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Research Article

Examining the Model Structure of the Strengths and Difficulties Questionnaire (SDQ)

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Abstract. The Strengths and Difficulties questionnaire (SDQ), proposed by R. Goodman (1997), has been used by researchers to measure social, emotional and behaviour difficulties in children. The SDQ includes four difficulty subscales, measuring emotional, conduct, hyperactivity and peer problems. It also includes a fifth subscale, measuring prosocial behaviour. Dickey and Blumberg (2004) suggested that the SDQ factor structure can be reduced to three dimensions comprising the prosocial, externalisation and internalisation subscales. Externalising problems combine conduct and hyperactivity, while internalising problems combine peer and emotional difficulties. A sample of 5200 local students aged between 4 and 16 years was used to investigate the factor structure underlying the teachers' version of the SDQ. Statistical analysis was conducted using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The study finds that the three-factor solution fits the data well. EFA establishes good internal consistency of these three factors. Moreover, several fit indices confirm this three-factor model through CFA. The externalisation construct linking hyperactivity and conduct problems is more robust than the internalisation construct linking emotional to peer problems. Through SEM, it was deduced that the Externalisation Factor dominates both the Internalisation and the Prosocial Factors. This implies that by controlling externalized behaviour leads to a better control of internalized and prosocial behaviours of students.

Keywords: Social emotional and behaviour difficulties (SEBD), Exploratory Factor Analysis, Confirmatory Factor Analysis, Structural Equation Modeling

Abbreviations

(AGFI) Adjusted Goodness-of-Fit Index, (CFI) Comparative Fit Index, (GFI) Goodness of Fit Index, (IFI) Incremental Fit Index, (LISREL) Linear Structural Relations, (KMO) Kaiser Meyer Olkin, (MI) Modification Index, (MIMIC) Multiple Indicators and Multiple Causes, (NFI) Normed Fit Index, (NNFI) Non-Normed Fit Index, (RFI) Relative Fit Index, (RMSEA) Root Mean Square Error of Approximation, (PRELIS) Preprocessor for LISREL, (PCA) Principal Component Analysis.

1 Introduction

The SDQ, devised by R. Goodman (1997), is a screening tool aimed at identifying the prevalence of social, emotional and behaviour difficulties (SEBD) among children. The SDQ comprises five subscales that measure emotional, conduct, hyperactivity and peer problems, together with prosocial behaviour. Each subscale has five items, all measured on a 3-point scale ranging from 0 to 2, where 0 corresponds to 'Not True', 1 to 'Somewhat True' and 2 corresponds to 'Certainly True'. Five of the items are reverse-coded since they are negatively worded. The score of each subscale ranges from 0 to 10; while the total difficulty score, which excludes the prosocial subscale ranges from 0 to 40. There are three versions of the SDQ; one is administered by the teacher, one by the parent and the other is self-administered by the student. These three SDQ versions have been translated in several languages, including Maltese. Cefai, Cooper and Camilleri (2008) validated the Maltese SDQ version through a process of forward and backward translations. The Maltese and English versions of the SDQ were administered to a number of teachers, allowing a two-week period between the administrations of the two versions.

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The reliability of the Maltese SDQ version was measured item by item, where correlations ranged from 0.82 to 0.98.

Despite the strong clinical use of the SDQ worldwide, several studies yielded mixed results in its structural validity. A number of researchers (Becker, Woerner, Hasselhorn & Banaschewski, 2004; Hawes & Dadds, 2004; R. Goodman, 2001; Smedje, Broman, Hetta & von Knorring, 1999) supported the R. Goodman (1997) five-factor model, by using principal component analysis on a forced five-factor structure solution. They found that each item factor loading weighed heavily on one subscale and cross-loading across subscales was minimal. Other studies supporting the five-factor structure include Ruchkin, Koposov and Schwab-Stone (2007) using the Belgian parent and teacher informant version of the SDQ, Van Leeuwen and Tyukin (2006) using the Russian self-report version of the SDQ and Woerner, Becker and Rothenberger (2004) using the German parent informant version of the SDQ. On the other hand, contrasting results were observed when the number of factors was unspecified. A study carried out by Koskelainen, Sourander and Vauras (2001) reported a three-factor solution, using the self-report version of the SDQ among 1458 Finnish adolescents aged 13–17 years. This factor solution combined the conduct with the hyperactivity subscale and the emotional with the peer subscale to form the externalisation and internalisation dimensions, while the prosocial dimension was retained. This three-factor model structure was also supported by Dickey and Blumberg (2004), who administered the parent SDQ version to a sample of 9574 parents of American children and adolescents aged 4–17 years. The three-step analytic procedure included PCA, EFA and CFA. The authors acknowledge that their failure to replicate the predicted five-factor solution observed in European samples might be attributed to the fact that several items were modified to be more understandable to American parents and indicative of behaviours of their children. Mellor and Stokes (2007) remarked that the five-factor CFA structure did not lead to an acceptable model fit when using the Norwegian self-report version of the SDQ and the Australian parent and teacher informant version of the SDQ. A. Goodman and Goodman (2010) highlighted that 'there is theoretical and empirical support' for an alternative three-factor structure.

2 Theory

The main objective of this study is to analyse the factor structure underlying the rating scores provided to the 25 SDQ items by means of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). EFA accounts for patterns of correlations existing among the observable variables in terms of smaller number of latent variables. In other words, EFA identifies the latent traits that influence the rating scores provided to the items. Once the factor structure is determined by EFA, the CFA model is fitted to verify the pattern of the factor loadings, the number of underlying dimensions (factors) and any covariances between the factors. Once CFA confirms the latent structure, the SEM model is fitted to assess the relationships between the latent variables. SEM is a statistical technique that assesses unobservable latent traits. It includes a measurement model that defines latent constructs, using several observable variables and a structural model that assigns relationships between the latent variables. Kaplan (2000) describes SEM as 'a class of methodologies that represent the hypotheses involving the means, variances and covariances of the observed data in terms of a smaller number of structural parameters which are defined by means of a hypothesized underlying model'. The links between constructs of a structural equation model can be estimated using the statistical software AMOS or LISREL.

2.1 The Factor Model

Let $\mathbf{X}$ be a set of p observable random variables with mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$. Suppose that $\boldsymbol{\Lambda}$ is a $(p \times q)$ matrix of factor loadings, $\boldsymbol{\eta}$ is a q-random vector of latent factors and $\boldsymbol{\varepsilon}$ is a p-random vector of error terms. If $q < p$, the q-factor model holds for $\mathbf{X}$ and is given by:

$$\mathbf{X} - \boldsymbol{\mu} = \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon}. \tag{1}$$

The following assumptions are imposed on $\boldsymbol{\eta}$ and $\boldsymbol{\varepsilon}$

$$\begin{aligned} &E(\boldsymbol{\eta}) = E(\boldsymbol{\varepsilon}) = \mathbf{0} \\ &\operatorname{Var}(\boldsymbol{\eta}) = \mathbf{I} \text{ and } \operatorname{Var}(\boldsymbol{\varepsilon}) = \boldsymbol{\Psi} \end{aligned} \tag{2}$$

where $\boldsymbol{\Psi}$ is a diagonal matrix with diagonal elements ψ_{ii} and $\mathbf{0}$ is the null vector/matrix. Under an EFA model, $\boldsymbol{\Sigma}$ is related to $\boldsymbol{\Lambda}$ and $\boldsymbol{\Psi}$ by:

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}\boldsymbol{\Lambda}' + \boldsymbol{\Psi}. \tag{3}$$

Consequently, the variance of $\mathbf{X}$ can be divided into two parts. One component includes the variance explained by the factors and the other includes the unexplained variance. If σ_{ii} is the variance of random variable X_i and $\lambda_{ij} = [\boldsymbol{\Lambda}]_{ij}$, then:

$$\sigma_{ii} = \sum_{j=1}^{q} {\lambda_{ij}}^2 + \psi_{ii}. \tag{4}$$

where $\sum_{i=1}^{q} {\lambda_{ij}}^2$ known as the communality, give the variance of X_i which is shared with the other variables through the common factors, while the specific variance ψ_{ii} explains the variability of X_i which is not shared with the other variables. Moreover, ${\lambda_{ij}}^2 = \mathrm{Cov}\,(X_i, \eta_j)$ which shows the extent to which the i^{th} observable random variable X_i depends on η_j.

2.2 The Structural Equation Model

The general Structural Equation Model comprises two models: the measurement model and the structural model. The former model is obtained using CFA; while the latter model is obtained through SEM. CFA tests how well the observable variables represent the smaller number of latent constructs. CFA confirms both the number of the underlying dimensions of the factors and the pattern of the factor loadings obtained at the exploratory stage. The main steps involved in conducting CFA are *model specification*, *model identification*, *model estimation*, *model evaluation* and if needed, *model re-specification.* The CFA model is defined as:

$$\mathbf{X} = \boldsymbol{\xi}\boldsymbol{\Lambda}_{\mathbf{X}} + \boldsymbol{\delta} \tag{5}$$

where $\mathbf{X}$ represents the vector of observed variables, $\boldsymbol{\xi}$ is the vector of latent variables, $\boldsymbol{\Lambda}_{\mathbf{X}}$ is a matrix of coefficients which describe the influence of the latent variables on the observed variables, and $\boldsymbol{\delta}$ is the vector of measurement errors. By convention, all variables in $\mathbf{X}$ and $\boldsymbol{\xi}$ of model (5) are assumed to be written as deviations from their means. Also, $\boldsymbol{\delta}$ is deemed to be uncorrelated with and it is also assumed that $E\,(\boldsymbol{\delta}) = \mathbf{0}$ and $E\,(\boldsymbol{\xi}\boldsymbol{\delta}') = \mathbf{0}$.

Each column of $\boldsymbol{\Lambda}_{\mathbf{X}}$ provides the factor loadings of a particular latent variable and the element $\lambda_{ij} = [\boldsymbol{\Lambda}_{\mathbf{X}}]_{ij}$ specifies the load of the i^{th} variable on the j^{th} factor. Under a CFA model, the variance-covariance matrix of $\mathbf{X}$ takes the form:

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}_{\mathbf{X}}\boldsymbol{\Phi}{\boldsymbol{\Lambda}_{\mathbf{X}}}' + \boldsymbol{\Theta}_{\boldsymbol{\delta}} \tag{6}$$

where $\boldsymbol{\Phi}$ is the variance-covariance matrix of the latent factors $\boldsymbol{\xi}$ and $\boldsymbol{\Theta}_{\boldsymbol{\delta}} = E\,(\boldsymbol{\delta}\boldsymbol{\delta}')$ is the variance-covariance matrix of the measurement errors $\boldsymbol{\delta}$. If the parameters are known and the model is correct, the population variance-covariance matrix will be reproduced exactly.

The model presented in (5) takes into account only one set of latent variables $\boldsymbol{\xi}$. In practice, we may have both exogenous and endogenous latent variables. An exogenous variable is an alternative way of referring to an exploratory variable. A variable is exogenous if its causes lie outside the model, that is, it is not caused by some other variable in the model. A variable is endogenous if it is determined by variables within the model; however it is only partially explained by the model. If both types of latent variables are taken into account then model (5) has to be redefined to include the endogenous variables $\boldsymbol{\eta}$. Let $\mathbf{Y}$ represent the p-vector of observed dependent variables. The measurement model for $\mathbf{Y}$ is given by:

$$\mathbf{Y} = \boldsymbol{\Lambda}_{\mathbf{Y}}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{7}$$

where $\boldsymbol{\eta}$ is a an m-vector of endogenous latent variables, $\boldsymbol{\Lambda}_{\mathbf{Y}}$ is a $(p \times m)$ matrix of model coefficients relating $\boldsymbol{\eta}$ and $\mathbf{Y}$ and $\boldsymbol{\varepsilon}$ is a p-vector of errors terms for $\mathbf{Y}$. By convention, all variables in $\mathbf{Y}$ and $\boldsymbol{\eta}$ of model (6) are assumed to be expressed as deviations from their means. It is also assumed that $\boldsymbol{\varepsilon}$ is uncorrelated with $\boldsymbol{\eta}$ and that $E\,(\boldsymbol{\varepsilon}) = \mathbf{0}$ and $E\,(\boldsymbol{\eta}\,\boldsymbol{\varepsilon}') = \mathbf{0}$. The variance-covariance matrix of $\mathbf{Y}$ takes the same form as (6). The structural equation for the latent variable model is given by:

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{8}$$

where $\boldsymbol{\eta}$ is an m-vector of latent endogenous variables, $\boldsymbol{\xi}$ is a n-vector of latent exogenous variables, $\boldsymbol{\Gamma}$ is an $(m \times n)$ coefficient matrix for the latent exogenous variables, $\mathbf{B}$ is an $(m \times m)$ coefficient matrix for the latent endogenous variables and $\boldsymbol{\zeta}$ is an m-vector of errors (disturbances). There are a number of assumptions underlying the structural model defined in (8). One of the model assumptions is that the matrix $(\mathbf{I} - \mathbf{B})$ exists and is non-singular. Two other assumptions are that the error terms ζ_is are uncorrelated with the exogenous variables in $\boldsymbol{\xi}$ and that $E\,(\zeta_i) = 0$. Another underlying assumption of the structural model is that ζ_i is homoscedastic and not auto-autocorrelated. The structural model comprises two variance-covariance matrices: $\boldsymbol{\Phi}$ is an $(n \times n)$ variance-covariance matrix of the latent exogenous variables $\boldsymbol{\xi}$ and $\boldsymbol{\Psi}$ is an $(m \times m)$ variance-covariance matrix of the error terms $\boldsymbol{\zeta}$.

3 Methodology

To carry out this study, a random sample of 1326 teachers was selected from 110 schools, of which 66 were primary and 44 were secondary schools, to investigate the social emotional and behaviour difficulties of 5200 students, using the teacher SDQ version. The random sample, which was collected in 2005–2006, comprised around 7% of the whole Maltese student population aged 6–16 years. To guarantee a representative sample, the students were stratified by gender, school-level, school-type and school region. The teachers were asked to assess the children under their supervision on each of the 25 items of the Maltese SDQ teacher version.

The five items related to emotional difficulties assessed anxiety, depression, fear and unhappiness. The five items related to hyperactivity assessed restlessness, inattention, distraction, over-activity and inability to finish work. The five items related to conduct problems assessed ill-temper and behaviour problems such as fighting, cheating, lying and stealing. The five items related to peer problems assessed poor relations with peers, bullying and loneliness and the five items related to prosocial behaviour assessed good qualities, such as being considerate, helpful, caring and kind to others.

After reverse-coding the five negatively worded items, the data was analysed using the facilities of the statistical software SPSS and LISREL. Cefai et al. (2008, 2009), Cefai and Camilleri (2011) estimate the prevalence of SEBD in Malta and identify the risk factors associated with social, emotional and behaviour difficulties. The studies revealed that according to teachers, 81.7% of the students had no to mild social emotional problems, 8.6% had moderate SEBD and the remaining 9.7% had severe difficulties. Males scored significantly higher than females in conduct and hyperactivity problems; whereas females scored significantly higher than males in emotional difficulties and prosocial behaviour. Moreover, the study shows that children with poor attainment and learning difficulties, who have health problems and receive psychological/educational interventions, are more likely to show SEBD problems. To accommodate the hierarchical structure of the data, where students are nested in classroom, which in turn are nested in schools, Camilleri, Cefai and Cooper (2011) use multilevel modelling to identify the significant risk factors of SEBD.

4 Data Analysis and Results

The aim of this paper is to confirm the 3-factor models using the teacher SDQ data collected in 2005–2006. Exploratory Factor Analysis, Confirmatory Factor Analysis and Structural Equation Modelling are used to identify the best model fit.

4.1 Internal Consistency

Cronbach Alpha (Cronbach, 1951) was utilised to assess the internal consistency of the items within every subscale. The items in the Conduct, Hyperactivity, Emotional and Prosocial subscales have satisfactory internal consistency and their Cronbach Alpha exceeded the 0.7 threshold values. The Peer subscale had a weak internal consistency, since its Cronbach Alpha just exceeded the 0.5 threshold. The item *Child gets on better with adults than children of same age* was weakly related to other items in this subscale.

4.2 Exploratory Factor Analysis

Exploratory Factor Analysis was used to assess the factorial validity of the whole SEBD data and to identify the number of latent dimensions underlying this dataset. Firstly, the Kaiser Meyer Olkin (KMO) measure of sampling adequacy was computed and Bartlett's test of sphericity was carried out to establish the presence of a latent structure. The KMO value, which gives an indication of the relative compactness of the correlations, was equal to 0.898, which exceeds the 0.5 threshold value. The Bartlett's test of sphericity, which tests whether the correlation matrix is significantly different from the identity matrix, yielded a p-value less than the 0.05 level of significance. Both results indicate a latent structure within the SEBD data and that EFA is essential to reveal this latent factor structure.

EFA was then carried out through the facilities of SPSS, using maximum likelihood estimation and Varimax rotation. This orthogonal rotation of the factor axes normally makes it easier to identify each observable variable with a single factor. The Kaiser's eigenvalue greater than 1 rule (Kaiser, 1960) and the scree plot identified three underlying factors. Since the rating scores are ordinal categorical responses, polychoric correlations are more appropriate to assess the relationships between the observable items than Pearson correlations. Consequently, the PRELIS interface available in the statistical software LISREL was used to compute the polychoric correlations of this dataset. The polychoric correlations ranged from 0.378 to 0.859 for the Emotional subscale items, 0.340 to 0.646 for the Hyperactivity subscale items, 0.320 to 0.728 for the Conduct subscale items, 0.080 to 0.534 for the Peer subscale items and 0.576 to 0.681 for the Prosocial subscale items. Undoubtedly, the Peer construct is the weakest structure; however, the Chi square test shows that most of the polychoric correlations are significantly different from 0. Moreover, the RMSEA values which assess the normality assumption of the underlying bivariate distributions are small and do not exceed 0.1, which implies no complications due to non-normality.

Violation of the bivariate normality assumption between two variables can cause complications in estimation if the RMSEA value exceeds 0.1 (Jöreskog & Sörbom, 2001). Analysis on the SEBD data shows that only two RMSEA values exceed 0.1, which include *Kind to kids* and *Caring* (0.118), *Kind to kids* and *Shares with others* (0.103). Thus CFA and SEM procedures were based on polychoric correlations.

The next step consisted in conducting EFA using the MINRES facility implemented in software LISREL (version 8.80), by fitting a three-factor model to the dataset using *varimax rotation.* Table 1 displays the factor loadings of this three-factor model. Stevens (2002) suggested a threshold value of 0.4 for these factor loadings when the sample size exceeds 150 observations and the number of variables exceeds 10. Factor 1, which represents the Externalisation dimension, comprises nine of the items in the Hyperactivity and Conduct subscales, including *Tempers*, *Obedient*, *Fights*, *Lies*, *Restless*, *Distractible*, *Fidgety*, *Reflective* and *Persistent.* The item *Steals from home, school or elsewhere*, which was included in the R. Goodman (1997) Conduct subscale, does not feature in the above Externalisation dimen-

Table 1: The factor loadings of three factors obtained through Varimax Rotation

Variable Description	External-isation Factor	Prosocial Factor	Internal-isation Factor
Tempers	**0.54**	0.20	0.08
Obedient	**0.56**	0.27	0.10
Fights	**0.62**	0.21	-0.01
Lies	**0.55**	0.27	0.09
Steals	0.22	0.12	0.11
Somatic	0.21	0.03	0.38
Worries	−0.04	−0.05	**0.62**
Unhappy	0.16	0.08	**0.60**
Clingy	0.12	0.06	**0.60**
Fears	-0.03	0.04	**0.67**
Restless	**0.77**	−0.04	−0.07
Fidgety	**0.80**	0.01	0.01
Distractible	**0.60**	0.20	0.27
Reflective	**0.54**	0.35	0.15
Persistent	**0.48**	0.31	0.27
Solitary	−0.11	0.25	**0.45**
Good Friend	0.05	0.25	0.22
Popular	−0.03	0.39	0.28
Bullied	0.09	0.12	**0.42**
Best with adults	0.12	−0.02	0.20
Considerate	−0.34	**−0.67**	−0.01
Shares	−0.20	**−0.64**	−0.06
Caring	−0.18	**−0.69**	−0.03
Kind to kids	−0.24	**−0.61**	−0.02
Helps out	−0.21	**−0.66**	−0.05

sion. This may be partly attributed to the fact that teachers are not aware of what children do at home. In fact, the vast majority of the teachers disagreed with this item, irrespective of the child's behaviour at school. Factor 2, which comprises all the items in Prosocial subscale, includes *Considerate*, *Shares*, *Caring*, *Kind to kids* and *Helps out*. Undoubtedly, the Prosocial construct is the stronger structure. Factor 3, which represents the Internalisation dimension, comprises six of the items in the Emotion and Peer subscales, including *Worries*, *Unhappy*, *Clingy*, *Fears*, *Solitary* and *Bullied*. The items *Has at least one good friend*, *Liked by other people of same age*, *Gets a lot of headaches stomach aches* and *Gets on better with adults than children of same age* which were included in the R. Goodman (1997) Peer and Emotion subscales, do not feature in the above Internalisation dimension. The items were the least related to other items in their respective subscales.

4.3 Confirmatory Factor Analysis (CFA)

A three-factor CFA model was then fitted to the whole SEBD sample, using the Weighted least squares (WLS) estimation technique. This is the appropriate estimation technique when analysing ordinal categorical responses (rating scores). The fitted model defines the relationships between the Externalisation, Prosocial and Internalisation dimension, whilst relaxing some of the assumptions posed in EFA. Various models were tested. Once a model was specified, the t-rule was used to assess whether the model is identified. Since the t-value for the model fit was 43, which is less than the $0.5q(q+1) = 210$ criterion, then the three-factor CFA model has model identification.

The model parameters were estimated, followed by a quality check of the model fit. The chi-square value, corrected for non-normality, did not satisfy its threshold criterion. With 165 degrees of freedom, the chi-square value (3362.7) yielded a very small p-value (less than 0.0001), which implies that the specified CFA model is not supported by the sample variance-covariance matrix. It should be noted, however, that the chi-square statistic inflates considerably with an increase in the sample size and is not useful for large data sets (Schumacker & Lomax, 2004). Moreover, most of the fit indices did not exceed their threshold values. According to Steiger (2007), Hu and Bentler (1999), Mac Callum, Browne and Sugawara (1996), Klein (2005), a good fit is achieved if CFI ≥ 0.95, TLI ≥ 0.90, RMSEA ≤ 0.06, GFI ≥ 0.90, NFI ≥ 0.95 and SRMR ≤ 0.07; an acceptable fit is achieved if CFI ranges between 0.90 and 0.95 and RMSEA ranges between 0.06 and 0.08.

To improve the model fit, a number of paths were added to the CFA model. The modification of indices (MI) facility, available in LISREL, displays the change in the chi square value when the model fit is modified. The first modification was the addition of an error covariance in the path diagram between the observed variables *Fidgeting* and *Restless*. These two terms have a similar meaning and are often interchanged inadvertently in speech. The corresponding MI value (345.6) is large and may indicate that these two observed variables may produce a sub-dimension within the Externalisation dimension. The second modification was the inclusion of an error covariance in the path diagram between the observed variables *Bullied* and *Solitary*. The corresponding MI value (120.3) is large, indicating a strong perceived link between bullied and solitary students. The three-factor CFA model was re-fitted using these two modifications. The t-value for the best model fit was 45, which is less than the $0.5q(q+1) = 210$ criterion, implying that this fitted three-factor CFA has model identification. The resulting parameter estimates of lambda-x, phi-paths and theta-deltas were all found to be significant since the corresponding z-scores exceed 1.96 for all observed variables.

Figure 1 displays the path diagram and corresponding WLS estimates of the three-factor CFA model. The path diagram shows the relationships between the three dimensions (Externalisation Internalisation and Prosocial factors) and their relationships with the twenty observed items.

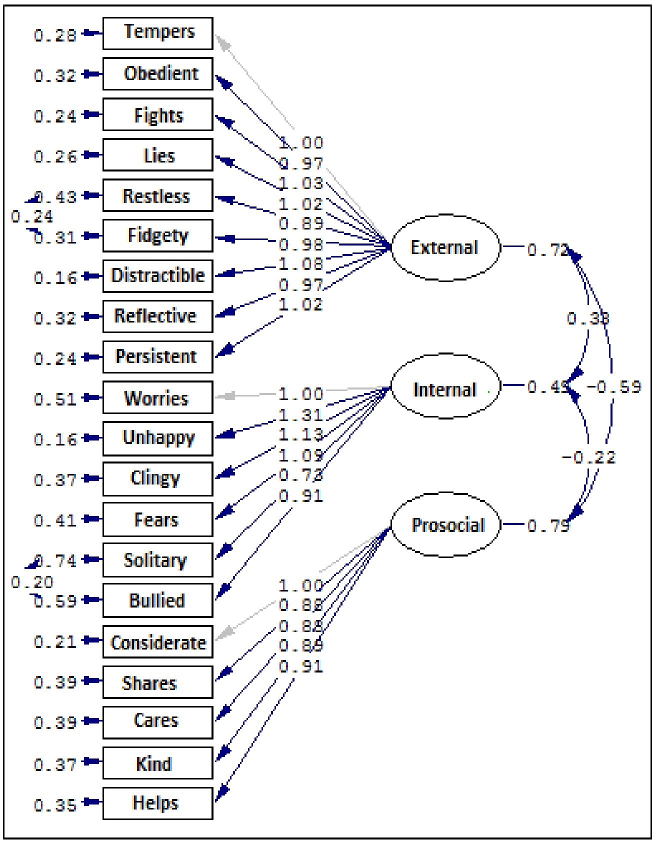

Figure 1: Path diagram of the three-factor CFA Model 1.

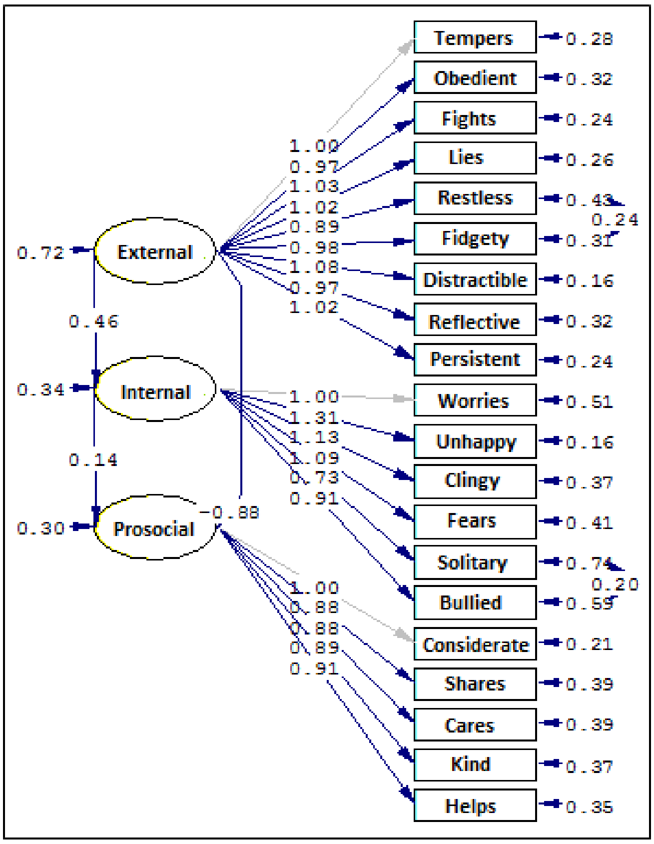

Figure 2: Path diagram of the three-factor SEM Model 2.

The Externalisation factor respectively explained 84%, 77%, 76%, 74% and 71% of the variances of the items *Distractible*, *Fight*, *Persistent*, *Lies* and *Tempers*. The Internalisation factor explains 91% of the variance of the item *Unhappy* and the Prosocial factor explains 79% of the variance of the item *Considerate*. The majority of the standardized factor loadings exceed 0.7, indicating that the latent factors strongly affect 18 of the observed variables and moderately affect the remaining 2 items: *Solitary* and *Bullied*. Furthermore, the CFI (0.93), GFI (0.98), AGFI (0.97), NFI (0.92), NNFI (0.92), IFI (0.93) and RFI (0.91) all exceed their threshold values indicating a well-fitted model. Moreover, the Hoelter's Critical N (393.5) exceeds the 200 cut-point and the RMSEA value (0.06) is less than the 0.07 threshold value suggested by Steiger (2007). All these fit indices satisfy their threshold criteria, which indicate that this three-factor CFA model (Model 1) fits the data well.

4.4 Structural Equation Modeling (SEM)

A three-factor structural equation model was also fitted on the dataset using LISREL to investigate the relationships between the latent variables. Essentially, this involves regressing latent variables on one another.

Figure 2 displays the path diagram of this three-factor SEM model, which displays the relationships between the three factors (Externalisation, Internalisation and Prosocial) and their relationships with the 20 observed items. Once the model is specified, the t-rule was used to check that the three-factor SEM has model identification. The model parameters were estimated using a weighted least squares estimation procedure. The corresponding factor loadings, phi-paths and theta-deltas estimates are all significant since their standard errors are less than half the value of the parameter estimates. Although in the final SEM the direct effect of the Externalisation factor on the Prosocial factor is strongly negative, there is an indirect positive effect through the Internalisation factor. Consequently, the total effect of the Externalisation factor on the Prosocial factor is equal to $-0.816\,(-0.88 + 0.46 \times 0.14)$. This implies that students who score high on externalising behaviour problems tend to score low on prosocial behaviour.

Figure 3 displays the completely standardized solution of the three-factor SEM model. Since none of these standardized estimates exceeds 1 in absolute value, then the solution is deemed to be acceptable. The CFI (0.92), GFI (0.98), AGFI (0.97), NFI (0.92), NNFI (0.91), IFI (0.92) and RFI (0.91) all exceed their threshold values

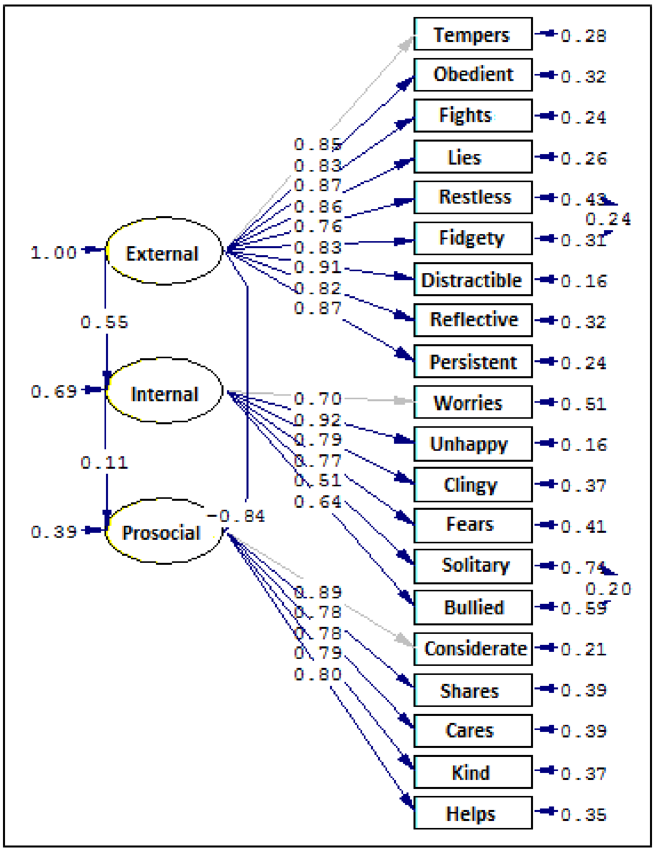

Figure 3: Standardised solution of the three-factor SEM Model.

by a small margin indicating a plausible fit. Furthermore, the Hoelter's Critical N (325.96) exceeds the 200 cut-point and the RMSEA value was (0.061) which is less than the 0.07 threshold value suggested by Steiger (2007). Although the SRMR value (0.18) exceeds the 0.1 criterion, it is still fairly close to 0. The chi-square value for the three-factor SEM model corrected for non-normality does not satisfy its threshold criterion, since the p-value is less than 0.05. However, this result will be ignored in light of the favourable results obtained from the various fit indices and the fact that large samples tend to yield large chi-square values. These results indicate that this three-factor SEM model fits the data well and achieves an acceptable level of construct validity.

The percentage variation of the Internalisation factor explained by the Externalisation factor is 31%, and the percentage variation of the Prosocial factor explained by the Externalisation and the Internalisation factors is 61%. The Externalisation factor respectively explains 84%, 76%, 76%, 74% and 72% of the variances of the items *Distractible*, *Fight*, *Persistent*, *Lies* and *Tempers*. The Internalisation factor explains 84% of the variance of the item *Unhappy* and the Prosocial factor explains 79% of the variance of the item *Considerate*. Moreover, Figure 3 shows that the Externalisation factor has a strong negative influence on the Prosocial factor (−0.84), which implies that children with externalising behaviour problems are less likely to display prosocial behaviour. Conversely, the Externalisation factor has a positive influence on the Internalisation factor (0.55), which implies that children with externalising behaviour problems are more likely to exhibit internalising behaviour problems. The Internalisation factor has a weak positive influence on the Prosocial factor (0.11), which may indicate that children with internalising behaviour problems tend to be more prosocial than children with externalising behaviour problems.

5 Conclusion

The study supports the three-factor structure model for the SDQ. Cronbach Alpha indicates good internal consistency between the items describing the Emotion, Conduct, Hyperactivity and Prosocial subscales; however, items of the Peer subscale have weak internal consistency. The KMO value and Bartlett's test support the use of factor analysis to identify latent structures within the data. The Kaiser's eigenvalue greater than 1 rule suggested a three-factor model. Moreover, a scree plot displaying the eigenvalues of all components plotted in descending order showed a scree elbow at the fourth component, complementing a three-factor rather than a five-factor model. The three latent factors, which were identified using EFA, load heavily on the items of the Externalisation, Internalisation and Prosocial dimensions. CFA confirms that the three-factor model provides a better fit to the data than the five-factor model proposed by R. Goodman (1997). The Externalisation dimension combines all the items of the Conduct and Hyperactivity subscales, excluding the item '*steals from home, school or elsewhere*'. The Internalisation dimension combines all the items of the Peer and Emotion subscales, excluding the items '*disliked by children of the same age*', '*gets on better with adults than with children of the same age*', '*Gets a lot of headaches stomach aches*' and '*has no good friends*'. On the other hand, the items of the Prosocial dimension were all retained.

SEM investigates the relationships between the three dimensions and identifies the Externalisation dimension as the dominant factor. SEM also reveals that the Externalisation dimension has a strong negative influence on the Prosocial dimension and a strong positive influence on the Internalisation dimension. The influence of the Internalisation dimension on the Prosocial dimension is weakly positive. These results clearly suggest that by targeting student externalisation behaviour problems, teachers and educators could be more effective in reducing student internalising behaviour problems and enhance prosocial attitudes in both primary and secondary schools.

CFA and SEM models ignore the nested hierarchical structure of the data where students are nested in classrooms, which are nested in schools. A recommendation for future research is to fit a multilevel structural equation model that accommodates both the hierarchical nested structure of the data, but also caters for the latent factor structure in the data. Another recommendation is to include student, classroom, school and home predictors in the model. Chih-Chien (2005) showed how MIMIC (*Multiple Indicators and Multiple Causes*) models can be used to serve this purpose because they accommodate both latent variables and explanatory variables.

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