ORIGINAL ARTICLE

MOTIVATION AND ENGAGEMENT LEVELS OF LEARNING IN EARLY ADOLESCENTS FROM LOW SOCIO-ECONOMIC DISTRICTS IN SRI LANKA

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Abstract

This study tried to find out the levels of motivation and engagement among early adolescents. Motivation and Engagement Scale-Junior School (MES-JS) was employed to collect data and the confirmatory factor analysis (CFA) was employed to measure the construct validity of the scale in relation to two low socio-economic districts. But it did not give a robust factor solution. Then, it was decided to conduct exploratory factor analysis (EFA). This paper aimed to investigate the EFA procedures conducted to derive a robust factor solution. MES-JS was administered among 100 Sinhala and 100 Tamil-medium eighth grade students (50 students from each gender) selected through the stratified random sampling method. Schools were represented by type 2 government schools which have the lowest achievement rates located in the Monaragala and Nuwara Eliya districts in Sri Lanka because they represented low socio-economic districts in Sri Lanka. The stratum used to select the students was based on the students' ethnicity, gender, and the number of classes in Grade 8 in each school. This study used the PCA method of extraction to determine the final factor solution. The method used was the scree test in combination with eigenvalues to decide the number of factors to retain. The EFA analyses derived four factors in relation to early adolescents' motivation and engagement in learning in two low socio-economic Sri Lankan districts. With an accurate and useful description of the underlying construct and with the theoretical meaning of the items in those factors, factors were named as "Failure Avoidance and Anxiety" (FAA), "Positive Motivation" (PM), "Uncertain Control" (UC), and "Positive Engagement" (PE). Further analyses should be employed using these newly derived factors to identify low socio-economic Sri Lankan early adolescents' motivation and engagement in learning. Accordingly, those identified four factors will contribute to understand of motivation and engagement among early adolescents in low socio-economic districts as those were derived considering the characteristics of those students through the EFA.

Keywords: Confirmatory Factor Analysis, Early adolescents, Engagement, Exploratory factor analysis, Low socio-economic districts, Motivation

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Introduction

Even though the Sri Lankan Government provides support for students at all levels of the school system, for example, free education, textbooks, school uniforms, subsidised public transportation and school meals, low participation in learning among secondary students is an issue warranting investigation, particularly in low socio-economic areas. Reports from the Central Bank of Sri Lanka (2015, 2016)[1,2], Ministry of Education (2011, 2014)[3,4] and Ministry of Education, UNICEF, and MG Consultants (2009)[5] suggest that this trend will continue unless schools radically shift their educational approaches and support for junior secondary students. This study investigated the levels of motivation and engagement amongst students in a number of schools in two low socio-economic districts of Sri Lanka. It investigated whether school-related conditions impact early adolescents' motivation and engagement in learning in low socio-economic districts in Sri Lanka, and, if so, what changes might be undertaken to remedy this situation.

Accordingly, low participation in learning of secondary students is a matter affirmed by examination, mostly in low socio-economic districts in Sri Lanka. One of the central factors contributing to this situation may be students' motivation and engagement in learning. The objective of this study is to develop a validated scale that would allow the measurement of early adolescents' motivation and engagement in learning in two low socio-economic Sri Lankan districts' school contexts.

Study Area

Motivation and Engagement Scale-Junior School

MES-JS measures primary and secondary school students' (ages 9-13) motivation and engagement to learn. In this study, the MES-JS (Martin, 2014)[6]was used to identify the least motivated and engaged students. After identifying them, school-related conditions impacting motivation and engagement in learning through the SDT perspective (intrinsic motivation) were examined.

Martin (2014a)[7] notes there have been a number of conceptual offerings to the study of motivation and engagement. Among the more dominant theories are attribution theory, self-worth motivation theory, need achievement theory, control theory, self-efficacy theory, expectancy-value theory, SDT and motivation orientation theory. The principle rationale for forming MES-JS (Martin, 2014)[6] was to incorporate a number of academic viewpoints and develop a structure that is actionable by teachers and understandable for students.

A framework that reproduces those theories is illustrated in Figure 1.

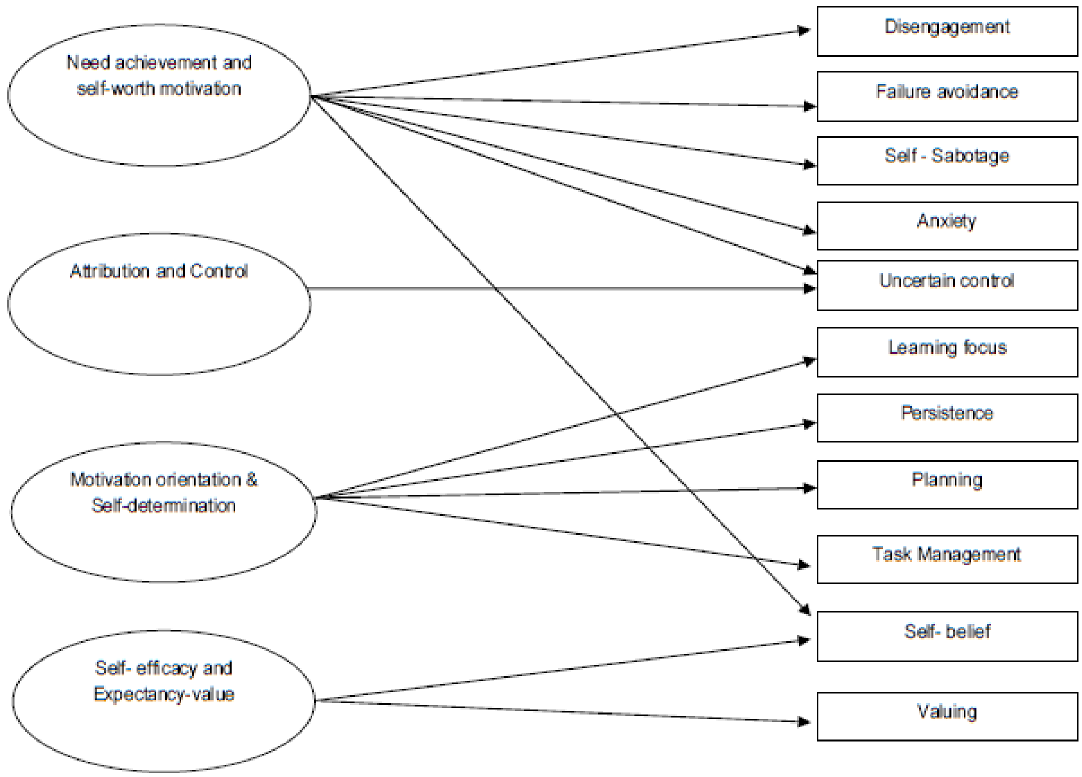


Figure 1. Central theoretical perspectives and associated constructs Adapted from Martin (2014a, p. 29)[7].

Martin (2014a)[7]noted that the second step in the formation of a measure was to propose a simple separation of measures into factors. These are called *boosters* (or adaptive dimensions), *mufflers* (or impeding/maladaptive dimensions), and *guzzlers* (or maladaptive dimensions). Boosters are consistent with booster thoughts and booster behaviours. Booster thoughts are consistent with self-belief, valuing and learning focus. Booster behaviours are consistent with planning, task management and persistence. Mufflers are consistent with anxiety, uncertain control and failure avoidance, while guzzlers are consistent with self-sabotage and disengagement.

On this scale, categories of scores centre on: (1) self-belief, valuing, and learning focus (booster thoughts); (2) planning, task management, and persistence (booster behaviours); (3) anxiety, failure avoidance, and uncertain control (mufflers); and (4) self-sabotage and disengagement (guzzlers). Accordingly, the MES-JS (Martin, 2014) measures six motivation and engagement boosters, three mufflers and two guzzlers; altogether, 11 factors are measured. Each of the 11 factors consists of four items, making up a 44-item Likert scale-type tool. For every item, students assess on a level of 1-'Disagree strongly', 2-'Disagree', 3-"Neither agree nor disagree', 4-'Agree' and 5- 'Agree strongly'.

Boosters are the thoughts and behaviours that reflect enhanced motivation and engagement in learning. They comprise self-confidence, a view that school is significant, being centred on learning, scheduling schoolwork, and trying hard. Motivation and engagement mufflers refer to constrained or impeded motivation and engagement. Motivation and engagement guzzlers refer to condensed motivation and engagement. Taken together, these boosters, mufflers and guzzlers comprise the Motivation and Engagement Wheel (Martin, 2003, 2005, 2007, 2009, & 2010)[8,9,10,11,12] as illustrated in Figure 2.

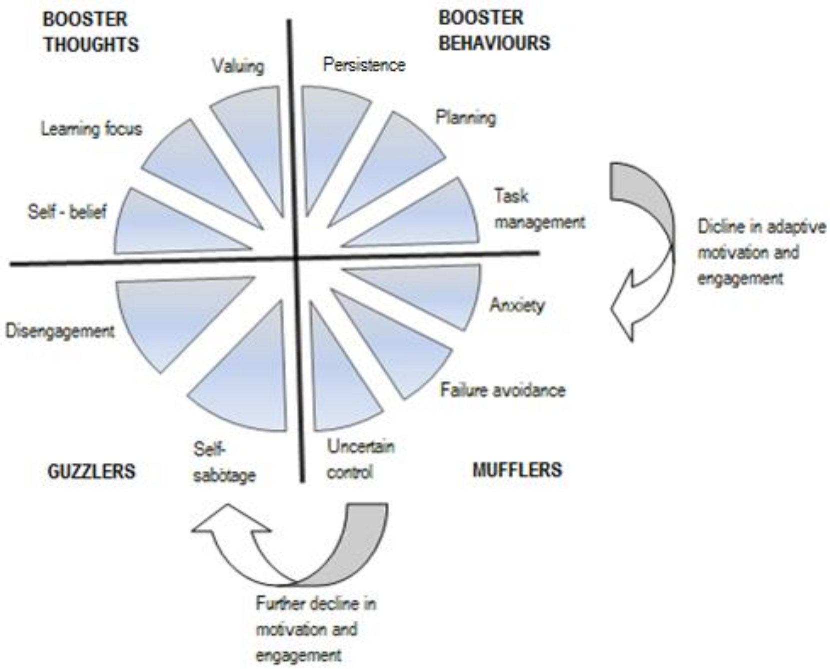


Figure 2. Motivation and engagement wheel Adapted from Martin (2014a, p. 31)[7].

Researchers can use the wheel with regard to the situational demands of the research project (Martin, 2014)[6]. Therefore, in this research, the wheel was considered in terms of motivation and engagement. Accordingly, booster thoughts equate to positive motivation, booster behaviours equate to positive engagement, mufflers equate to negative motivation and guzzlers equate to negative engagement.

Materials and Methods

This study tried to find out the levels of motivation and engagement among early adolescents. Motivation and Engagement Scale-Junior School (MES-JS) was employed to collect data and the confirmatory factor analysis was employed to measure the construct validity of the scale in relation to two low socio-economic districts. But it did not give a robust factor solution. Then, it was decided to conduct exploratory factor analysis (EFA). This paper aimed to investigate the initial CFA procedures and then EFA procedures conducted to derive a robust factor solution. MES-JS was administered among 100 Sinhala and 100 Tamil-medium eighth grade students (50 students from each gender) selected through the stratified random sampling method. Schools were represented by type 2 (Classes conducted up to Grade 10) government schools located in the Monaragala and Nuwara Eliya districts in Sri Lanka. For this study, the type 2 government schools chosen were those in the Monaragala and Nuwara Eliya districts in Sri Lanka because they represented both Sinhala-medium and Tamil-medium schools. Students who were studying in the eighth grade in the selected schools were included in the target population. Eighth grade students were elected purposively for three reasons: (1) the study was based on early adolescent students and eighth-graders are at that particular stage; (2) the majority of the students in those areas leave the school at eighth or ninth grades; (3) the MES-JS was designed for students in the 9-13 age range and the average age of students in this study was 12.8 years. The stratum used to select the students was based on the students' ethnicity, gender and the number of classes in Grade 8 in each school.

Results and Discussion

Conducting confirmatory factor analysis

Psychometric property assessment is an important element in quantitative research development, particularly where existing surveys and questionnaires are applied in different socio-cultural contexts. Accordingly, this research paid particular attention to the importance of construct validity.

The MES-JS has 11 second-order factors (self-belief, valuing, learning focus, planning, task management, persistence, anxiety, failure avoidance, uncertain control, self-sabotage, and disengagement) and four first-order factors (positive motivation (PM), positive engagement (PE), negative motivation (NM), and negative engagement (NE)). Griffiths et al. (2022) indicate that "CFA allows researchers to gain an understanding as to how much of the variance in a transition item is accounted for by the change in the underlying trait they are attempting to measure" (p.37)[13]. Therefore, CFA was conducted for the model based on those lower order and higher order factors using the statistical software package SPSS-Amos 24. It should be noted that CFA was conducted for the full sample, and it was not conducted for the two cultural groups as the sample size was not adequate.

Determination of a model fit is made by examining the standardised regression weights, which should be a minimum of 0.5 (Hair, Anderson, Tatham, & Black, 2006)[14] and an assessment of the minimum threshold values of the different goodness-of-fit index values available (Hooper, Coughlan, & Mullen, 2008)[15]. The tests and threshold values used are shown in Table 1.

Table 1
Tests and goodness of fit requirements for survey CFA

Goodness of Fit Test	Threshold Value
Ratio between chi-squared and degree of freedom ($\chi 2$ /d*f*)	~ 2.0
Comparative Fit Index (CFI)	0.90
Tucker-Lewis Index (TLI)	0.90
Root mean square error of approximation (RMSEA)	0.80
Standardised root mean square residual (SRMR)	0.06

The PM factor model is illustrated in Figure 3 and shows a poor model fit, as indicated by the following goodness-of-fit index values: $\chi 2$ /d*f*= 4.14, CFI= .79, TLI= .73, RMSEA= .120, and SRMR =.001. Also, a considerable number of the regression weights for individual items were lower than or close to the expected 0.5 threshold.

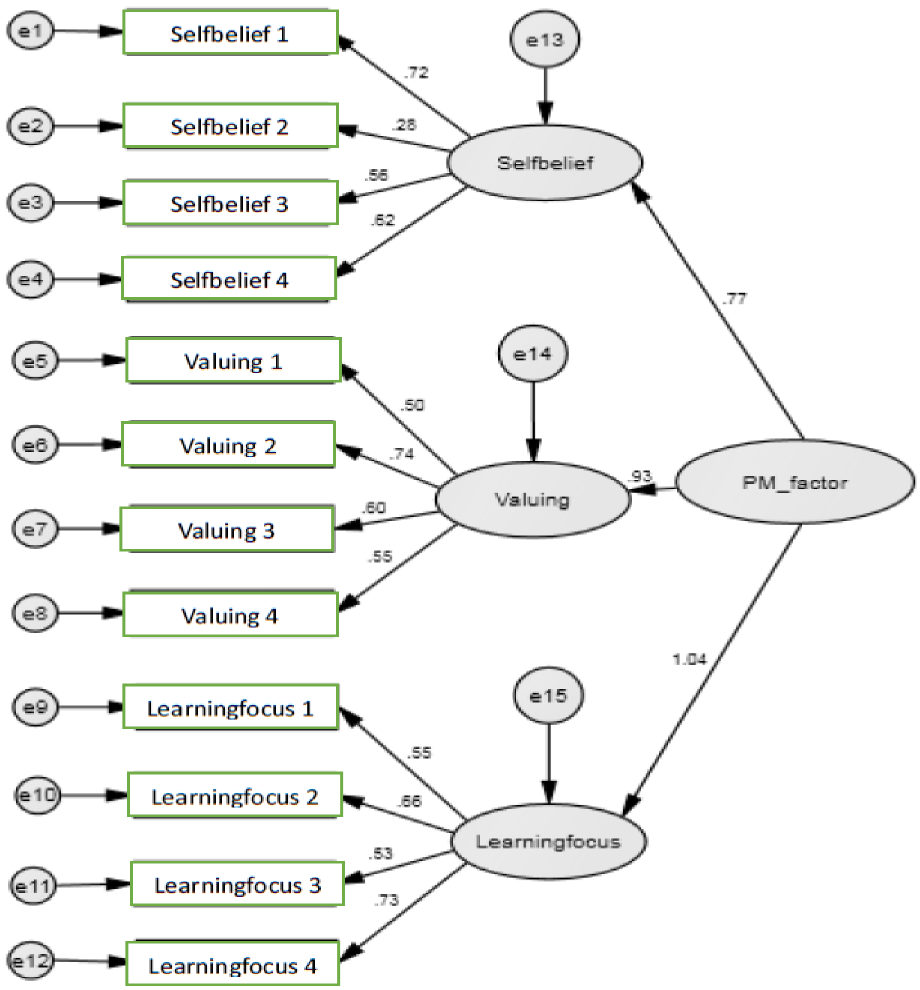


*Figure 3***.** PM factor model

The PE factor model is illustrated in Figure 4. The factor showed a poor model fit, as indicated by the following goodness-of-fit index values: $\chi 2$ /d*f*= 1.82, CFI= .89, TLI= .86, RMSEA= .061, and SRMR =.164. Also, four items demonstrated regression weights lower than the expected threshold level.

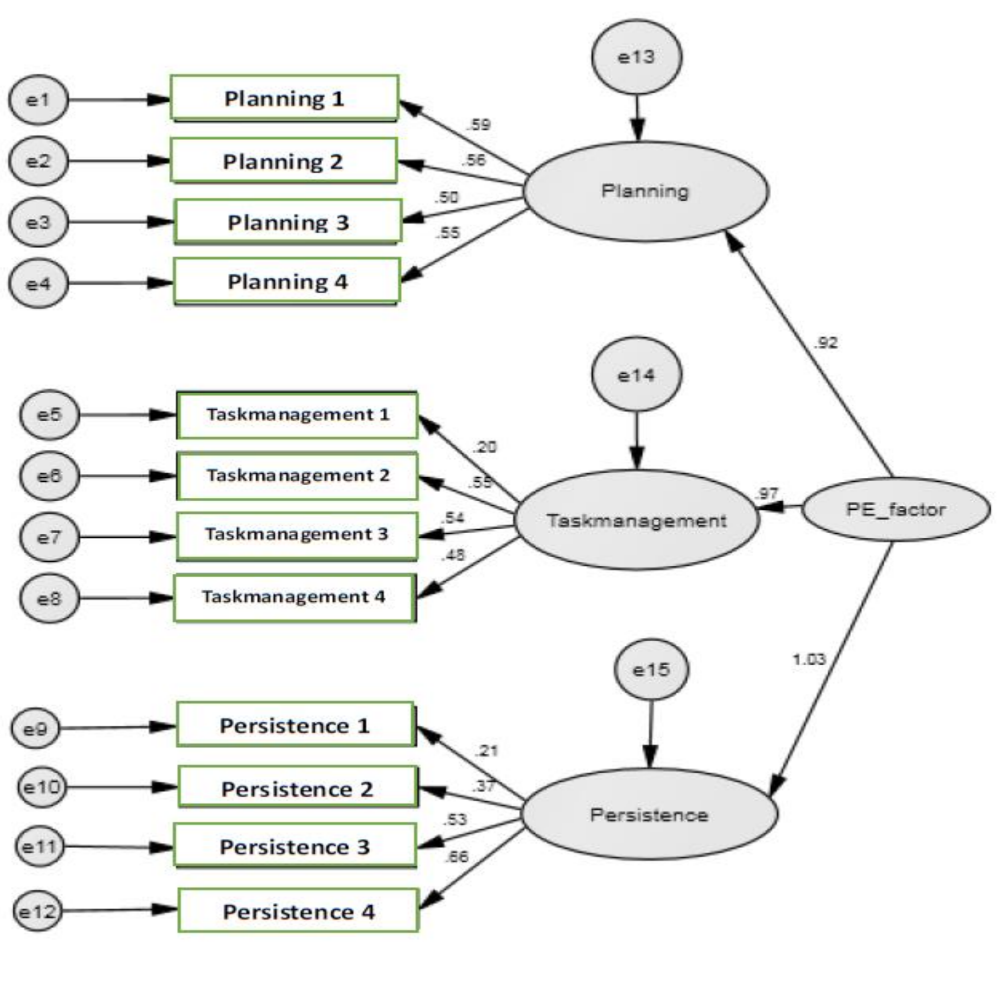


Figure 4. PE Factor model

The NM factor model is illustrated in Figure 5. The factor showed poor model fit, as indicated by the following goodness-of-fit index values: $\chi 2$ /d*f*= 2.83**,** CFI= .81, TLI= .76, RMSEA= .092, and SRMR =.001. Also, five items demonstrated regression weights lower than the expected level.

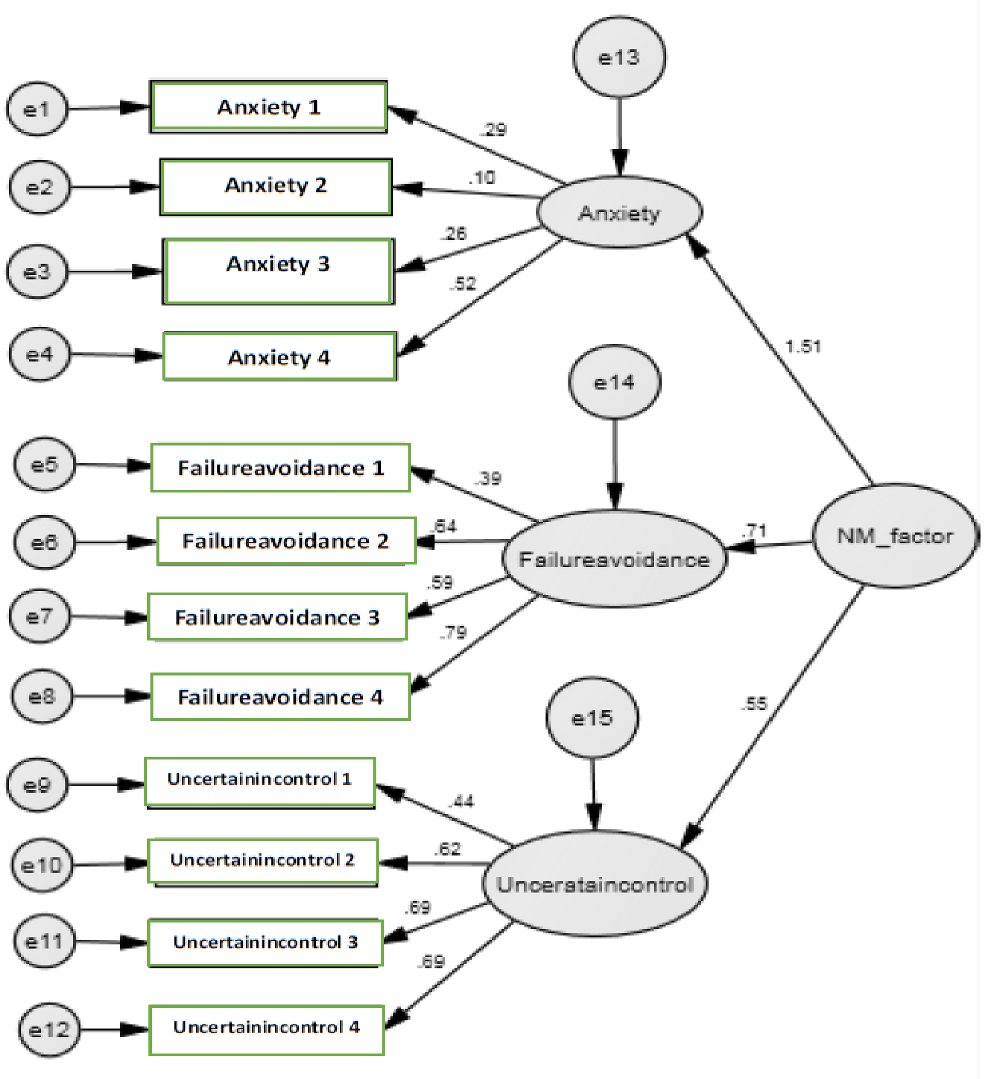


Figure 5. NM factor model

The NE factor model is illustrated in Figure 6. The factor showed a poor model fit, as indicated by the following goodness-of-fit index values: $\chi2$ /d*f*= 1.47, CFI= .96, TLI=.95, RMSEA= .047, and SRMR =.524. Also, three items demonstrated regression weights lower than the expected 0.5 level.

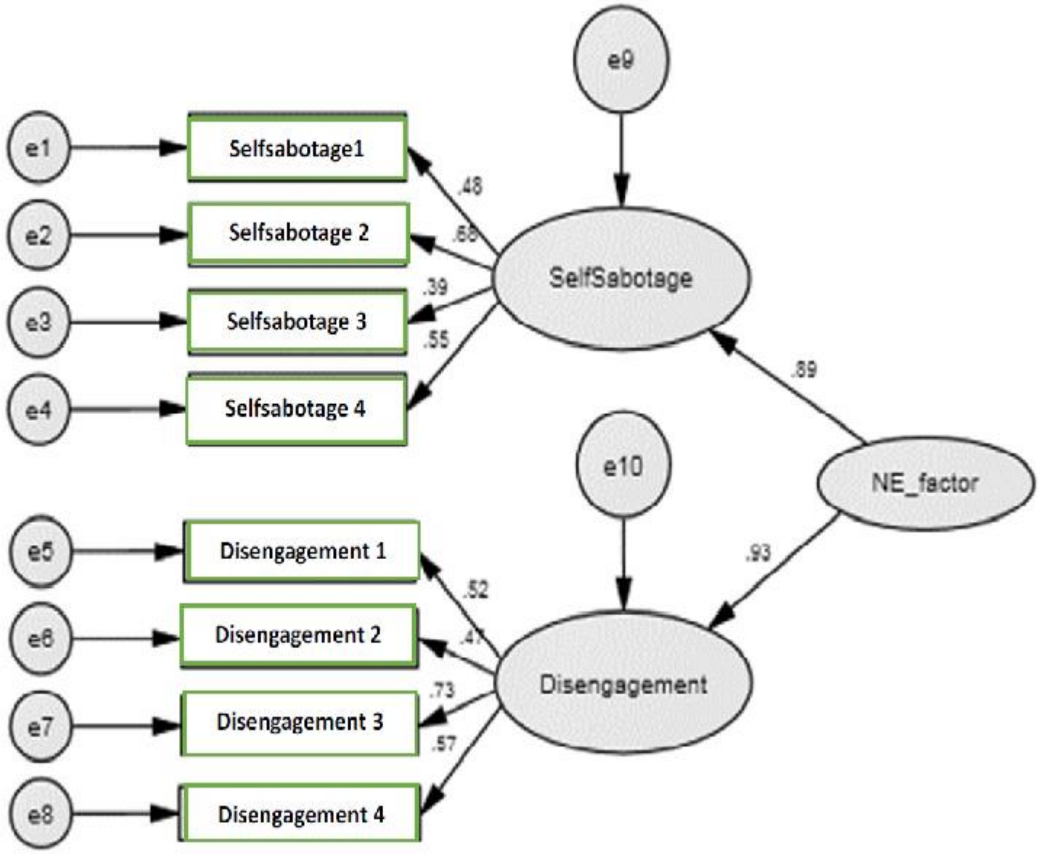


Figure 6. NE factor model

All the goodness-of-fit index values for all the factors are summarised in Table 2.

Table 2
Goodness-of-fit index values for higher order factors of MES-JS

Factor	χ2	df	χ2 /df	CFI	TLI	RMSEA	SRMR
PM	211.49	51	.14	0.79	0.73	0.12	0.001
PE	93.13	51	1.82	0.89	0.86	0.061	0.164
NM	144.61	51	2.83	0.81	0.76	0.092	.001
NE	28.04	19	1.47	0.96	0.95	0.047	.524

As noted above, the goodness-of-fit index values for all factors in MES-JS did not show a good fit with the current study sample. Also, a considerable number of the regression weights for individual items were lower than the expected level for all the factors.

The conclusion is that Martin's (2014)[6] data structure was not appropriate for use in this study. It was, therefore, decided to conduct an EFA for the current sample to obtain a robust factor solution. As already noted, the EFA was conducted for the full sample and not for each of the two cultural groups because the sample size of each group was not big enough.

Conducting exploratory factor analysis

Before conducting the EFA, several factors were considered to develop decision pathways for analysing the data: sample size, sample size to variable ratio (*N:p* ratio), factorability of the correlation matrix, and the Kaiser-Meyer-Olkin measure of sampling adequacy/Bartlett's Test of Sphericity.

Method of data extraction

Mvududu and Sink (2013)[16] explained that PCA is the most practical way of extracting components. Its main goal is to condense a large number of items (e.g. 40) to a far smaller number of components (e.g. 4). Similarly, Abdi and Williams (2010)[17]noted that the objectives of PCA are to extract the most significant information from the data table, and condense the size of the dataset by keeping only significant information, thereby simplifying the description of the dataset. Cooksey (2014)[18] explained that PCA merges variables in a subjective way to create components, and those components account for the maximum amount of variability in the scores. Kline (1994)[19] argued that components are actual factors because they are obtained directly from the correlation matrix. This study used the PCA method of extraction to determine the final factor solution.

Rotation

Yong and Pearce (2013)[20] advise rotation of factors for better interpretation and, further, argue that un-rotated factors are unreliable. Orthogonal rotations highlight uncorrelated factor, while oblique methods permit the factors to be correlated. Varimax, quartimax, and equamax are usually obtainable orthogonal methods of rotation; oblique methods are direct oblimin, quartimin, and promax (Osborne & Costello, 2009)[21]. Correlations between factors are predictors in the social sciences: if the factors are correlated, orthogonal rotation results might reveal important information and oblique rotation might present a more precise result (Costello & Osborne, 2005)[22]. Therefore, for this study, the direct oblique rotation method was employed.

Number of factors to retain

It is important to select which criterion is most suitable for the study when deciding on the number of factors to be extracted. There are many heuristic devices for helping to decide on the number of factors to retain. Among them, for this study, two devices were employed, eigenvalue and scree test. Kaiser (1960)[23] advocated that a criterion (Kaiser's criterion) that could be employed to decide the number of factors to retain is those with an eigenvalue greater than 1. However, as argued by Child (2006)[24], an eigenvalue is only suitable for utilisation in PCA. Only factors having an eigenvalue larger than 1 are regarded as common factors.

In relation to the scree plot, the number of factors to be retained is interpreted as the number of data points that are above the break (point of inflection), although some authors argue for retention of the factor at the inflection point. Kline (1994)[19] advocates for the cut-off point for factor rotation at the point where line changes slope. The scree test is reliable if the sample size is at least 200 (Osborne & Costello, 2009; Yong & Pearce, 2013)[21,20], which was available in the current study. In this study, the method used was the scree test in combination with eigenvalues to decide the number of factors to retain.

Exploratory factor analysis outcomes

According to Maskey, Fei, and Nguyen (2018)[25] "EFA helps in reducing large number of indicator variables into limited set of factors based on correlations between variables" (p.92). Therefore, EFA has been used for this study and the procedures followed are discussed next.

Data extraction

The correlation matrix was examined and items were excluded from the analysis where they demonstrated limited (less than 0.30) inter-item correlations; 16 items were retained and included in the EFA. In this study, the KMO ratio was .754, indicating the size of the dataset was suitable for factor analysis. The Bartlett's test of sphericity was significant (Chi-square (105) = 887.54, p=.001) indicating that the items, as a collective, were suitable for factor analysis. The communalities items in the EFA ranged from .494 to .708 indicating a suitable variance in the items by the factors with an eigenvalue greater than 1.

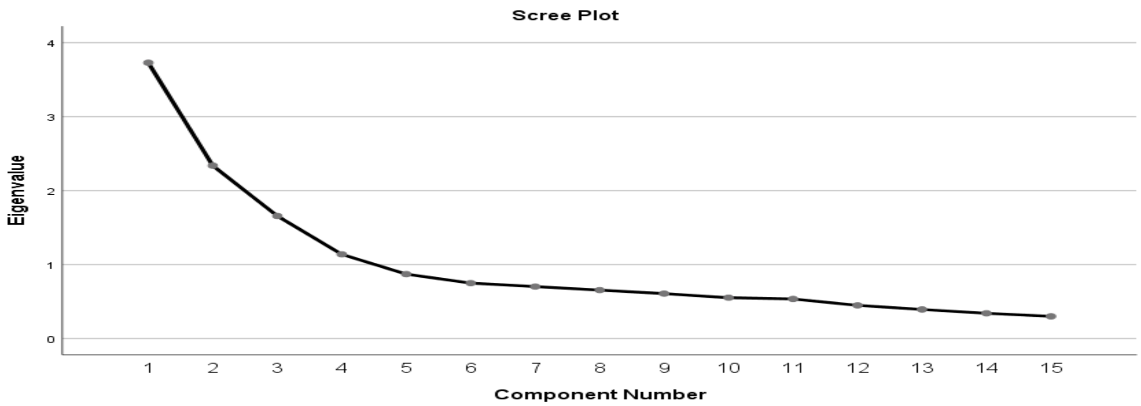
An examination of the eigenvalues (Table 3) and scree plot (Figure 7) indicated a four-factor solution.

Numbers of factors to retain

Table 3
Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.728	24.853	24.853	3.728	24.853	24.853	2.789
2	2.336	15.576	40.429	2.336	15.576	40.429	2.696
3	1.656	11.041	51.471	1.656	11.041	51.471	2.098
4	1.137	7.582	59.053	1.137	7.582	59.053	2.555
5	.870	5.798	64.850				
6	.748	4.987	69.837				
7	.701	4.676	74.513				
8	.654	4.360	78.874				
9	.606	4.039	82.913				
10	.551	3.674	86.586				
11	.534	3.558	90.144				
12	.448	2.985	93.129				
13	.392	2.611	95.740				
14	.340	2.267	98.007				
15	.299	1.993	100.000				

Extraction method: principal component analysis.



a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Figure 7. PCA scree plot

The items in the four-factor solution demonstrated factor loadings between .601 and .823, while the four factors accounted for 59.05% of the total variance. In relation to the social sciences, the variance explained is usually as small as 50 to 60% (Pett, Lackey, & Sullivan, 2003)[26]. The EFA analyses derived four factors in relation to early adolescents' motivation and engagement in learning in the Sri Lankan low socio-economic context. The new factors that emerged will be labelled in the next section.

Naming the factors

Factor labelling is a subjective, theoretical, and inductive process (Pett et al., 2003)[26]. Henson and Roberts (2006)[27] suggested that the meaningfulness of latent factors is eventually reliant on researcher definition. It is significant that the labels or settings reproduce the theoretical and conceptual aim (Williams, Onsman, & Brown, 2010)[28].

For naming the factors, the theoretical basis of Martin's MES-JS was considered. In the MES-JS there are four higher order factors: positive motivation (booster thoughts), positive engagement (booster behaviours), negative motivation (mufflers), and negative engagement (guzzlers). Each higher order factor contains lower order factors*: positive motivation* – self-belief, valuing, and learning focus; *positive engagement* – planning, task management, and persistence; *negative motivation* – anxiety, failure avoidance, and uncertain control; and *negative engagement* – self-sabotage and disengagement (Figure 2).

In this study, factor one comprised three items related to "failure avoidance" and one item related to "anxiety". Factor two comprised two items related to "learning focus" and two items related to "valuing". Factor three consisted of three items related to "uncertain control". The fourth factor contained one item related to "planning", one item related to "persistence", and two items related to "task management".

Accordingly, with an accurate and useful description of the underlying construct and with the theoretical meaning of the items in those factors, factor one was named as "Failure Avoidance and Anxiety" (FAA), as it represents two lower-order factors (failure avoidance and anxiety) in negative motivation. Factor two was named "Positive Motivation" (PM), as it represents two lower-order factors (valuing and learning focus) in positive motivation. The third factor was named "Uncertain Control" (UC), as it represented the majority of items in the uncertain control lower-order factor related to negative motivation. The fourth factor was named "Positive Engagement" (PE), as it represented all lower-order factors (planning, task management and persistence) in positive engagement. Overall, FAA and UC represent students' negative motivation for learning, and PM and PE represent students' positive motivation and engagement in learning in low socio-economic districts in Sri Lanka. Accordingly, those identified four factors will contribute to understand of motivation and engagement among early adolescents in low socio-economic districts as those were derived considering the characteristics of those students through the EFA.

Conclusion

In this study, MES-JS (Martin, 2014)[7] was employed to determine the motivation and engagement levels of early adolescents in two low socio-economic districts in Sri Lanka. Since, the scale did not provide a robust factor solution with those two low socio-economic education contexts, EFA was conducted. Principal component Analysis was employed to extract the factors. Then, to decide the number of factors to be retained scree test in combination with eigenvalues was used. Accordingly, four factors were derived, and they were named FAA, PM, UC, and PE. It is recommended that further analyses should be employed using these newly derived factors to identify low socio-economic Sri Lankan early adolescents' motivation and engagement in learning. And then identify the issues behind their low motivation and engagement in learning and take measures to increase their participation and ultimately achievement in learning.

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