STUDENT ENGAGEMENT AS A MEDIATOR TO INCREASE INTEREST IN STEM AREAS. J. A. Carmona Reyes[1], S.L. Attai[2], J. York[3], K. Ranney[4] and T.W. Hyde[1] , [1]CASPER (*Center for Astrophysics, Space Physics and Engineering Research), 100 Research Pkwy, Waco, Texas 76704.* Jorge_Carmona_Reyes@baylor.edu, [2]*Participating Independent School District*, [3]Education Service Center Region 12, *2101 W Loop 340, Waco, TX 76712,* [4]Huckabee, Inc. *801 Cherry St Ste 500, Fort Worth, TX 76102*

Introduction: Decreased interest in STEM areas is reflected in the low numbers of individuals entering any career path related to physics or any specific area of physics [1]. Current efforts to change this trend includes increasing student engagement; however, it is critical to understand what student engagement is and how it can be measured [2]. This is currently being researched using the well-established theory known as Self-Determination [3] and mathematical models known as Rasch models. This novel approach is being used to create instruments to measure student engagement for elementary school students and document the correlation between student engagement and academic attainment.

Student Engagement: Defining student engagement is a complex process given that student engagement mediates at different levels of interaction for different environments (e.g., school, classroom, peers). This gives rise to multiple hypotheses for student engagement at the high school level and above, but only limited information exists for elementary school students. Understanding and intervening using student engagement at this age level is the best opportunity to maximize positive impact.

Student Engagement Theory. Based on a literature review, pilot studies and the expertise of the authors a student engagement hypothesis has been developed. This hypothesis assumes that three main components of student engagement exist: Behavioral, Cognitive and Emotional engagement. Behavioral is related to the effort and participation of the student, Cognitive is related to the processes and techniques the student uses to act on metacognition activities and Emotional is related to student relationships with peers and the environment. This hypothesis is represented in the path model shown in figure 1.

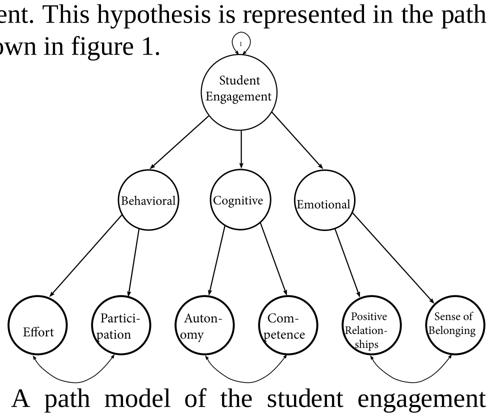


Figure 1. A path model of the student engagement hypothesis described in the text.

Rasch models: The mathematical models used to test the previously mentioned hypothesis are derived from developing a process to determine the difficulty (β) of the questions used to measure student engagement. In this case these questions measure student engagement by determining how much a student endorses the idea presented in the question. The harder the question the less level of endorsement will be observed and vice versa. This ranking is then linearized using a logarithmic function to normally distribute the results, allowing the creation of a scale that can be compared across different administrations of the instrument. Once the difficulty of the questions is determined, the participant raw scores can be transformed creating a linear scale that ranks the level of endorsement of the overall idea measured by an instrument. (This scale is known as the ability of the participant (θ)). Subtraction of the ability scale from the difficulty scale then provides the probability distributions. For dichotomized data (i.e., Yes or No) equation 1 can be used to estimate the participants ability scale (θ) by taking its derivative and solving for θ. This equation uses the difficulty score for each of the items or questions (β_i) to measure the idea of engagement, the category or Likert-scale option the participants selected (x_i) and the total raw scores (r) for each of the participants.

$$P(X = x|\theta, \beta) = \prod_i [1 + e^{(\theta-\beta_i)}]^{-1} \cdot e^{(r\theta)} \cdot e^{-\sum_i \beta_i x_i} \quad (1)$$

For polytomous data equation 2 equates the raw score of an individual (for a given set of questions) to the difficulty and ability scale. In this case, the first derivative can now be obtained to solve for θ to estimate the ability scale for each individual.

$$r = \sum_{i=1}^{k} \sum_{h=1}^{m_i} \frac{e^{(h\theta+\widehat{\beta i h})}}{\sum_{l=0}^{m_i} e^{(h\theta+\widehat{\beta i l})}} \quad (2)$$

In both cases (dichotomous and polytomous data) the difficulty scale is estimated using Conditional Maximum Likelihood estimators. In the case of dichotomous data, the Linear Logistic Test Model (LLTM) was used while for the polytomous data the Linear Partial Credit Model (LPCM) was employed. This type of analysis allows the efficacy of the instrument to be determined. For the dichotomous data this is accomplished by plotting the cumulative probability distribution function of the items or questions used in the instrument. Since the data was transformed using natural log functions, it is expected that the majority of the information will be enclosed in -3 and +3 logit units' range (an analog unit to standard deviation). Figure 2 shows the resulting cumulative probability curves also known as Item Characteristic Curves. Concaveness changes at the 0.5 probability level, indicating the location or ability level required to have an equal probability of answering yes or no on the item.

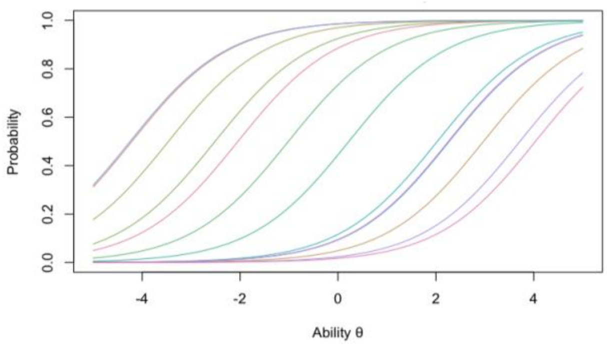


Figure 2. Item Characteristic Curves for dichotomized data. This set of items represent the concept of student engagement. The data spans from -4 to 4 logit units with no major gaps between the items.

For polytomous data, instead of plotting all the items in one single graph each item is plotted according to the different options available in the Likert-scale. In this case the crossing of the different categories (e.g., never, seldom, often, always) is shown. If there are consecutive crossing of the curves without skipping one curve the item is considered appropriate. Disordered crossing may indicate that the item is not suitable to measure the idea. Figure 3 shows the item characteristics curve for a polytomous dataset where crossings are in the proper order. In this case, these locations can be used to determine the level of ability required to answer the question pose at each of the Likert-scale categories.

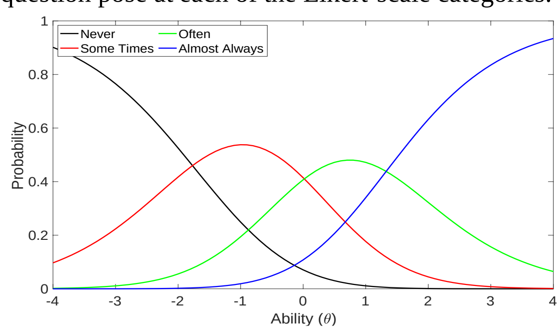
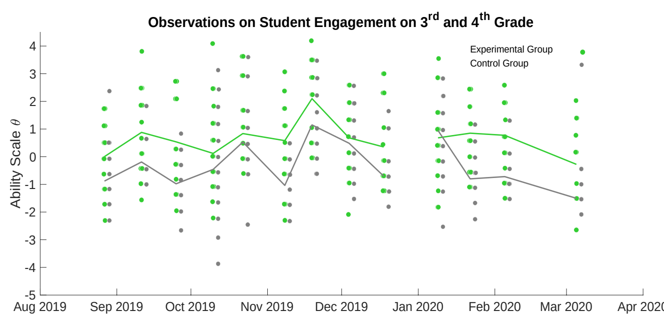


Figure 3. Item Characteristic Curves for polytomous data.

Results: This analysis was run using the eRm library from R and Matlab software. The eRm library provides the difficulty parameters which are then saved into a .csv file and used in Matlab. Finding an analytical solution for the derivative of equation 1 and 2 is difficult; however, using the Newton-Raphson method, estimates of the ability scale can be obtained. Using this technique provided results indicating that the hypothesis mentioned above is tenable according to data obtained from a sample of 600 participants in an elementary school from a Southwestern region of the US. The results show that the instrumentation created to measure student engagement is stable and has sufficient reliability to indicate changes that take place on student engagement due to designed interventions (see figure 4). In this case participants were divided into two groups, one with flexible furniture and pertinent professional development and one with traditional furniture and no professional development.

Figure 4. Results on observed student engagement on elementary school students.



These results were correlated against student academic metrics with the results showing a correlation between the student engagement differences measured and the participants' academic progress.

Conclusions: This research has produced both a hypothesis that has since been tested for a group of elementary school students and a set of instruments that have been shown to produce valid and reliable results. More work is necessary to reach generalizability but the technique has already proven that student engagement can be increased with proper intervention. As such, this provides an avenue to plan and test interventions that can help students build confidence and trust in developing the skills necessary to enter into STEM areas and specifically into physics career paths.

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References: [1] Thomas, E., Morales, G., Brown, M., Carter, T., Correll, D., Gentle, K., Post-Zwicker, A., Schultz, K., Steiner, D., & Scime. E. (2003) *Journal of fusion energy* 22, no. 2 (2003): 139-172. [2] Carmona Reyes, J., Attai, S., Altmann, R., Davis, J., York, J., Ranney, K. Beaird, E., & Hyde, T. (2020). Bulletin of the American Physical Society. [3] Deci, E. L., & Ryan, R. M. (1980). *The Journal of mind and Behavior*, 33-43.