INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT

OPEN ACCESS JOURNAL

Vol 12, Issue 2, (2023) E-ISSN: 2226-6348

Confirmatory Factors Analysis of Scale Measuring Secondary School Students' Learning Behaviours

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To Link this Article: http://dx.doi.org/10.6007/IJARPED/v12-i2/18113 DOI:10.6007/IJARPED/v12-i2/18113

Published Online: 22 June 2023

Abstract
Learning behaviours are a visionable factor and essential for researchers to understand when enhancing students' learning process. This paper aims to validate the Learning Behaviours Instrument (LBI) using a Confirmatory Factor Analysis (CFA). This instrument consists of 13 items and is measured using a 10-point rating scale. The Learning Behaviours (LB) construct consists of three (3) sub-constructs: Avoidance Style Approach (ASA), Active Feedback (AF), and Personal Control (PC). This study used 237 secondary students as the sample after data cleaning. The second-order CFA result showed unidimensionality, validity, and reliability for the measurement model achieved. The measurement model of the LB construct is accepted. It can be fitted into a structural model for further analysis to understand LB among secondary students towards their academic performance.
Keywords: Learning Behaviours, Avoidance Style Approach, Personal Control, Active Feedback, Behaviour, Avoid, Active, Control.

Introduction

Education plays a fundamental part in creating great-value new generations to keep support a top class of technology development and drastic changes for better future growth. Students' behaviour is essential to learning (Belle, 2017; Olusegun & Adelayo, 2017; Turner et al., 2002). In a previous study, Bandura's Social Cognitive Theory (SCT) was explained as the extension of the behaviourism theory that emphasises the importance of behavioural factors, environment, and individual cognitive in the learning process, where behaviours able affect cognitive and the environment and vice versa work as reciprocal relationships between behaviour, individual cognitive, and the environment. Researchers should emphasise learners' behaviours and acceptance process more than focusing solely on response content and delivery (Winstone et al., 2017). Learning behaviours in this study explained how students respond to items in the self-description and self-administered questionnaires with a 10-point rating scale.

Numerous studies on understanding and enhancing student performance have been conducted nationally, where practical feedback can be created and sent. However, there is minimal information regarding the role or relevance of learners' behaviour (Winstone et al., 2017). Besides, the research found that low support for performance goals may be positively associated with avoidance behaviour among students (Turner et al., 2002). Avoidance is a crucial fear characteristic of threatening stimuli or situations (Krypotos et al., 2015). However, without realising it, low-performance students tend to avoid action, are less active in giving feedback and have difficulty in self-control during their learning process. Necessary to conduct research that can understand student learning behaviour factors so that more effective strategies can apply.

Behaviour is one of the more influential determinants of future eventualities, and people may be partly free to the degree that they can influence future conditions by managing their behaviour (Bandura, 1974). Important to acknowledge the reciprocal relationships that arise between behaviour, personal (internal) and the environment when understanding how individuals learn (Harinie et al., 2017). Theory Reciprocal in Social Science highlights the importance of triadic factors, where in this theory, human behaviours play an essential role in understanding the human learning process. Previous research suggests that educators' capture requirements may negatively affect some students' attendance and study behaviour (Voelkel et al., 2023). Grades have been shown to affect students' engagement with feedback negatively and indicate that grades may represent one of the significant obstacles to the beneficial use of feedback (Jönsson & Panadero, 2018). At the same time, previous research findings also indicate educators can affect students' negative behaviour (Belle, 2017). Applications of self-control practices demonstrate that people can adjust their behaviour in preferred directions by organizing environmental conditions most likely to produce it and managing self-reinforcing consequences to uphold it (Bandura, 1974). Because apart from hoping for students' active feedback, students tend unconsciously to avoid and control their learning behaviour during learning. Therefore, this paper's research validates the importance of students' avoidance style approach, active feedback, and personal control as student learning behaviours factors.

Human beings tend to give active feedback toward something they are interested in. Avoid a discomfort or dislike condition where an avoidance style approach will occur. Plus, all these controls by human or student personal control toward the situation they encounter. This research aims to validate the adapted and modified instrument items from the previous study that fulfil student needs while reflecting on learning behaviours that can help figure out their learning process. This study used CFA to test the unidimensionality, validity, and reliability of LBI.

Methodology

This study aims to validate the measurement model of Learning Behaviours (LB) using CFA. The instrument consists of 13 items of self-description and a self-administered questionnaire with a 10-point rating scale. After data cleaning, a total of 237 secondary students were sampled. In this study, IBM-SPSS-AMOS 24.0 software has been used. Structural Equation Modelling (SEM) is a confirmatory method providing a comprehensive means for validating latent constructs in the measurement model using CFA validating procedure (Awang, 2015; Awang et al., 2018, 2023; Hair et al., 2019). CFA is almost invariably applied during scale development to examine the latent structure of a test instrument (Brown, 2015). In CFA, there are three (3) assessments: unidimensionality, validity, and reliability of latent construct (Awang, 2015; Awang et al., 2018, 2023; Hair et al., 2019).

Results and Discussion

Figure 1 shows the result for the CFA output diagram result. Correlating error terms of two redundant items able help improve model fit (Awang et al., 2023; Hair et al., 2019; Zainol, 2018). To improve the fitness indexes, e5 and e6 have been correlated with the results shown on the right side of Figure 1. The RMSEA value from 0.088 improves to 0.077, less than 0.08 made fitness indexes for the model achieved.

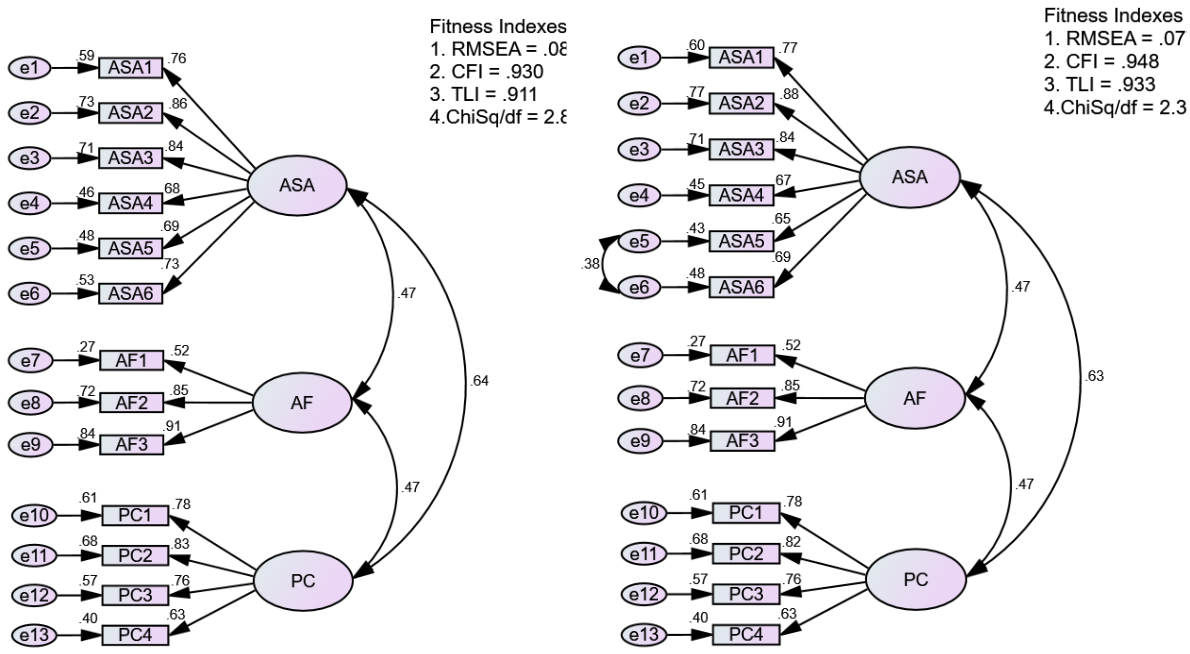

Figure 1. The measurement model for LBF sub-construct

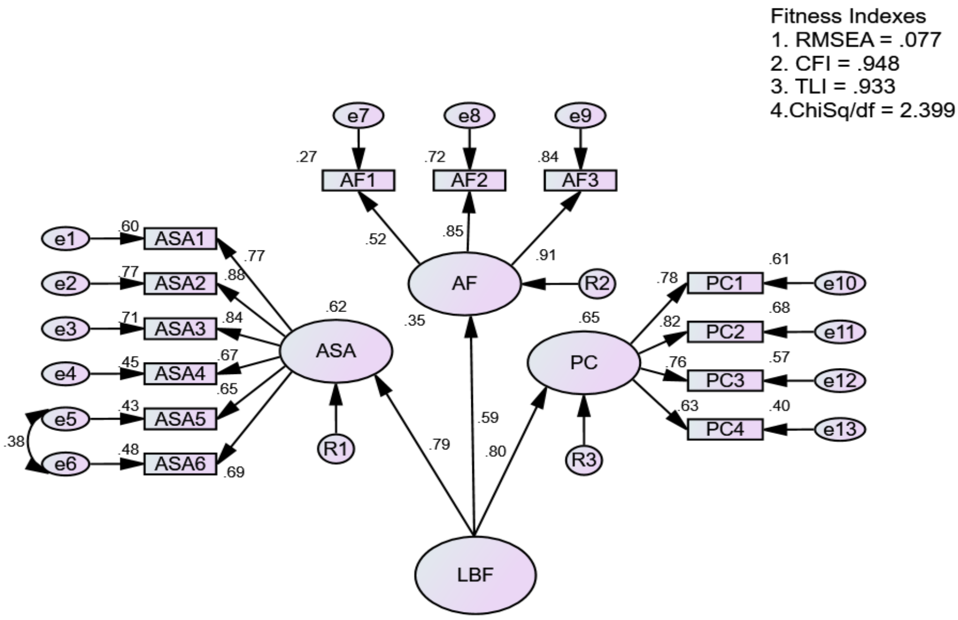

Figure 2. The Second Order CFA for LBF

The first assessment of the CFA validity is unidimensionality. Figure 2 and Table 1 show the factor loading for every item, and the sub-constructs are more than 0.5. The result shows the unidimensionality for the measurement model is archived.

Table 1
The Factor Loading value for items and sub-constructs

Sub-construct	**Item**	**Factor Loading**	
Avoidance Style Approach (ASA)	ASA1	0.77	0.79
	ASA2	0.88	
	ASA3	0.84	
	ASA4	0.67	
	ASA5	0.65	
	ASA6	0.69	
Active Feedback (AF)	AF1	0.51	0.59
	AF 2	0.85	
	AF 3	0.91	
Personal Control (PC)	PC1	0.78	0.80
	PC2	0.82	
	PC3	0.76	
	PC4	0.63	

The second assessment in CFA is validity. Validity consists of three (3) type: Convergent validity requires an Average Variance Extracted (AVE) value should at least 0.5, construct validity contain three (3) categories of model fit (absolute fit, incremental fit, parsimonious fit), and discriminant validity test using Fornell–Larcker and Heterotrait-monotrait (HTMT) approach. Table 2 shows the AVE value for the sub-constructs and construct. The listed AVE values are more than 0.5. The convergent validity for the LBF measurement model is achieved.

Table 2
The Average Variance Extracted (AVE)

Construct	**Sub-Construct**	**Item**	**AVE (Minimum 0.50)**	
Learning Behaviours Factor (LBF)	Avoidance Style Approach (ASA)	ASA1	0.57	0.537
		ASA2		
		ASA3		
		ASA4		
		ASA5		
		ASA6		
	Active Feedback (AF)	AF1	0.604	
		AF 2		
		AF 3		
	Personal Control (PC)	PC1	0.564	
		PC2		
		PC3		
		PC4		

The result for construct validity is shown in Table 3. The index value for absolute fit (RMSEA=0.077) is less than level acceptance 0.08, the index value for the incremental fit (CFI=0.948, TLI=0.933) is more than 0.9, and the parsimonious fit (ChiSq/df=2.399) less than 3.0 the fitness indexes for the measurement model have been achieved since all values fulfil the level of acceptance for each model fit category.

Table 3
The Fitness Indexes for CFA

Model Fit Category	**Name of index**	**Level of acceptance**	**Index value**	**Result**
Absolute Fit Index	Root Mean Square of Error Approximation (RMSEA)	RMSEA (<0.08)	0.077	Achieved
Incremental Fit Index	Comparative Fit Index (CFI)	CFI (>0.90)	0.948	Achieved
	Tucker-Lewis Index (TLI)	TLI (>0.90)	0.933	Achieved
Parsimonious Fit Index	Chi-Square/Degree of Freedom (Chisq/df)	Chisq/df (<3.0)	2.399	Achieved

In this study, discriminant validity has been tested using Fornell–Larcker and HTMT approach. Where Fornell–Larcker approach majority used by researchers and supports initial evidence of discriminant (Fornell & Larcker, 1981; Hair et al., 2019; Henseler et al., 2015). In recent years, many studies have highlighted the HTMT method in variance-based SEM in social science research (Henseler et al., 2015). Most often, the HTMT approach uses the SmartPLS software found to be more sensitive to detecting discriminant validity compared to Fornell–Larcker approach (Ab Hamid et al., 2017). This research uses the Master Validity Tools plugin Gaskin's team produced in 2019 to test HTMT. The Master Validity Tools plugin can run using IBM-SPSS-AMOS 24.0 software (Gaskin et al., 2019) and is the improved version of the previous HTMT plugin (Gaskin & James, 2019). The HTMT test using the AMOS plugin is also suggested in Teo et al (2022) article. Table 4 shows Fornell–Larcker Discriminant Validity Index Summary for LBF Sub-constructs, and Figure 3 displays steps and result output for the HTMT approach using the IBM-SPSS-AMOS plugin. Fornell–Larcker Discriminant Validity Index Summary showed the square root of the AVE value (ASA=0.75, AF=0.78, PC=0.75) for each sub-construct is greater than the inter-sub-construct correlation value. While the HTMT result output in Figure 3 shows no warning mean discriminant validity in the HTMT approach also achieved for the measurement model.

Table 4
Fornell–Larcker Discriminant Validity Index Summary for LE Sub-constructs

Sub-Constructs	**ASA**	**AF**	**PC**
Avoidance Style Approach (ASA)	**0.75**		
Active Feedback (AF)	0.47	**0.78**	
Personal Control (PC)	0.63	0.47	**0.75**

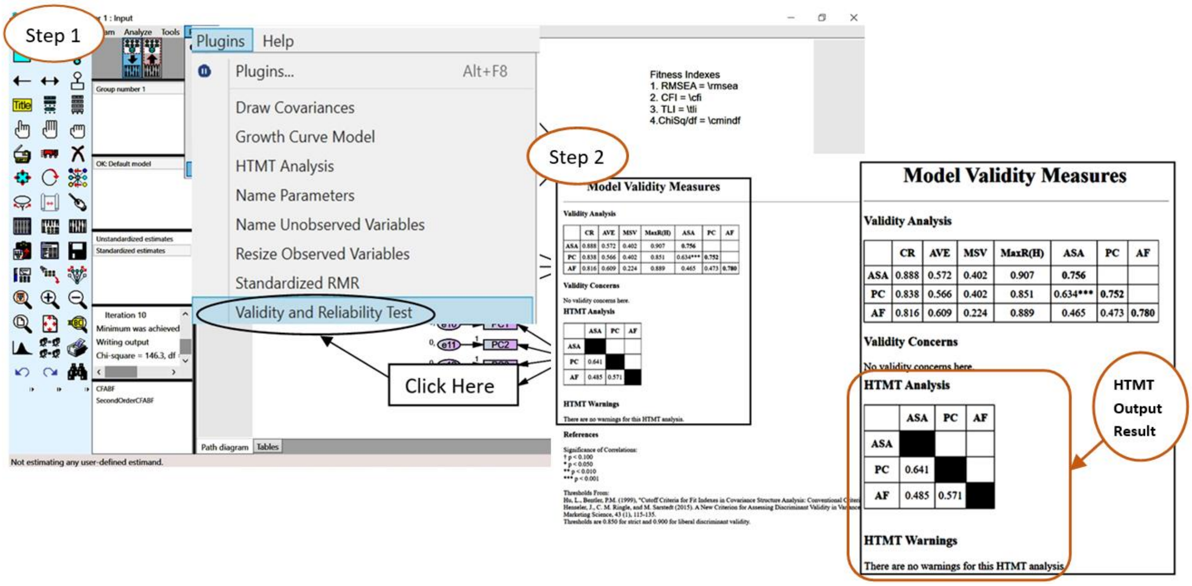

Figure 3. IBM-SPSS-AMOS plugin HTMT Analysis Result

The final assessment in CFA is reliability. Reliability for the measurement model is measured using the Composite Reliability (CR) for sub-construct and construct. Table 5 shows CR values for the sub-construct (ASA=0.89, AF=0.81, PC=0.84) and construct (LBF=0.77) are more than 0.60. The result proved the reliability of the measurement model achieved.

Table 5
Composite Reliability (CR) for the sub-constructs

<table>
<tr><th>Construct</th><th>Sub-Construct</th><th colspan="2">CR (≥0.60)</th></tr>
<tr><td rowspan="3">Learning Behaviours Factor (LBF)</td><td>Avoidance Style Approach (ASA)</td><td>0.89</td><td rowspan="3">0.77</td></tr>
<tr><td>Active Feedback (AF)</td><td>0.81</td></tr>
<tr><td>Personal Control (PC)</td><td>0.84</td></tr>
</table>

The result shows three (3) assessments, unidimensionality, validity, and reliability in CFA (Awang, 2015; Awang et al., 2018, 2023; Hair et al., 2019) for the LBF measurement model, have been achieved. The assessment of normality distribution for data needs to be conducted after the CFA assessment and before the researcher proceeds with SEM (Awang et al., 2023; Muda et al., 2018; Zainol, 2018).

Vol. 12, No. 2, 2023, E-ISSN: 2226-6348 © 2023

Table 6
Assessment of Normality

Item	min	max	skewness	c.r.	kurtosis	c.r.
AF1	1	10	**-0.046**	-0.286	-0.947	-2.977
AF2	1	10	**-0.722**	-4.540	-0.402	-1.263
AF3	1	10	**-0.627**	-3.941	-0.342	-1.074
PC1	1	10	**-0.762**	-4.788	-0.128	-0.401
PC2	1	10	**-0.645**	-4.051	-0.239	-0.752
PC3	1	10	**-0.420**	-2.638	-0.641	-2.016
PC4	1	10	**-0.531**	-3.337	-0.191	-0.599
ASA1	1	10	**-0.547**	-3.435	-0.105	-0.331
ASA2	1	10	**-0.592**	-3.718	-0.193	-0.608
ASA3	1	10	**-0.592**	-3.719	-0.314	-0.986
ASA4	1	10	**-0.556**	-3.494	0.007	0.023
ASA5	1	10	**-0.423**	-2.657	-0.224	-0.703
ASA6	1	10	**-0.476**	-2.993	-0.223	-0.701
Multivariate					51.022	19.887

Table 6 shows the result assessment of normality for the research data skewness value (with bold) falling between -1.0 and 1.0, meaning the data is a normal distribution. The result indicated Critical Region (CR) for the skewness does not exceed 7.0. Thus, the LBI can advance to further research and proceed with SEM.

Conclusion
Overall, the validity of CFA for LBI has been achieved. The research also proves the importance of validating CFA for LBI using IBM-SPSS-AMOS software. This instrument is suitable for use in a secondary school context to facilitate educator understanding of students' learning behaviours that contribute to or affect students' achievement and performance.

Acknowledgement
The authors extend appreciation to the Ministry of Education Malaysia for grand permission to conduct research involving National Secondary School students. Truly thankful to the teachers and students that participated in this research.

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