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Identifying ranges of student mental health using Latent Class Analysis

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Introduction

The prevalence of child and adolescent mental health disorders over the last 50 years has been increasing (Maras and Kutnick, 1999; Zubrick, et al., 2000) to the extent that it is now of major concern in Australia (Richardson and Prior, 2005; Stanley, 2007; Sawyer, 2004; Sawyer et al., 2000). Reports from Sawyer and colleagues (Sawyer, Arney et al. 2001; Sawyer, Miller-Lewis et al. 2007; Sawyer, Sarris et al. 1990) record the prevalence of mental health disorders for Australian children and adolescents at approximately 13 to 21 per cent, according to self-report or parent information. In order to counter this trend, national initiatives, such as KidsMatter[1] (Slee et al., 2009), have been trialled with the intention of improving the mental health outcomes for Australian primary school children.

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[1] KidsMatter (2006) is a primary school mental health promotion, prevention and early intervention initiative and is designed as a whole-school approach aimed to (a) improve the mental health and well-being of primary school students, (b) reduce mental health problems among students, and (c) achieve greater support and assistance for students experiencing mental health problems. KidsMatter was developed in collaboration with the Commonwealth Government Department of Health and Ageing, *beyondblue: the national depression initiative*, the Australian Psychological Society, Principals Australia and supported by the Australian Rotary Health Research Fund.

Effective evaluation of such initiatives and their subsequent regard by policy makers depends in part on the suitability of judgements made about students' mental health. Decisions about measuring student mental health were of central concern in designing the evaluation[2] of the KidsMatter Pilot Initiative and resulted in the use of multiple scales completed by multiple informants on multiple occasions in multiple settings (Askell-Williams et al., 2008; Dix et al., 2008; Gregory et al., 2008). The broad purpose of the study was to evaluate the effectiveness of KidsMatter Stage 1 Pilot Phase.

Teacher and parent assessments of students' mental health based upon data from the evaluation of KidsMatter were collected through the use of four different scales in 100 primary schools across Australia. A strength of the evaluation was that it did not rely upon just one instrument or one informant to assess student mental health. However, these multiple instruments from multiple informants provided a challenge when it came to classifying each child's mental health status at the beginning of the two year pilot study. While there were children for whom parents and teachers rated consistently across the four scales and in agreement with each other, there were other children for whom the reports from parents and teachers were contradictory. One simple explanation for such contradictions might be that the child acted differently at school than they did at home. An important challenge of the evaluation was to determine how best to bring these various assessments together in order to identify the appropriate mental health status of each child. A technique called Latent Class Analysis was considered to be the best approach and is the focus of this chapter.

Assessing student mental health

Four different measures of mental health were developed and administered to parents and teachers of 4970 mainly 10 year-old primary school students in 100 KidsMatter schools. The first measure of mental health was Goodman's (2005) *Strength and Difficulties Questionnaire* (SDQ). The SDQ was developed as a brief mental health screening instrument and is widely used in many nations, including Australia (Levitt et al., 2007). Perceptions of the child's mental health difficulties, in terms of, hyperactivity, conduct problems, emotional symptoms and peer problems are combined to give a score ranging between normal (0) to abnormal (40).

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[2] The data for this paper were gathered as part of the evaluation of KidsMatter and the author is grateful to members of the consortium based in the Centre for Analysis of Educational Futures at Flinders University for their expertise in designing and undertaking this large evaluation.

The other three scales provided assessments of the five core groups of indicators of students' social and emotional competencies identified by the Collaborative for Academic, Social and Emotional Learning (CASEL, 2006), namely, self-awareness, self-management, social awareness, relationship skills, and responsible decision making, as well as students' optimism and problem solving capabilities. The first instrument, called the *Child Social and Emotional Competencies* (SEC) scale, was purposefully designed to give a measure of child protective factors. Teacher and parent views about the child's ability to maintain positive relationships, solve problems, consider others, and make responsible decisions ranged between low competencies (strongly disagree=1) to high competencies (strongly agree=7). Although the SEC scale is strictly a measure of competencies rather than mental health, a canonical correlation of -0.91 between SEC and the SDQ suggests that it is an effective measure of positive mental health attributes.

The second measure of mental health was the specifically developed, *Mental Health Strengths* scale (MHS) and, like the SEC, scores ranged between low strengths (1) to high strengths (7). The MHS provided teacher and parent perceptions of the child's positive mental health in terms of optimism and coping skills. The final scale for student mental health was the *Mental Health Difficulties* scale (MHD). Like the SDQ, the MHD scale placed those with few difficulties at the low end (1) and those with many difficulties at the high end (7). The MHD scale provided teacher and parent perceptions of the child's mental health difficulties in terms of poor behaviour and anxiety.

Confirming the scales

Each scale was first subjected to confirmatory factor analysis. Factor analytic procedures have been widely used, especially in the behavioural sciences, to assess the construct validity of a scale (for example, see Dix, 2007). However, it was also found that many of the items exhibited a skewed distribution, so usual methods involving factor analysis and other traditional techniques were considered to be inappropriate. For example, the outliers evident in the SDQ can distort correlations and the variance-covariance matrix, so the outliers may also distort the factor analysis.

Accordingly, the determination of scale validity and reliability required the use of distribution-free techniques in preference to using transforms to normalise data. Given the non-normal distributions and the large sample size, it was seen as appropriate to use asymptotically distribution-free (ADF) estimation provided in AMOS (Arbuckle,

2007) for each structural equation model (Browne, 1984; Garson, 2009; Hox, 1998; Kline, 1998; Tabachnick and Fidell, 2001). Asymptotically distribution-free estimation does not assume multivariate normality, and for this reason it was preferred over maximum-likelihood estimation methods.

In the interests of simplicity, it was desirable that the item structures were the same for parent and teacher scales, so scores were averaged (N=4,970). This had the additional benefit of reducing missing data, for which completeness was required. The remaining missing values were then replaced using the non-parametric median (rather than mean) of nearby points as an approximation for a complex sample, where design effects arise due to the nested nature of students within schools.

The criteria for rejecting items were based on a significance level of 0.05 and a minimum loading of 0.3. The indices selected for goodness-of-fit were, the Root mean square error of approximation (RMSEA≤0.08), the Standardised root mean square residual (SRMR≤0.1), the Tucker-Lewis index (TLI≥0.9), and the Comparative fit index (CFI≥0.9). These indices perform better than other indices under non-normal distribution conditions and are less sensitive to sample size (Fan, et al., 1999; Marsh, et al., 1988; Schumacker and Lomax 2004).

Table 1 presents a summary of the confirmatory factor analysis (ADF) in terms of the goodness of fit indices and number of items.

Table 1. Summary of the confirmatory factor analysis (ADF), with goodness of fit indices, assessment of normality, and number of items

Mental Health Scales	RMSEA	SRMR	TLI	CFI	Mardia's coefficient	No of items
Social and Emotional Competencies (SEC)	0.10	0.056	0.57	0.72	44.67	7
Mental Health Difficulties (MHD)	0.06	0.035	0.87	0.93	28.33	3
Mental Health Strengths (MHS)	0.06	0.035	0.87	0.93	28.33	3
Strengths and Difficulties Questionnaire (SDQ)	0.05	0.062	0.61	0.67	125.01	20

In addition, analysis of normality is also summarised in Table 1, with the reporting of the multivariate kurtosis value, known as Mardia's coefficient. Values of 1.96 or less mean there is non-significant kurtosis. Values greater than 1.96 mean there is significant kurtosis, which means significant non-normality (Garson, 2009). In all cases, Mardia's coefficient was well above the cut-off, and confirmed the need for non-parametric methods.

The structural models for the Child Social and Emotional Competencies scale (SEC) scale, the Mental Health Strengths (MHS) and Mental Health Difficulties (MHD) scales, and the Strengths and Difficulties Questionnaire (SDQ), along with the shortened versions of the items that comprise them, are presented respectively in Figures 1, 2 and 3. The factor loadings in each figure are well above the 0.3 cut-off and indicating that the items meaningfully reflect the concepts being measured, further suggesting that there is good internal scale validity.

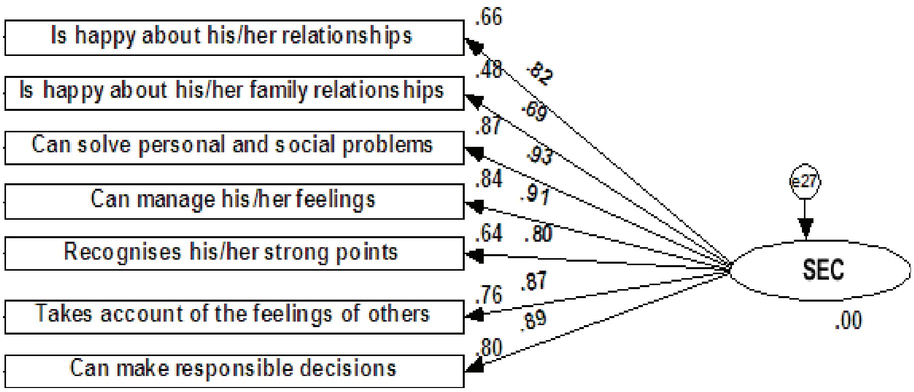

Figure 1. The Child Social and Emotional Competencies scale, showing for each item, the variance explained and the factor loading

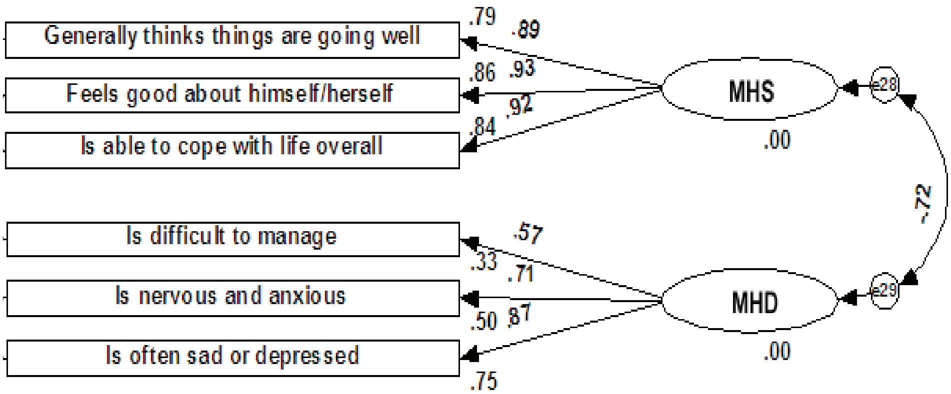

Figure 2. The Mental Health Strengths scale and Mental Health Difficulties scale, showing for each item, the variance explained, the factor loading and the correlation

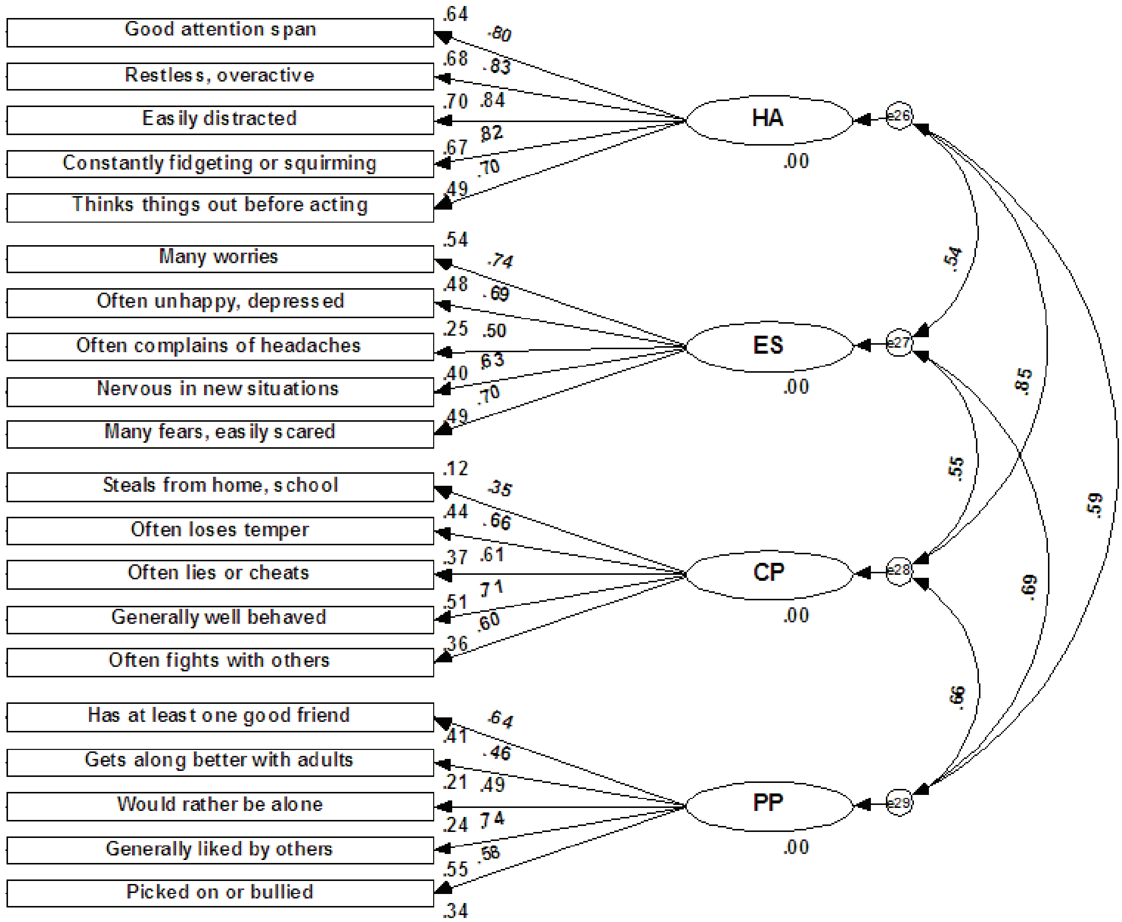

Figure 3. Total Strengths and Difficulties (SDQ) with subs-scales of hyperactivity (HA), emotional symptoms (ES), conduct problems (CP) and peer problems (PP), showing for each item, the variance explained, the factor loading and the correlations

Latent Class Analysis

Preliminary analysis of the SDQ and SEC were presented in an article by Dix et al. (2008), which concluded that there was reasonable agreement between parent and teacher ratings of the same child. Further evidence is presented in Figure 4 based on the canonical analysis (ADF) of parent and teacher reports for 4332 children[3], and shows a medium standardised correlation of 0.53 between parent and teacher ratings of the same child on the same scales.

[3] Some cases with missing data were removed from the ADF analysis, which requires complete data.

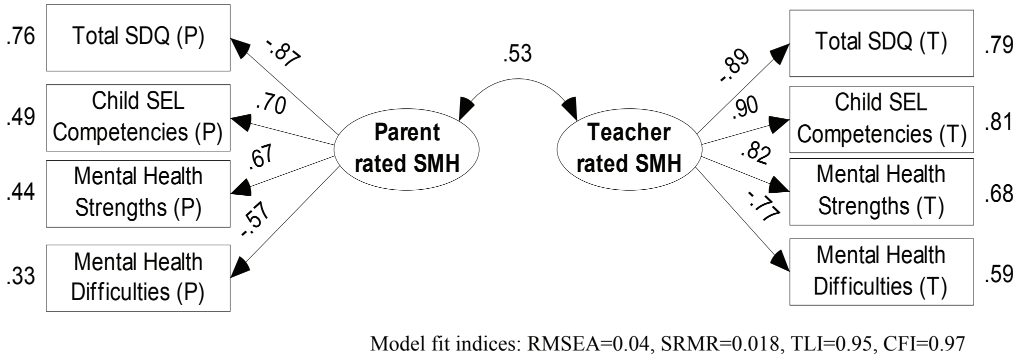

Figure 4. Canonical correlation of parent and teacher ratings of student mental health

Clearly, there were children for whom parents and teachers agreed, but there were also children for whom parent and teacher ratings were in contradiction between each other and between the different measures. The challenge, and the main focus of this discussion, was how then could a single score for student mental health be assigned to the student, particularly for those students where there was poor agreement between the multiple informants and multiple instruments?

One strategy found in the literature (Veenstra et al., 2008) was to select only students for whom there was agreement between parents and teachers. Based only on achieving agreement on the SDQ, this method would result in the unacceptable loss of 44 per cent of the data. Further losses in data would occur if the other measures of mental health were also applied in this way. Clearly, this was not a viable approach and alternative methods were considered.

Attention was drawn to the use of Latent Class Analysis (LCA), which is a statistical method for finding subtypes of related cases (latent classes) from multivariate categorical data, using the program MPlus version 5.2 (Muthén and Muthén, 2007). The benefits of using LCA, was its non-reliance on assumptions of normality, its ability to manage complex nested data and missing data, and because it has several advantages over conventional regression analyses that use total scores or cut-off scores (van Lier et al., 2003).

Preparation of the data was first necessary in order to change scale data into categorical data. Accordingly, Goodman's (1997) cut-point for parent and teacher rated SDQ ranges were differentially applied. For teachers, the cut-points were 'normal range' (0-11), 'borderline range' (12-15), and 'abnormal range' (16-40). For parents, the cut-points were more generous, with 'normal range' (0-13), 'borderline range' (14-16), and 'abnormal range' (17-40). The visual binning command in SPSS

(2001) was used. Appropriate cut-point ranges for the other measures of mental health (SEC, MHS, and MHD) were then determined by using the percentage of students in each of the normal, borderline and abnormal ranges. Once again, SPSS was used to undertake the analysis for each of the parent and teacher variables. Combined into this already complex categorisation process, the positively viewed scales (SEC and MHS) were reverse coded to align with the negatively viewed scales (SDQ and MHD). Accordingly, the resulting ranges for each of the four scales were labelled 'normal' (1), 'borderline' (2), and 'abnormal' (3).

The decision to use Goodman's labels for each category was not taken lightly and alternative labels that encompassed concepts of strengths and difficulties were considered. However, in the interests of avoiding confusion, alternative labels were not adopted, since the SDQ was being used and Goodman's cut-point percentages were being applied to the other three scales. The resulting data file contained the categorised variables from parents and teachers for each student at the beginning of the evaluation.

Preliminary latent class analysis in MPlus was conducted, taking into consideration missing data and clustering at the school level, using the four parent-rated and four teacher-rated scales of mental health. Three classes were requested and revealed that for one groups of students, exhibiting scores within the normal range, there was good separation of probability estimates and good agreement between parents and teachers. However, for the other two classes of students, the difference between raters was of more influence than the difference between students. One reason for this could be that students exhibit different behaviours at home than they do at school. A practical approach was taken and equivalent parent and teacher scales were averaged to form four combined measures.

Figure 5 presents the resulting probability estimates of the three classes for Time 1. The vertical axis can be interpreted as the probability of being in the 'normal' range. Accordingly, students with scores the 'abnormal' range have the lowest probability and are near the bottom of the graph. Conversely, students with scores in the 'normal' range have the highest probability of being considered to exhibit normal behaviours. Each probability graph also shows that combining parent and teacher data sets was highly effective in overcoming their differences, with good separation between the probabilities.

The MPlus input file was prepared and is presented here.

```
Title:
 Student Mental Health LCA: Occasion 1.
Data:
 File is SMH1.dat ;
Variable:
 names = schid sid SDQ SEC HMHS MHD;
 usevariables = sid SDQ SEC HMHS MHD;
 categorical = SDQc SDQ SEC HMHS MHD;
 missing are all(-1);
 cluster = schid;
 classes = class(3);
Analysis:
 Type=mixture;
 Type=missing;
 Type=complex;
Plot:
 type is plot3;
 series is SDQ (1) SEC (2) MHS (3) MHD (4);
Savedata:
 file is SMH1.txt ;
 save is cprob;
 format is free;
Output:
 tech11 tech14;
```

The most immediate interpretation of the probability typologies presented in Figure 5, is that the category of borderline is indicative of students ‘at risk’ of experiencing mental health problems, and not just an intermediate group half-way between the normal and abnormal groups, and it suggests that three groups are appropriate.

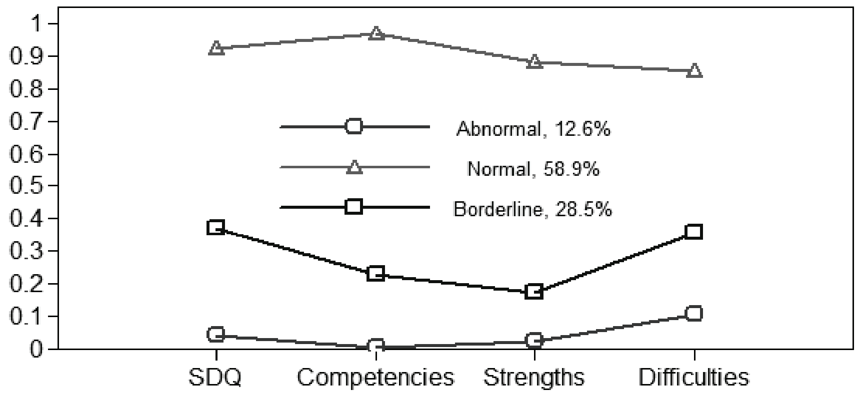

Figure 5. Latent class probabilities of being ‘normal’ on Time 1 (N=4970)

Although visually convincing, goodness of fit measures were considered in order to assess further whether the right number of classes was chosen. The Vuong-Lo-Mendell-Rubin test and the bootstrapped parametric likelihood ratio test were requested to compare the model with K classes (in this case 3 classes) to a model with K-1 classes (2 classes). The results are presented in Table 2 and show that on Time 1 the Vuong-Lo-Mendell-Rubin test had a probability-value of 0.058 and the Lo-Mendell-Rubin adjusted LRT test had a p-value of 0.059. If the probability-value is less than 0.05, the K model is superior and additional classes are added until the p-value for the statistic is greater than 0.05, at which point the previous model is accepted (Smith et al., Lo et al., 2001). The tests were marginal suggesting that two classes were possibly sufficient and that three classes might not really be needed. However, the bootstrapped parametric likelihood ratio test had a p-value of 0.000 and suggested that three classes were better than two classes. UCLA (2009) reported unpublished results that indicated the bootstrap method might be more reliable. Moreover, the three class model fitted the theoretical expectations. Accordingly, three classes were chosen and are identified in Figure 5 as normal, borderline and abnormal.

Table 2. Latent class analysis tests for number of mental health classes

Vuong-Lo-Mendell-Rubin Likelihood Ratio Test For 2 (H0) Versus 3 Classes	**Time 1**
H0 Loglikelihood Value	-61234.207
2 Times the Loglikelihood Difference	1180.335
Difference in the Number of Parameters	10
Mean	14.328
Standard Deviation	939.493
P-Value	0.0581
Lo-Mendell-Rubin Adjusted Lrt Test	
Value	1166.628
P-Value	0.0595
Parametric Bootstrapped Likelihood Ratio Test For 2 (H0) Versus 3 Classes	
P-Value	0.0000

From the output file produced from the latent class analysis, classes were appropriately coded and the file was saved. The reconstructed student data file contained, in addition to the student's identification number, the probability scores of being in each class, along with their final assigned group. This last variable achieved the definitive placement of each student into one category of mental health, be it normal, borderline or abnormal. It optimised the available data and overcame the challenge of contradictory reports from multiple informants on multiple scales of mental health. It did this for all students and also dealt with the problem of missing data by avoiding the need to impute.

Composite student mental health Status

Through the use of LCA a new composite measure of student mental health status was created, which could then be used in conjunction with other variables for subsequent more refined analyses.

One immediately useful outcome of the analysis, shown in Figure 5, was the percentage of students in each group. The classification using LCA of students in the groups of abnormal (13%), borderline (28%) and normal (59%) mental health status provides an initial examination of student mental health. The results for students considered to be abnormal come close those reported by Sawyer and colleagues, of 13 to 21 per cent, mentioned at the beginning of this chapter.

However, Goodman's SDQ was based on norms of only 10 per cent of the Australian child population being abnormal, and another 10 per cent being considered borderline (Mellor, 2005). In comparison, the sample of 4970 10 year-old children participating in this study and based on the averaged parent and teacher SDQ categories, resulted 10 per cent of children considered borderline, but 15 per cent considered abnormal. One further comparison, which is clearly to be avoided, considers the sample with cases of non-agreement between parents and teachers removed. Under these conditions, the normal group was grossly inflated with only 2 per cent considered borderline and 8 per cent considered abnormal. Table 3 summarises the comparisons and suggests that LCA inflates the borderline group but better accounts for the differences between parent and teacher reports on multiple measures.

Table 3. A comparison of frequencies of students in normal, borderline and abnormal categories according to different assessments of mental health

Mental Health Scales	Normal	Borderline	Abnormal
Goodman's SDQ Norms (2005)	80%	10%	10%
Sample SDQ with non-agreement removed	90.49%	1.76%	7.75%
Sample SDQ with parent and teacher averaged	75.95%	9.53%	14.51%
Student Mental Health Status using LCA	58.90%	28.50%	12.60%

Further comparison between the identification of students based only on the SDQ total difficulties (parent and teacher versions) and the composite measure of student mental health are profiled against each of the mental health scales in Figure 6. By doing so, a character profile of the normal, borderline and abnormal groups can be compared and judgements made about how effectively the profiles reflect theoretical expectations of each group.

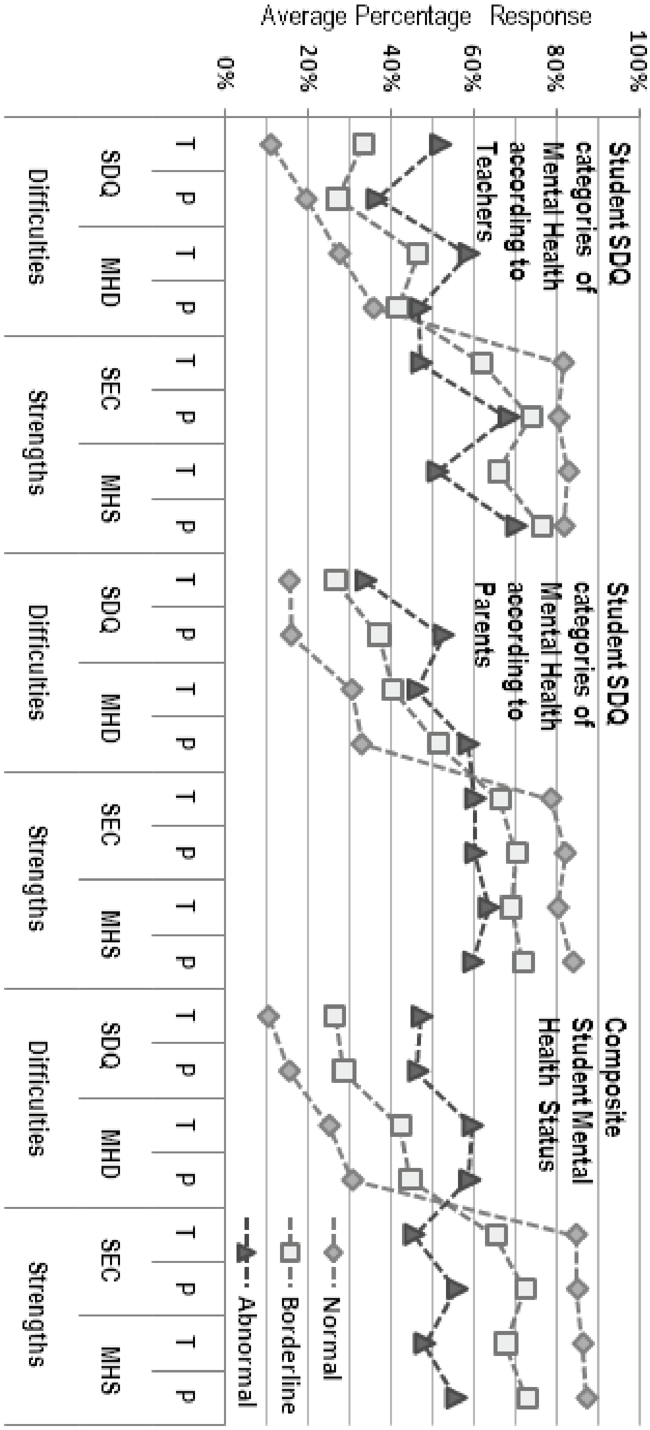

Figure 6. Profiles for the categories of mental health according to teacher and parent ratings on the SDQ only, compared with composite mental health status

One clear pattern across each method of categorisation, shown in Figure 6, is that students identified as being normal are reported as having the lowest difficulties and the highest strengths. Conversely, students identified as being abnormal tend to have the most difficulties and the fewest strengths. Those students identified as borderline, fall somewhere between the normal and abnormal groups. This general pattern matches our theoretical understanding of these groups. However, the agreement within measures provides a different perspective. While the profiles for the normal groups and, to a lesser extent, the borderline groups in each method of categorisation are similar, the profiles for the abnormal groups are markedly different. Those students identified as abnormal by parents and teachers based on SDQ difficulties alone, show characteristics of having more strengths than difficulties, similar in profile to the borderline groups. The separation between borderline and abnormal groups is less distinct for these SDQ-derived categories. In comparison, the general trend evident in the abnormal group, as defined by the composite measure of mental health, shown in the last set of Figure 6, presents a near-horizontal profile and achieves the greatest separation between the three groups. It would suggest that the composite measure better identifies students into their appropriate categories, since they reflect characteristics that more closely align to theoretical expectations. Accordingly, by using LCA and assessing student mental health status on dimensions of strengths as well as difficulties, in addition to bringing together multiple informant perspectives, results in the more accurate identification of students' mental health status. The importance of accurately assessing the number of children with mental health difficulties has ramifications for policy makers and the importance they place on initiatives such as KidsMatter. Potentially, it is the difference between whether 20 per cent of children stand to benefit from such initiatives, or twice that amount.

While the analysis presented in this chapter has resulted in a useful assessment of student mental health, there is need to further explore better ways to bring together multiple measures from multiple informants. For example, the use of categorical diagnostic constructs (normal, borderline, abnormal) resulted in loss of valuable information by regarding those who scored just below the diagnostic threshold as non-cases. Further analyses using MPlus will be undertaken that examine intact standardised scales at the subscale level to identify patterns in the differences between parent and teacher informants, in order to more accurately identify the underlying dimensions of students at risk of, or experiencing, mental health problems.

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