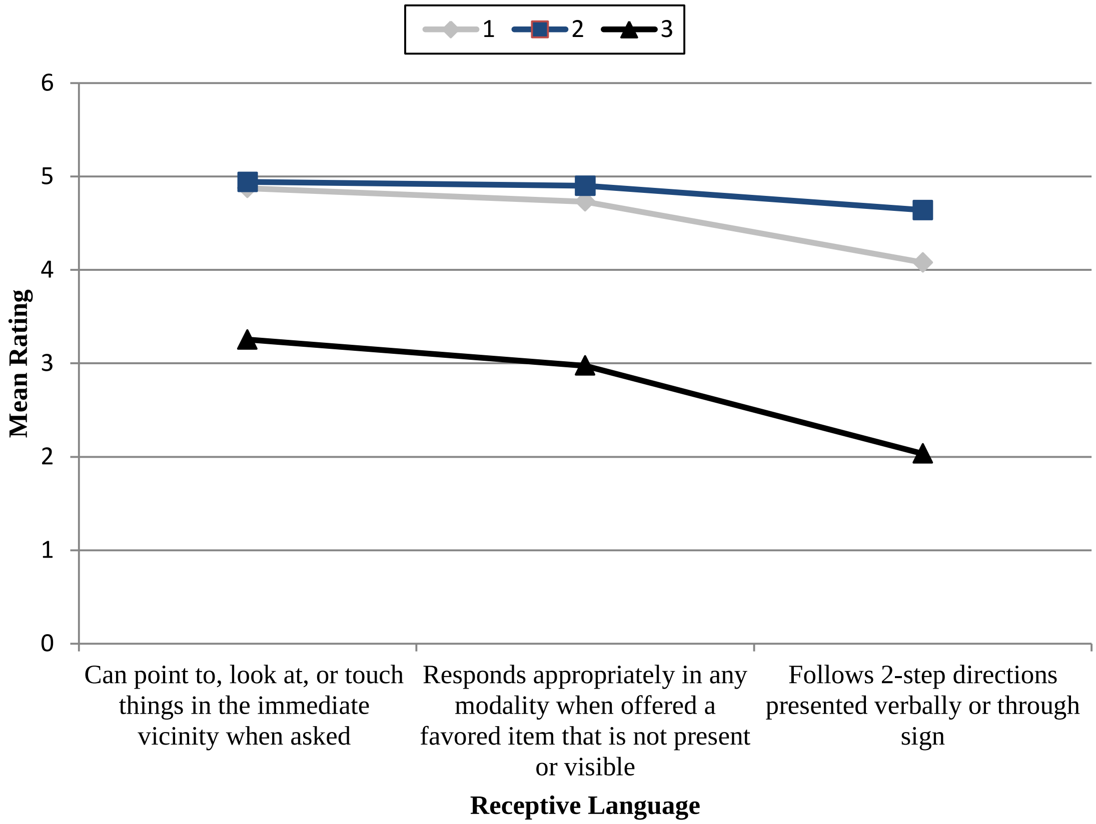

Figure 5. Cluster solution by receptive language ratings. Primary educators rated students within cluster one and two similarly. Educators consistently rated cluster three students as less able in this domain.

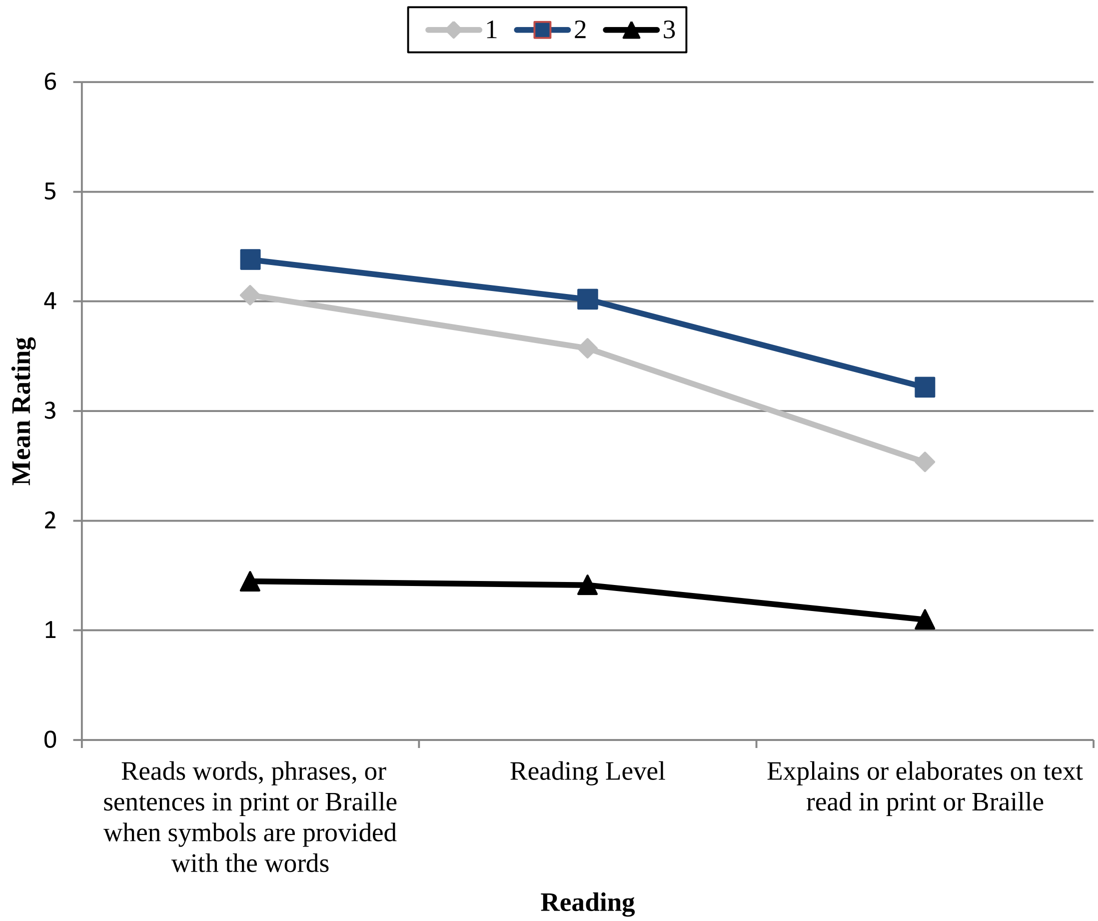

Figure 6. Cluster solution by reading ratings.

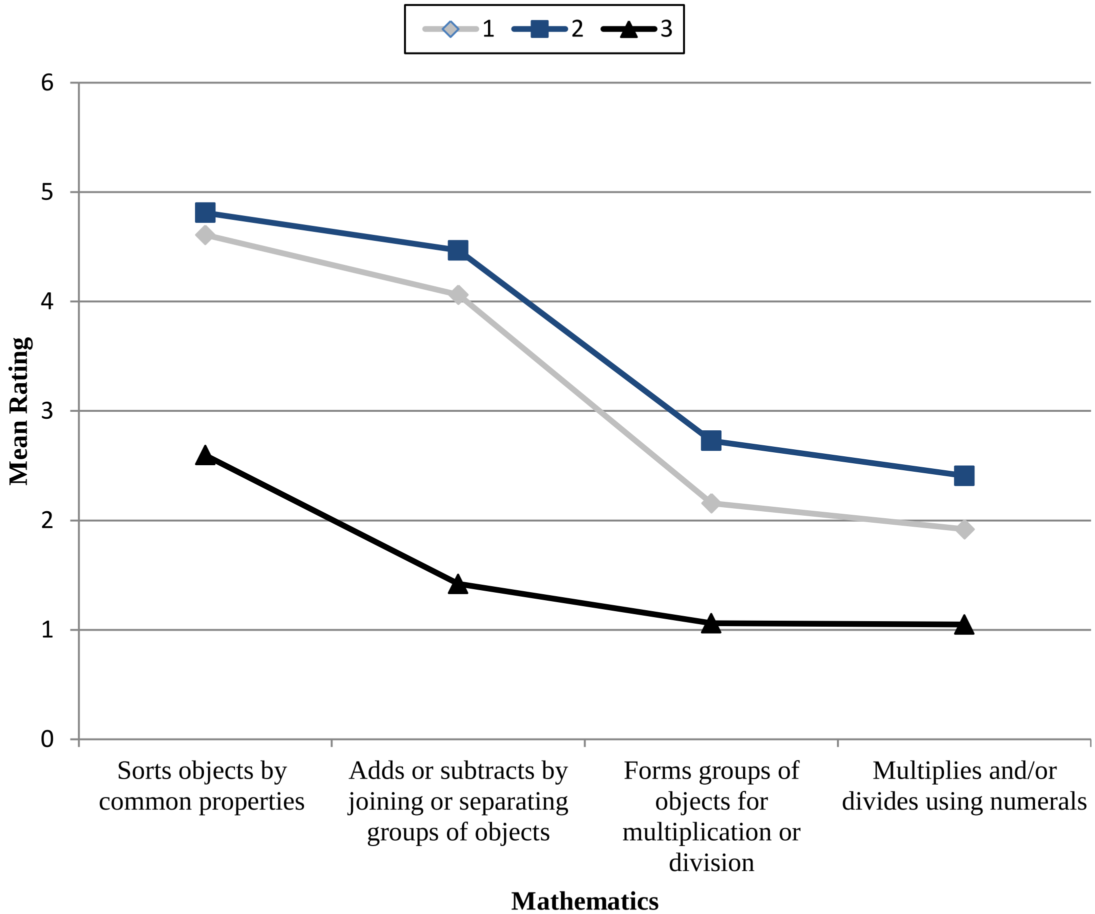

Figure 7. Cluster solution by mathematics ratings.