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Engagement in classroom learning: Ascertaining the proportion of students who have a balance between what they can do and what they are expected to do

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Abstract

Student engagement in classroom learning was conceptualised as a balance between two attributes. In order for students to be engaged, the tasks expected of them should be commensurate with their ability to complete these tasks. That is, a balance between their learning capabilities and the expectations of their learning. Of interest was the proportion of students with this balance.

First, 194 Years Eight to Twelve students were interviewed by two researchers on six aspects of the expectations of their learning and five aspects of learning capabilities. Second, 1760 Years Eight to Twelve students responded to 15 self-report items about the expectations of their learning and 12 self-report rating scale items about their learning capabilities. Rasch model common-person test equating methods were then applied separately to the data from the two sources. The proportions of students with ‘equivalent’ learning capabilities and expectations of learning scores were approximately 80% for the two samples.

The results support the theoretical basis for the Capabilities Expectations Model of engagement. Significantly, methods for estimating the proportion of students engaged in their classroom learning were presented and assessed. Instrumentation reliability within and between methods was evidenced.

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Background

Models of latent traits often postulate relations between two or more variables or sub-constructs. The relation between variables can be represented mathematically as an algebraic expression or graphically as a plot on a Cartesian plane (two variables). The following sections examine the theory underpinning two of these models – The Experience Fluctuation Model of flow and the Expectations Capabilities Model of student engagement in classroom learning. These are followed by a brief overview of test equating to show how the Rasch model can be used to estimate equivalence between data from two measures to garner evidence for the construct validity of a latent trait model.

The Experience Fluctuation Model of flow

According to Csikszentmihalyi (1990), when people described optimal experiences (situations which are highly enjoyable), they often use the term flow. Flow is to the "… spontaneous, seemingly effortless aspect of such experiences" (Csikszentmihalyi & Schneider , 2000, p. 97). A recurring aspect of descriptions of flow is the balance between perceived high levels of challenge and high levels of skill - the task is demanding but the enjoyment of the experience also derives from having the skills necessary to complete the task (Massimini, Csikszentmihalyi & Carli, 1988). From this perspective, flow is a function of challenge and skills. Challenge and skill have been measured and above average levels on these two dimensions are assumed to indicate flow. One approach to measuring flow uses the Experience Sampling Method (ESM) (Hekter, Schmidt & Csikszentmihalyi, 2007) in which data is collected from an individual at regular intervals over a prolonged period. For example every 30 minutes over several days. The mean level of perceived experiences is calculated for this person and then his/her experiences are classified relative to this level. Figure 1 below, the Experience Fluctuation Model, provides a visual representation of flow by plotting challenge and skill on a Cartesian plane. Other categories or conditions of experiences such as anxiety, apathy and relaxation can also be represented by the Experience Fluctuation Model (Csikszentmihalyi & LeFevre, 1989; Nakamura, 1988).

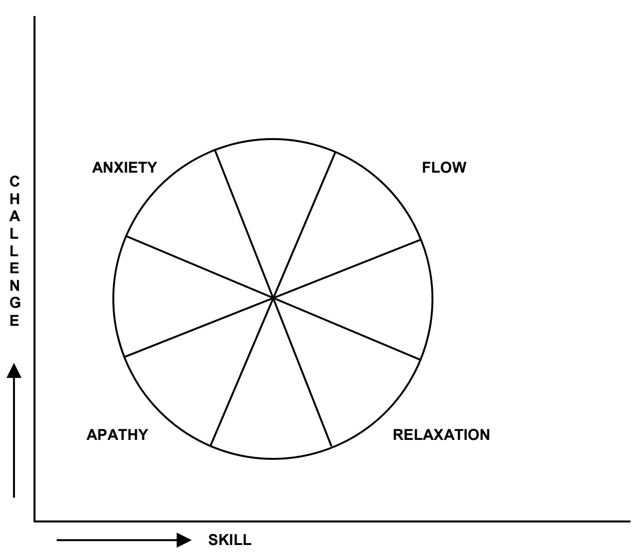

Figure 1 The Experience Fluctuation Model

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The Expectations Capabilities Model of student engagement in learning

Cavanagh, Kennish and Sturgess (2008), found reference to flow theory in the literature on student engagement and they noted similarities between flow and engagement. They proposed that "… a student who is engaged within a particular situation is expected to have a balance between the perceived level of the challenge being faced and his/her perceived capability to meet the incumbent requirements" (Cavanagh, Kennish & Sturgess, 2008, p. 15). The flow theory terms of 'challenge' and 'skills' were replaced by' expectations of learning' and 'learning capabilities', terms that more accurately describe attributes of students and learning. The Expectations Capabilities Model of student engagement in classroom learning is visually represented in Figure 2 below.

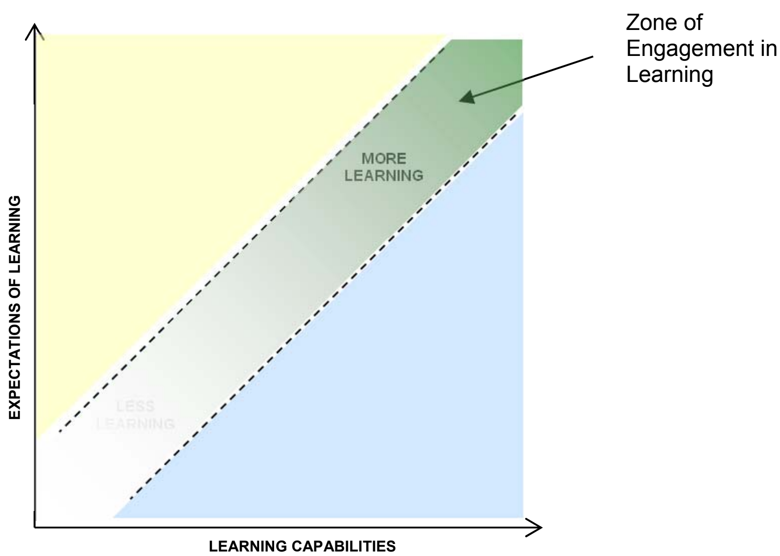

Figure 2 The Expectations Capabilities Model

The diagonal zone is a region where the capability of a student to complete a task is commensurate with the difficulty of what is expected of the student. Students in this zone at a particular time and in a particular situation, have a balance between what they are capable of doing and what is required of them. When high expectations are placed on highly capable students, it is anticipated they will learn more and more quickly. Less capable students can still be engaged provided the expectations of them are not too high. It is anticipated these students will learn less and at a slower rate.

While the Model has application for explaining phenomena such as engagement in learning in an illustrative way, it is speculative in the absence of operational definitions and measures. Overcoming this theoretical deficiency requires measures of expectations of learning and of learning capabilities, and a technique for identifying students who have a balance between these two aspects of their learning. Previous research into the model has developed operational definitions, constructed measures and collected observational and self-report data (Cavanagh, 2011; Cavanagh & Kennish, 2009). However, quantifying the balance between expectations and capabilities has received less attention. There is a need to establish criteria for demonstration of equivalence between expectations and capabilities scores. And then, to ascertain in particular situations, the proportion of students with scores meeting these criteria.

Test equating using the Rasch model

There are often occasions when comparisons are required of estimates of ability or attitudes made at different times, with different populations or using different instruments. Traditionally, Classical Test Theory is applied with student performance presented as the proportion of items answered correctly. This requires all the students to be tested with the same items. Similarly estimating item difficulty requires all the items to be administered to the same students. These are serious limitations when comparing test scores for the same students at different times, at the same time for students in different year cohorts, from different tests, or from a combination of these conditions. Alternatively, the Rasch model approach creates measures which are invariant over time and between groups of persons. Item difficulty is not dependent on the persons tested and the scores of the persons are not dependent on the subset of items administered. These properties of data that fit the Rasch model enable test scores to be compared provided there are some common items, or some common persons sitting both tests. Further advantages of the approach are the plotting of person ability estimates and item difficulty estimates on linear scales, and estimation of a standard error for each person's score and each item's difficulty. Interval data are available for subsequent mathematical operations and when statistics such as t-values are calculated, the level of significance is calculated from the person score errors.

The current study used Rasch model test equating to examine equivalence between paired-sample expectations scores and capabilities scores. The purpose was to determine the degree of equivalence on the assumption that the scores were related but not necessarily measuring the same sub-construct.

Research questions

Two methods of common-person test equating were applied One method used t-tests to estimate the number of students with equivalent scores (95% confidence interval) (RUMM2030 Andrich, Sheridan & Luo, 2012). The other used a graphical process in which control lines for a 95% confidence band were constructed from the standard errors in individual scores and then the number of coordinates within the band was counted (see Bond & Fox, 2007). Both methods were applied to researcher-completed data and also to student self-report data. The research questions were:
1. For the researcher-completed data, what proportion of students have t-values within a 95% confidence interval?
2. For the self-report data, what proportion of students have t-values within a 95% confidence interval? and
3. What proportion of students have expectations and capabilities score coordinates within a 95% confidence band around a diagonal through the mean estimates?

Methodology

The researcher-completed data were obtained from interviews of 194 secondary school students. The sample comprised Years Eight to Twelve students, boys and girls, city and country students. They were asked about their experiences in either English, Mathematics, Science or Society and Environment classes. The researchers rated each student on six-point scales for six aspects of expectations of learning and five aspects of learning capabilities (see Cavangh, 2009). The student self-report data were obtained from 1760 students responding to 27 items on a three-point scale – strongly agree, agree and disagree. (see Cavanagh, 2012). Fifteen of the items were about expectations of learning and twelve were about learning capabilities.

Data from both sources were entered into RUMM2030 (Andrich, Sheridan & Luo, 2012) and separate analyses were performed. Two sub-tests were created in each analysis, one for expectations of learning and one for learning capabilities. Person scores (estimated in logits) and standard errors were estimated for each person for each sub-test.

The first equating procedure involved estimation of t-values for each student's two sub-test scores, plotting the distribution of these values and then identifying the students with values exceeding the 5% significance level. This procedure was applied to the researcher-completed data and then the self-report data. The second equating procedure commenced by calculating the mean scores for the sub-tests and adjusting these so there was a common mean score. The coordinates of the adjusted sub-test scores were then plotted on a Cartesian plane (expectations of learning scores on the vertical axis and learning capabilities scores on the horizontal axis), using Excel. The standard errors in each pair of

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student sub-test scores were then used to construct the control lines for a band of 95% confidence. A visual inspection of the scatterplot was then made to count the number of students with scores within the band.

Results

For the researcher-completed data (N= 194), the mean Rasch calibrated scores were 0.52 logits (standard deviation 1.61 logits) for expectations of learning and 1.40 logits (standard deviation 1.74 logits) for learning capabilities. The person separation index (proportion of variance in the calibrated scores considered true) was 0.84 for expectations of learning and 0.89 for learning capabilities.

For self-report data (N= 1760), the mean Rasch calibrated scores were 0.53 logits (standard deviation 1.61 logits) for expectations of learning, and 0.66 logits (standard deviation 1.61 logits) for learning capabilities. The person separation index (proportion of variance in the calibrated scores considered true) was 0.87 for expectations of learning and 0.84 for learning capabilities.

The researcher-completed data fitted the Rasch Rating Scale model very well – low residual values (<± 2.5) and high Chi Square probability values (> 0.05). The student self-report data fitted less well due to dependency between several of the items.

T-value procedure

Figure 3 below shows the distribution of t-values for the researcher-completed data (N= 194). 17.4% (34 students) lie outside of the 95% confidence interval.

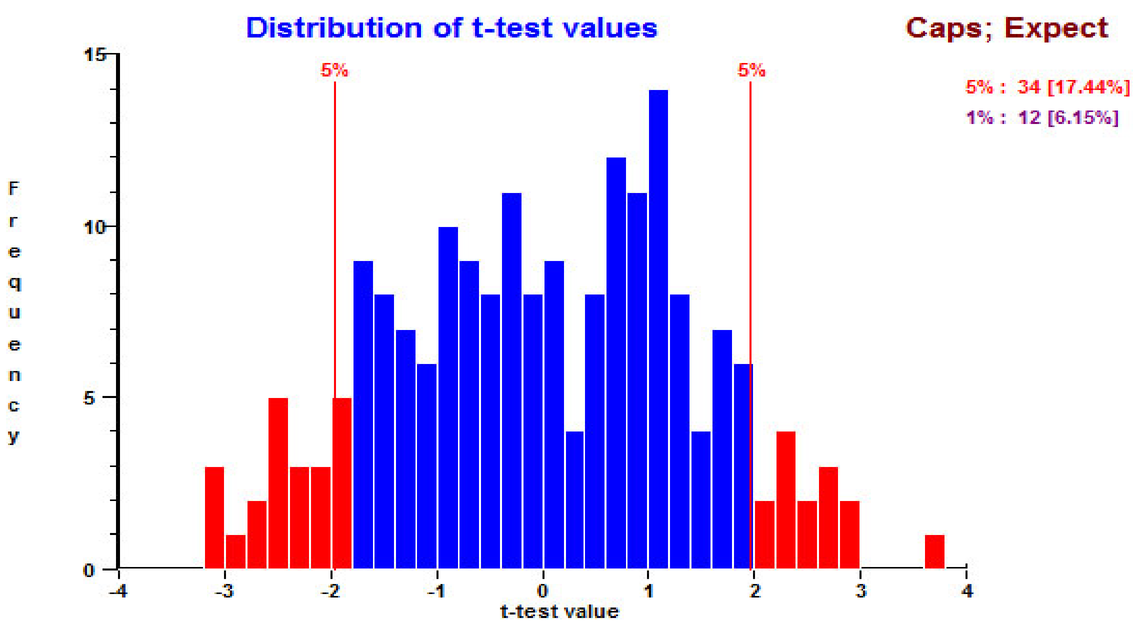

Figure 3 Distribution of t-values (N= 194)

Figure 4 below shows the distribution of t-values for the self-report data (N= 1760). 17.9% (312 students) lie outside of the 95% confidence interval.

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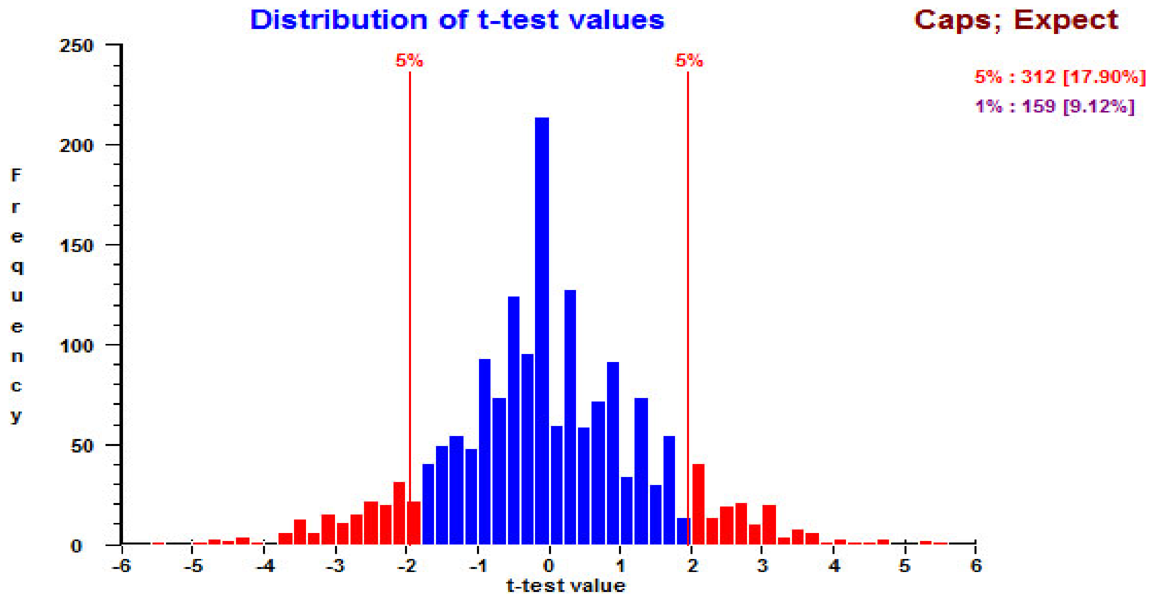

Figure 4 Distribution of t-values (N= 1760)

Confidence band procedure

Figures 5 and 6 are scatterplots of the expectations and capabilities scores for the researcher-completed data and the self-report data.

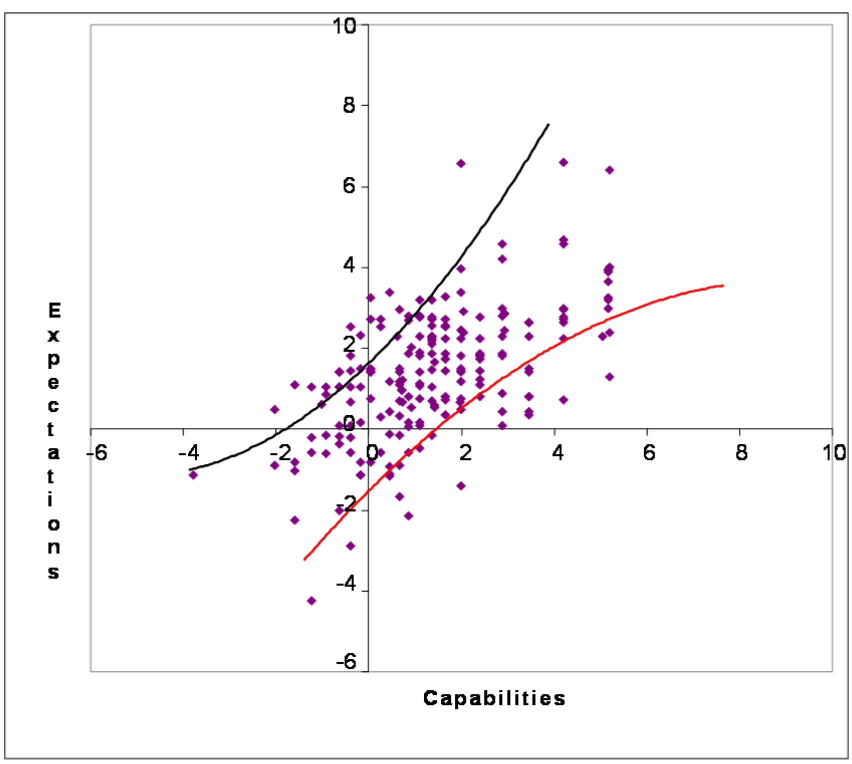

Figure 5 Scatterplot of expectations and capabilities scores (N= 194)

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Approximately 15 (18%) of the 194 coordinates are outside of the 95% confidence bands. The approximation is due to the difficulty in counting coordinates close to the control lines.

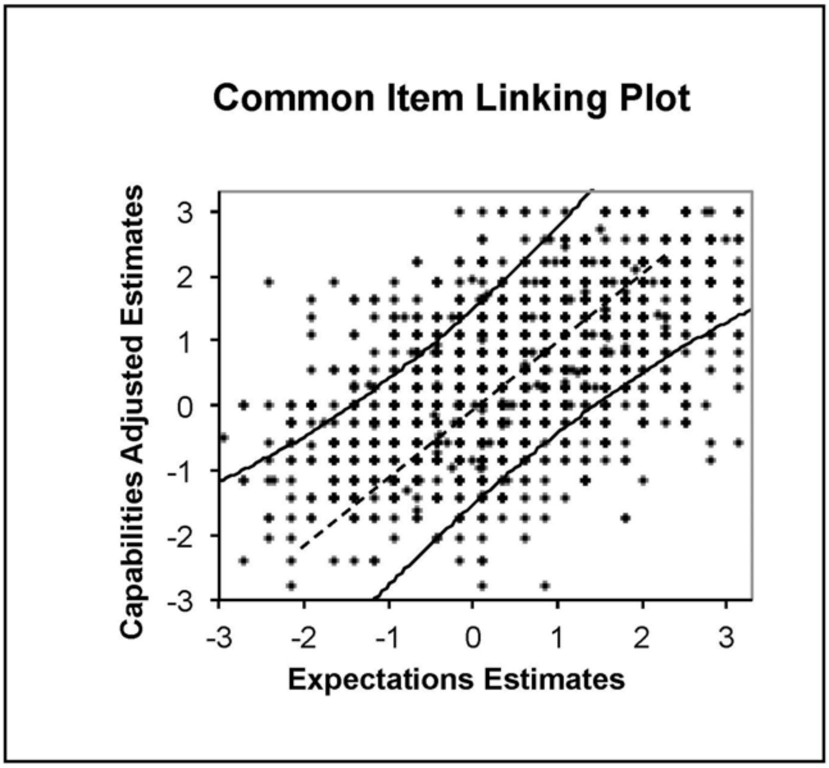

Figure 6 Scatterplot of expectations and capabilities scores (N= 1760)

The density of coordinates makes counting numbers of scores outside of the confidence band difficult and inaccurate.

Conclusion

The proportions of students with equivalent (95% confidence interval) in the researcher-completed sample and the self-report sample were very similar – respectively 82.6% and 82.1%. The confidence bands procedure produced a similar value for the researcher-completed sample. These findings are evidence for the representation of student engagement in learning presented in the Expectations Capabilities Model.

Approximately 80% of the students measured would lie within the diagonal zone of engagement. This value provides a reference point for further research using measurement and the Expectations Capabilities Model.

Both Rasch model test equating methods calibrate scores on an interval scale and then paired scores including standard errors for each score, are used for the analysis. This can be compared with traditional methods that use raw scores and correlational analyses. The requirements for data fitting the Rasch model are stringent and the results of subsequent analyses can be interpreted with confidence.

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