Received: 06-07-2025 | Revised: 21-07-2025 | Accepted: 24-08-2025

DOI: 10.23916/00202501050420

Couns-Edu
The International Journal of Counseling and Education

Constructing College Academic Resilience Scale: Using Multifactor and Polytomous Rasch Model

Siti Dini Fakhriya [1]* | Kusumasari Kartika Hima Darmayanti [1] | Jesyia Meyrinda [1] | Tsurayya Syarif Zain[2] | Mawaddah Ramadhan [1] | Indah Lestari [1] | Kenya Janesa Liandri [1] | Liya Triyani [1] | Annisa Syifa Azzahrah [1] | Silvia Afnes [1]

[1] Universitas Islam Negeri Raden Fatah Palembang, South Sumatra, Indonesia

[2] Politeknik Negeri Sriwijaya, South Sumatra, Indonesia

Correspondence Email:
sitidinifakhriya_uin@radenfatah.ac.id*

Keywords
Academic resilience, college academic resilience scale, confirmatory factor analysis, polytomous Rasch model, undergraduate students

Abstract

Academic resilience is crucial for students. It enhances their ability to manage academic difficulties, which underscores its importance in educational settings. This study aims to develop and validate the College Academic Resilience Scale (CARS), which assesses academic resilience in undergraduates. 200 undergraduate students from South Sumatra, Indonesia, were used to analyze using the multifactor confirmatory factor analysis model and the polytomous Rasch model. This measure consists of five dimensions that measure academic resilience, indicating that an overall analysis of items in academic resilience instruments using Rasch modeling has good validity and reliability. Furthermore, more research on measurement validation is needed in diverse cultures and countries.

INTRODUCTION

The concept of academic resilience has garnered significant attention in educational research, as it pertains to students' ability to thrive in the face of challenges and adversity within academic settings. Understanding the factors that contribute to academic resilience is crucial for developing effective interventions and support systems for students. Furthermore, research indicates that fostering an environment that promotes social support and self-efficacy can significantly enhance students' resilience, thereby improving their overall academic performance despite challenges (Babakova, 2019).

Academic resilience can be measured in various ways, both as a unidimensional and multidimensional construct. The Academic Resilience Scale (ARS), established by Martin and Marsh (2003, 2006), is a unidimensional measure of academic resilience that consists of a 5-C model of academic resilience, which consists of commitment (perseverance), control, calm (low anxiety), coordination (planning), and confidence (self-efficacy). It has six items that show how students respond to challenges in the classroom, including receiving a low grade on an assignment. The Academic Resilience in Mathematics scale (Ricketts et al., 2017), on the other hand, is unique to the field of mathematics ('I know where to get help if I am having difficulty with math').

According to Martin and Marsh (2006), commitment involves showing students the importance of strategy and effort in attaining improvement, which in turn promotes a focus on mastery. Acknowledging

How to cite this article: (2025). Fakhriya, S. D., Darmayanti, K. K. H., Meyrinda, J., Zain, T. S., Ramadhan, M., Lestari, I., Liandri, K. J., Triyani, L., Azzahrah, A. S., & Afnes, S. (2025). Constructing College Academic Resilience Scale: Using Multifactor and Polytomous Rasch Model. *COUNS-EDU: The International Journal of Counseling and Education, 10*(2), 46–63. https://doi.org/10.23916/00202501050420.

that students have control over the results of their decisions and actions, self-control is one way to show how effort and strategy adjustments are made to achieve goals (Martin & Marsh, 2006). Fear of failing is a common cause of anxiety in students (Covington, 1992). By increasing self-confidence, learning how to handle mistakes, fostering a collaborative environment in all academic endeavours, and adopting a success mindset, it is crucial to lessen the fear of failing (Martin & Marsh, 2006). Plans are crucial for achieving objectives, working in an environment with a clear purpose, and using self-control or regulation techniques to improve planning and persistence. Plans are crucial for achieving objectives, working in an environment with a clear purpose, and using self-control or regulation techniques to improve planning and persistence (Zulfikar et al., 2022). The key component of academic resilience that influences people's behaviour and attitude when they encounter difficulties is self-efficacy (Cassidy, 2015). To enhance students' self-confidence, learning needs to be restructured to optimize opportunities for success (Martin & Marsh, 2003).

More generally, research has advocated academic resilience as a multifaceted phenomenon. Colp (2015) defined academic resilience as a second-order component comprising five first-order elements and tested it with 23 items, whereas He (2014) used 12 items to assess three first-order factors. In both cases, exploratory and confirmatory factor analyses confirmed the concept of academic resilience as a multidimensional entity. The most well-known multi-dimensional measure is the Academic Resilience Scale-30 (Cassidy, 2016), a comprehensive tool that covers all aspects of resilience. The Academic Resilience Scale (ARS-30) has been designed explicitly as a multidimensional tool to evaluate cognitive-affective and behavioural responses to adversity in academic settings (Cassidy, 2016). The validation of the Academic Resilience Scale across different cultural contexts has demonstrated its adaptability and robustness across diverse populations (Cui et al., 2023).

Research has also highlighted the importance of cultural considerations in understanding academic resilience, particularly among Black college students (Mills, 2021). Moreover, the development of academic resilience scales tailored to specific populations, such as undergraduates in Taiwan, has been emphasized to capture the unique aspects of resilience within different cultural contexts (Homaedi et al., 2022) (Li et al., 2019). Studies have also explored the impact of academic resilience on academic performance during crises like the COVID-19 pandemic (Dwiastuti et al., 2022).

The Academic Resilience Scale for undergraduates focuses on cognitive perception, emotional management, and problem-solving ability to capture the core of academic resilience (Li et al., 2019). Research has stressed the need to evaluate academic resilience at various stages to understand its progression and influence, particularly during stressful periods such as exams or thesis writing (Kumalasari, 2023). Understanding the complex nature of academic resilience and cultural nuances allows educators and institutions to undertake tailored interventions to improve undergraduate students' capacity to overcome challenges and prosper in their academic pursuits in Indonesia. The potential impact of this work on the Indonesian population underscores the significance of developing reliable and valid measurement tools for assessing and comprehending students' resilience levels, thereby guiding interventions and support systems to enhance academic success.

This study aimed to examine the psychometric properties of the College Academic Resilience Scale (CARS), which refers to Martin and Marsh (2003, 2006). Unlike Martin and Marsh (2003, 2006), who compiled the measurement of academic resilience based on the one-dimensionality of commitment, control, calm, coordination, and confidence, CARS is oriented towards the multidimensionality of the 5-C model. Therefore, the confirmatory factor analysis test used to test construct validity is a multifactor model to confirm each item that makes up the 5-C model on academic resilience. In addition, this study also evaluated reliability using the polytomous Rasch model.

METHODS

Participants

Table 1 illustrates the demographic characteristics of the sample. The participants in this study were 200 undergraduates in Indonesia, consisting of 156 females (78%) and 44 males (22%) and from age groups ranging from under 19 years old, to over 21 years old with an average age of 20 years old and consisted of various universities in South Sumatra province.

Table 1. <Participant characteristics>

Chategories	*f*	%
Sex differences		
Females	156	78.0
Males	44	22.0
Age		
Under 19	55	27.5
19-21	135	67.5
Above 21	10	5.0
Backgrounds		
Universitas Sriwijaya	21	10.5
Universitas Islam Negeri Raden Fatah Palembang	123	61.5
Universitas PGRI Palembang	10	5.0
Universitas Sumatera Selatan	11	5.5
Universitas Muhammadiyah Palembang	7	3.5
Universitas Kader Bangsa	3	1.5
Universitas Bina Darma	3	1.5
Universitas Baturaja	7	3.5
Poltekkes Kemenkes Palembang	8	4.0
Politeknik Negeri Sriwijaya	7	3

Design and Procedures

This study applied quantitative research methods (Gravetter & Forzano, 2018). Quantitative methods are used to measure students in South Sumatra, where data is generated in the form of numerical data and then analyzed with statistical and psychometric approaches. The statistical analysis used descriptive analysis with a descriptive research strategy (Gravetter & Forzano, 2018). In addition, this study aimed to test the validity and reliability of the development of measuring instruments that measure academic resilience.

The number of participants who contributed to the study was more than 200, which in determining the sample size in this study refers to Loehlin and Beaujean (2017), who states that the recommended sample size for factor analysis and structural equation analysis is 200 or more. In conducting the research, we used incidental sampling (Gravetter & Forzano, 2018), which means that students in South Sumatra who are willing to become research participants and participate in this study are research participants. After the participants agreed to participate in the study, they were asked to complete an informed consent form, indicating that they participated voluntarily without coercion. This study followed ethical research, which is based on the Declaration of Helsinki (Association, 2013), the Belmont Report (Anon, 1979), and research and publication standards based on the American Psychological Association (Association, 2019), in the context of research involving human beings. Then, this research took place after obtaining permission to conduct research from the Faculty of Psychology, Universitas Islam Negeri Raden Fatah Palembang.

Measurement

The College Academic Resilience Scale (CARS) questionnaire contains 29 statements consisting of various items to evaluate academic resilience, specifically to increase student confidence, management, and reduce anxiety experienced by students. This questionnaire was developed based on the underlying theories, research, and literature from Martin and Marsh (2003, 2006). The reliability estimation technique based on factor analysis in this study uses the Omega Coefficient (ω) and Theta Coefficient (θ) approaches with the help of M*plus* 0.8 software (Muthén & Muthén, 2017). Item analysis with the Rasch Model approach using jMetric software version 4.1.1. The parameters used to assess the quality of items in IRT are Item Difficulty, Distinguishing Power, and Reliability. In Rasch analysis, there are three different estimation stages considered: (i) Calibration of examinee ability and item difficulty, (ii) Estimation of fit (iii) Assessment of one-dimensionality using Principal Component Analysis (PCA) of Rasch residuals (Bond et al., 2020).

Statistical Analysis

Descriptive analysis

This study conducted a descriptive analysis test, which was used to determine the normality of data distribution, central tendency, and variability (Gravetter et al., 2021). The normality test indicates whether the data is normally distributed, which is symmetrical or skewness, which in this study uses skewness (± 2) and kurtosis (± 7) (Hair et al., 2019). Furthermore, this study applies the mean and standard deviation scores to conduct descriptive analysis tests. In addition, this study also displays the results of correlations between dimensions (i.e., confidence (self-belief), coordination (planning), control (a sense of control), composure (anxiety), and commitment (persistence) Martin and Marsh (2003, 2006) that make up CARS. To conduct the descriptive analysis, this study used Jamovi 2.3 (Jamovi, 2022).

Multifactor model

Confirmatory factor analysis is the relationship between observed variables and continuous latent variables, which is part of classical test theory (Muthén & Muthén, 2017), which in this study used *Mplus* version 7. Confirmatory factor analysis is one of the construct validity tests (Raykov & Marcoulides, 2011). The multifactor model is one of the models of confirmatory factor analysis, which consists of continuous factor indicators (Muthén & Muthén, 2017). In this study, there are seven interconnected continuous factors, namely (1) Confidence (self-belief); (2) Coordination (planning); (3) Control (a sense of control); (4) Composure (anxiety); and (5) Commitment (persistence) (Martin & Marsh, 2006). Model fit refers to goodness of fit indices in the form of absolute fit index (i.e., Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR)) and incremental fit index (i.e., Comparative Fit Index (CFI) and Tucker-Lewis's index (TLI)) (Hair et al., 2019).

Both the absolute fit index and the incremental fit index refer to Hu and Bentler (1999), where the Comparative Fit Index (CFI) > 0.95, Tucker-Lewis's index (TLI) > 0.95, Root Mean Square Error of Approximation (RMSEA) < 0.06, and Standardized Root Mean Square Residual (SRMR) < 0.08. Furthermore, this study also reported the results of 90% CI RMSEA≤ 0.05 (Raykov & Marcoulides, 2011) and probability RMSEA≥ 0.05 (Raykov & Marcoulides, 2011). Meanwhile, analysis at the item level using cutoff factor loading (factor loading > 0.32) (Tabachnick & Fidell, 2021) and estimated SE (t-value > 1.96) (Raykov & Marcoulides, 2011).

In addition to psychometric testing on multifactors for models and items, confirmatory factor analysis tests also produce (McDonald, 2013) McDonald's Omega (ω), Average Variance Extracted (AVE), and Composite Reliability (CR). McDonald's Omega (ω) is used to determine reliability, as is Cronbach's Alpha. AVE is one method to test validity with construct validity / convergent validity (Cheung et al., 2024; Dos Santos & Cirillo, 2023; Hair et al., 2021). Meanwhile, McDonal's ω and CR are used to determine reliability (Cheung et al., 2024; Flora, 2020). McDonal's ω, AVE, and CR are applied to each of the factors that make up CARS, with respective cutoffs of McDonald's ω ≥ 0.70 (Hancock & An, 2020; McNeish, 2017; Reise et al., 2013), AVE ≥ 0.50 (Fornell & Larcker, 1981) and CR ≥ 0.70 (Hair et al., 2019). In this study, the three of McDonald's Omega (ω), Average Variance Extracted (AVE), and Composite Reliability (CR) were estimated based on each of the factors that make up academic resilience.

Polytomous Rasch model

Rasch Rating Scale Model (RSM), also called Rasch Polytomous model developed by Andrich (1978) for polytomous data (data with >= 2 ordinal categories) provides estimated values including (a) Person locations, (b) Item Difficulties, (c) threshold values (fixed across items). The Rasch Polytomus model is a generalization of the dichotomous Rasch model from the concept of item response theory (IRT) which is a measurement model that has potential application in contexts whose purpose is to measure a trait or ability through a process in which responses to items are scored with sequential integers (Urbina, 2014). In this case, partial credit models are often used to identify different levels of categories. For example, in the use of Likert scales, rating scales, and educational assessment items that score successively higher integers to indicate increasing levels of competence or achievement. When compared to classical test theory, IRT has several advantages, namely: (1) item statistics are independent of the estimated sample, (2) scores are evaluated independently based on the difficulty level of the test items, (3) item analysis incorporates the fit between test items and the respondent's level of knowledge, (4) analysis does not require parallel tests to determine the level of reliability, (5) item statistics and question answering ability scores are both reported on the same scale (Bond et al., 2021). The scoring model using the rating scale model has an equation value : $in\ [\frac{P_{ni\ (x\ =\ \mathcal{K})}}{P_{ni\ (x\ =\mathcal{K}-1)}}]\ =\ \theta_n\ -\ \delta_i\ -\ \mathcal{T}_k$ = θ is the value of person's ability, d the value of item difficulty, and the value of thresholds estimates items. The Rasch Rating Scale Model (RSM) assumes that the threshold structure is fixed across items. The relative distance between thresholds is the same across items, but items still have different levels of difficulty. Thresholds only move up or down the logit scale (Andrich & Marais, 2019).

RESULTS AND DISCUSSIONS

Descriptive Statistics Testing

Table 2 is the result of descriptive statistical analysis based on each dimension contained in CARS. In detail, confidence shows M = 3.24 and SD = 0.532. Coordination indicates M = 2.92 and SD = 0.624. Control indicated M = 3.03 and SD = 0.521. Composure indicated M = 1.92 and SD = 0.381. Commitment resulted in M = 3.25 and SD = 0.558. Meanwhile, the distribution of data on confidence, coordination, control, composure, and commitment is normally distributed. The reference for normal distribution is based on (Hair et al., 2019), with a range of skewness ± 2 and kurtosis ± 7. In this study, the findings of skewness and kurtosis show in the range of skewness ± 2 and kurtosis ± 7, which are detailed as confidence (skewness = -0.828, kurtosis = 1.63), coordination (skewness = -0.261, kurtosis = 0.116), control (skewness = 0.070, kurtosis = -0.387), composure (skewness = -1.11, kurtosis = 0.43), and commitment (skewness = -0.491, kurtosis = 0.048).

Table 1 also summarizes the correlation results between dimensions. The results of the correlation analysis between dimensions show that all five dimensions of CARS are significantly related. Confidence is significantly positively related to coordination (r = 0.663, p < 0.001), control (r = 0.696, p < 0.001), and commitment (r = 0.655, p < 0.001). However, confidence was significantly negatively related to composure (r = -0.287, p < 0.001). Then, coordination was significantly positively correlated with control (r = 0.611, p < 0.001) and commitment (r = 0.614, p < 0.001), but coordination was significantly negatively correlated with composure (r = -0.291, p < 0.001). Next, control was significantly negatively correlated with composure (r = -0.4017, p < 0.001) and significantly positively correlated with commitment (r = 0.669, p < 0.001). Lastly, composure was significantly negatively correlated with commitment (r = -0.315, p < 0.001).

Table 2. <Descriptive statistics testing>

Dimension	M	SD	Skewness	Kurtosis	*1*	*2*	*3*	*4*	*5*
Confidence (self-belief)	3.24	0.532	-0.828	1.630	-				
Coordination (planning)	2.92	0.624	-0.261	0.116	0.663***	-			
Control (a sense of control)	3.03	0.521	0.070	-0.387	0.696***	0.611***	-		
Composure (anxiety)	1.92	0.381	-1.110	0.430	-0.287***	-0.291***	-0.401***	-	
Commitment (persistence)	3.25	0.558	-0.491	0.048	0.655***	0.614***	0.669***	-0.315***	-

*** p < 0.001

Table 3 is the result of the multifactor model for confirmatory factor analysis and the results of the Rasch model for measurement in the form of a rating scale / polytomous based on 29 CARS items. Of the 29 items, 3 items were eliminated due to the factor loading t-value (on confirmatory factor analysis) and the unweighted mean square value on the Rasch model. Therefore, based on the results of the item analysis, 26 items explain the five factors/dimensions that measure academic resilience.

Items were retained with the criteria of estimated SE (t-value > 1.96) (Raykov & Marcoulides, 2011) and factor loading (factor loading > 0.32) (Tabachnick & Fidell, 2021). Out of 29 items, item 11 on coordination (planning) was eliminated because factor loading = -0.288 < 0.32) and t-value = -4.068 (< 1.96). In addition, in composure (anxiety), two items were eliminated (i.e., item18 and item19), each of which item18 (factor loading = -0.630, t-value = -11.127) and item19 (factor loading = -0.354, t-value = -4.899) had factor loadings and t-values that did not match the cutoff.

Furthermore, after the three items were removed, the factor loading values ranged from 0.267-0.859, and the t-value ranged from 3.603 to 34.708. Tabachnick and Fidell (2021) state that factor loading > 0.32, which means that item 20 (which later, after item analysis, became item 18) with a factor loading value = 0.267, which indicates that the item is eliminated. However, item 20 was retained because the t-value was above 1.96 (Raykov & Marcoulides, 2011).

The College Academic Resilience Scale (CARS) has an initial number of 29 items; 3 items are canceled because they do not meet the fit criteria in the Rasch model. From the analysis results obtained, 26 items fit the Rasch model. The results of summary statistics using the jMetrik 4.1.1 program can be seen in Table 2.

In table 3, it can be seen that the value of the item fit level from the outfit means-square (UMS) column for each item has an accepted value of 0.5 < MNSQ < 1.5, which means that the 26 items on the Collage Academic Resilience Scale (CARS) scale function normally in making instruments or instruments according to the model to measure student competence in academic resilience. According to Bond et al. (2020) if the item meets the MNSQ value criteria, it means that the item is good and needs to be revised or replaced. In contrast to the level of item difficulty, which is consistent, the level of suitability of this item is strongly influenced by the size of the sample. The results of the item difficulty level (item measure) on the Rasch Rating Scale Model (RSM) the higher the value, the more difficult it is to choose "agree" (Urbina, 2014), it can be seen in the difficulty column, there is item 11 (3.49 > 0.70), item 3 (1. 67 > 0.70), item 17 (1.23 > 0.70) and item 21 (1.21 > 0.70) where respondents find it difficult to choose the agree option while for item 19 (-3.26 < 0.30), item 8 (-1.96 < 0.30), and item 9 (-1.24 < 0.30) respondents find it very easy to choose the agree option.

Furthermore, it can be seen in the column number on communalities referring to the Measure of Sampling Adequacy (MSA) number, ranging from 0 to 1, with MSA criteria> 0.5 (Urbina, 2014). 26 items have communalities values above> 0.5, so all of these items can be continued for differential item functioning (DIF) analysis. In the Rasch model, item bias can be found with DIF (differential item functioning). Items with DIF found ($p < 0.05$) are recommended to be re-evaluated (Bond et al., 2020). The results of the DIF test on CARS are 24 items that have a DIF value> 0.05, meaning that 24 CARS items do not have item bias and can be trusted for the accuracy of instrument measurement on the concept of academic resilience and two items, namely 5 and 19, have a value of <0.05, meaning that the item needs to be revised again.

Table 3. <Psychometric testing for factorial and polytomous models at the item level>

Items	Factorial Model		Polytomous Rasch Model			
	Factor Loading	Estimated/SE	Difficulty	UMS*	h^2	DIF
Item1[a]	0.691	15.704	-0.29	0.79	0.76	0.58
Item2[a]	0.720	17.811	-0.18	0.83	0.80	0.88
Item3[a]	0.348	5.240	1.67	1.05	0.56	0.65
Item4[a]	0.653	13.709	-0.72	0.87	0.78	0.90
Item5[a]	0.701	16.451	0.35	0.82	0.79	0.01
Item6[a]	0.728	18.311	-0.84	0.66	0.60	0.29
Item7[b]	0.595	11.506	0.16	0.92	0.94	0.36
Item8[b]	0.727	15.325	-1.96	0.92	0.86	0.15
Item9[b]	**0.859**	23.720	-1.24	0.70	0.71	0.77
Item10[b]	0.695	15.990	-0.45	0.67	0.69	0.93
Item11[c]	0.738	18.043	3.49	1.02	0.61	0.05
Item12[c]	0.769	21.516	-0.39	1.00	0.80	0.28
Item13[c]	0.746	18.749	-0.60	0.71	0.64	0.91
Item14[c]	0.636	13.478	-0.09	0.71	0.71	0.17
Item15[c]	0.601	11.704	-0.32	0.98	0.95	0.33
Item16[c]	0.350	5.323	0.17	0.89	0.89	0.34
Item17[d]	0.345	4.853	1.23	1.30	0.82	0.06
Item18[d]	**0.267**	**3.603**	1.02	1.23	0.83	0.85
Item19[d]	0.546	8.570	-3.26	1.06	0.34	0.01
Item20[d]	0.811	13.829	1.12	0.68	1.40	0.11
Item21[e]	0.768	23.596	1.21	0.78	0.74	0.12
Item22[e]	0.579	11.097	-0.61	0.58	0.72	0.41
Item23[e]	0.752	22.007	0.81	1.41	1.51	0.38
Item24[e]	0.850	**34.708**	0.18	0.93	0.97	0.62
Item25[e]	0.712	18.570	-0.39	0.72	0.68	0.47
Item26[e]	0.825	30.890	0.41	1.16	1.16	0.73

*UMS = Unweighted Mean Square
*h^2 (communalities) = > 0.5
**DIF*= > 0.05

*UMS = 0.50 – 1.50
[a]Item1 – Item6 = Confidence (self-belief); [b]Item7 – Item10 = Coordination (planning); [c]Item11 – Item16 = Control (a sense of control); [d]Item17 – Item20 = Composure (anxiety); [e]Item21 – Item26 = Commitment (persistence)

The College Academic Resilience Scale (CARS) has an initial number of 29 items; 3 items were eliminated because they did not meet the fit criteria in the Rasch model. From the analysis results obtained, 26 items fit the Rasch model. The summary statistical results are presented in Table 4. The results of item analysis take into consideration three (3) parameters in assessing the quality of items that will be used to assess students' abilities, namely item difficulty (p), item discriminating power (D), and item reliability (r). The results are presented in Table 4. The summary statistics presented in Table 4 show that, for a total of 26 items with 200 participants, the mean score was 25.78 (SD = 6.15). Mean item difficulty (p) and mean item discrimination are 0.43 and 0.22, respectively. This statistic reveals that the test has an adequate reliability index; the index is 0.876, which is higher than the recommended value of 0.70 (Bond et al., 2020).

Table 4. <Summary item statistics>

Parameter	Value
Number of items	26
Number of Responses	200
Reliability (Alpha)	0.876
Mean Scores	25.78
S.D	6.15
Mean P	0.43
Mean r_{pbi}	0.41

The mean item difficulty of 0.43 is within the required standard for a moderately difficult item with a discrimination index of 0.41, which is excellent for the entire test (Urbina, 2014). The results presented in Table 3 above show that the item analysis showed that 19 or 73.08% of the items had satisfactory item statistics (D > 0.20). These items met the minimum requirements for inclusion in the final version of the test. However, 7 (26.93%) based on the predefined criteria were recommended for revision from the test, having (D > 0.19). This means that 7 items can be included in the final test with minor revisions. The internal consistency reliability of the test items was assessed and found acceptable with a Cronbach's alpha value of 0.876.

Multifactor Model Findings

Table 5 summarizes the results of the factorial model and polytomous Rasch model. The factorial model test was conducted twice. The first factorial model is CARS with 29 items, and the second factorial model is CARS with 26 items after item analysis. The results of the factorial model on CARS with 29 items were found with χ^2 (367) = 956,310, *p* = 0.0000, Comparative Fit Index (CFI) = 0.798, Tucker-Lewis index (TLI) = 0.776, Root Mean Square Error of Approximation (RMSEA) = 0.090, 90% CI Root Mean Square Error of Approximation (RMSEA) = 0.083-0.097, probability Root Mean Square Error of Approximation (RMSEA) = 0.000, and Standardized Root Mean Square Residual (SRMR) = 0.076. Referring to Hu and Bentler (1999), the cutoffs on fit indices are as Comparative Fit Index (CFI) > 0.95, Tucker-Lewis's index (TLI) > 0.95, Root Mean Square Error of Approximation (RMSEA) < 0.06, and Standardized Root Mean Square Residual (SRMR) < 0.08. Thus, the Comparative Fit Index (CFI), Tucker-Lewis index, and Root Mean Square Error of Approximation (RMSEA) were found with a poor fit index. In addition, when looking at the results of the

90% CI Root Mean Square Error of Approximation (RMSEA) and probability Root Mean Square Error of Approximation (RMSEA) are also found with a poor fit index. This is due to the accepted value is 90% CI RMSEA≤ 0.05 (Raykov & Marcoulides, 2011) and probability RMSEA≥ 0.05 (Raykov & Marcoulides, 2011) However, in this model 1, Standardized Root Mean Square Residual (SRMR) was found to be a good fit with Standardized Root Mean Square Residual (SRMR) < 0.08 (Cho et al., 2020; Hu & Bentler, 1999).

Table 5 for model 2 was found with χ^2 (266) = 403.741, p = 0.0000, Comparative Fit Index (CFI) = 0.949, Tucker-Lewis's index (TLI) = 0.938, Root Mean Square Error of Approximation (RMSEA) = 0.051, 90% CI Root Mean Square Error of Approximation (RMSEA) = 0.041-0.061, probability Root Mean Square Error of Approximation (RMSEA) = 0.432, and Standardized Root Mean Square Residual (SRMR) = 0.052. Based on the results of the factorial model for model 2, Root Mean Square Error of Approximation (RMSEA), 90% CI Root Mean Square Error of Approximation (RMSEA), probability Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) were found to be a good fit. This refers to the suggested cutoff Root Mean Square Error of Approximation (RMSEA) < 0.06 (Hu & Bentler, 1999; Xia & Yang, 2019), and Standardized Root Mean Square Residual (SRMR) < 0.08 (Hu & Bentler, 1999), 90% CI RMSEA≤ 0.05 (Raykov & Marcoulides, 2011), and probability RMSEA≥ 0.05 (Raykov & Marcoulides, 2011). Meanwhile, the cutoff for Comparative Fit Index (CFI) and Tucker-Lewis's index (TLI) is > 0.95 (Hu & Bentler, 1999; Xia & Yang, 2019), and this study found Comparative Fit Index (CFI) = 0.949 and Tucker-Lewis's index (TLI) = 0.938. Hair et al. (2019) mentioned that the Comparative Fit Index (CFI) and Tucker-Lewis's index (TLI) = 0.95 are in the good-fitting model category, but the Comparative Fit Index (CFI) and Tucker-Lewis's index (TLI) = 0.90 were found to be weak. In addition, Hair et al. (2019) suggested that the Comparative Fit Index (CFI) and Tucker-Lewis's index (TLI) above 0.90 is an inappropriate determination of incremental goodness-of-fit. Thus, the Comparative Fit Index (CFI) and Tucker-Lewis's index (TLI) were found to be poor fit indices.

Polytomous Rasch Model

In Table 5, it is known that the instrument on the College Academic Resilience Scale (CARS) has a total of 26 items consisting of five (5) factors. The first factor, which is confidence, consists of 6 items (CARS1-CARS6), the results of the Rasch model analysis show that the value of item measurement reliability = 0.9681 (> 0.94) means that 6 items are very good at measuring confidence, Person Measurement Reliability = 0.7521 (0.67-0.80) means that student responses in answering the six items are good at measuring confidence, Item Strata Separated = 5. 5090 (4-5), Person Strata Separated = 0.7521 (0.67-0.80), the second factor Coordination 4 items (CARS7-CARS10), item measurement reliability value = 0.9822 (>94), Person Measurement Reliability = 0.7521 (0.67-0.80), Item Strata Separated = 5.5090 (4-5) Person Strata Separated = 4.7417 (4-5). The third factor, a sense of control, 6 items (CARS12-CARS17), item measurement reliability = 0.9646 (>94), Person Measurement Reliability = 0.7608 (0.67-0.80), Item Strata Separated = 5.2205 (4-5), Person Strata Separated = 3.7836 (3-4). The fourth factor, composure 6 items (CARS20-CARS23), the value of item measurement reliability = 0.9918 (>94), Person Measurement Reliability = 0.7238 (0.67-0.80), Item Strata Separated = 10.994 (>5), Person Strata Separated = 5. 7948 (>5) And the fifth factor commitment 6 items (CARS24-CARS29), the value of item measurement reliability = 0.8994 (0.81-0.90), Person Measurement Reliability = 0.7910 (0.67-0.80), Item Strata Separated = 2.9905 (2-3) Person Strata Separated = 2.9456 (2-3).

Table 5. <Psychometric Results for College Academic Resilience Scale>

Psychometric Results	Suggested Cut-off	Value
Factorial Model		
Model 1. (CARS with 29 items)		

Psychometric Results	Suggested Cut-off	Value
χ^2(df)	No significance	956.310 (367)*
Comparative Fit Index (CFI)	$>$ 0.95	0.798
Tucker–Lewis's index (TLI)	$>$ 0.95	0.776
Root Mean Square Error of Approximation (RMSEA)	$<$ 0.06	0.090
90 % CI Root Mean Square Error of Approximation (RMSEA)	$\leq$ 0.05	0.083-0.097
probability Root Mean Square Error of Approximation (RMSEA)	$\geq$ 0.05	0.000
Standardized Root Mean Square Residual (SRMR)	$<$ 0.08	0.076
Model 2. (CARS with 26 items)		
χ^2(df)	No significance	403.741 (266)*
Comparative Fit Index (CFI)	$>$ 0.95	0.949
Tucker–Lewis's index (TLI)	$>$ 0.95	0.938
Root Mean Square Error of Approximation (RMSEA)	$<$ 0.06	0.051
90 % CI Root Mean Square Error of Approximation (RMSEA)	$\leq$ 0.05	0.041-0.061
probability Root Mean Square Error of Approximation (RMSEA)	$\geq$ 0.05	0.432
Standardized Root Mean Square Residual (SRMR)	$<$ 0.08	0.052
Polytomous Rasch Model		
Item Measurement Reliability		
Confidence (self-belief)	> 0.94	0.9681
Coordination (planning)	> 0.94	0.9822
Control (a sense of control)	> 0.94	0.9646
Composure (anxiety)	> 0.94	0.9918
Commitment (persistence)	81-.90	0.8994
Person Measurement Reliability		
Confidence (self-belief)	0.67-0.80	0.7521
Coordination (planning)	0.67-0.80	0.7554
Control (a sense of control)	0.67-0.80	0.7608
Composure (anxiety)	0.67-0.80	0.7238
Commitment (persistence)	0.67-0.80	0.7910
Item Strata Separated		
Confidence (self-belief)	4-5	5.5090
Coordination (planning)	> 5	7.4320
Control (a sense of control)	4-5	5.2205
Composure (anxiety)	> 5	10.994
Commitment (persistence)	2-3	2.9905
Person Strata Separated		
Confidence (self-belief)	4-5	4.7417
Coordination (planning)	4-5	4.7573
Control (a sense of control)	3-4	3.7836
Composure (anxiety)	> 5	5.7948
Commitment (persistence)	2-3	2.9456

*p = 0.0000

Table 4 displays the summary results of the validity and reliability analysis with *Mplus* version 7, which consists of McDonald's Omega (ω), Average Variance Extracted (AVE), and Composite Reliability (CR). Average Variance Extracted (AVE) and Composite Reliability (CR) were analyzed simultaneously. Average Variance Extracted (AVE) is part of the construct validity section, a convergent validity (Fornell & Larcker, 1981), which estimates construct validity by determining the average latent construct variance explained by several items/observed variables (Dos Santos & Cirillo, 2023). Fornell and Larcker (1981) formulated the Average Variance Extracted (AVE) formula as follows below.

$$Average\ Variance\ Extracted\ (AVE) = \frac{\sum_{i=1}^{p} \lambda_i^2}{\sum_{i=1}^{p} \lambda_i^2 + \sum_{i=1}^{p} Var\ (\varepsilon_i)} = \frac{1}{p}\left(\sum\nolimits_{i=1}^{p} \lambda_i^2\right)$$

The above equation involves standardized factor loading based on each item that makes up a construct (Cheung et al., 2024). Therefore, the Average Variance Extracted (AVE) formula proposed by Fornell and Larcker (1981) shows the overall average standardized factor loading squared on all indicators of this academic resilience construct. Meanwhile, the suggested cutoff for Average Variance Extracted (AVE) is > 0.50 (Fornell & Larcker, 1981). Thus, the Average Variance Extracted (AVE) findings on CARS show that control (Average Variance Extracted (AVE) = 0.339) and composure (Average Variance Extracted (AVE) = 0.212) do not show convergent validity due to the Average Variance Extracted (AVE) value below 0.50. On the other hand, confidence (Average Variance Extracted (AVE) = 0.654), coordination (Average Variance Extracted (AVE) = 0.516), and commitment (Average Variance Extracted (AVE) = 0.689) show convergent validity with Average Variance Extracted (AVE) above 0.50.

Table 4. <McDonald's Omega (ω), Average Variance Extracted (AVE), and Composite Reliability (CR) results>

Dimension	McDonald's ω	AVE	CR
Confidence (self-belief) (item 1 – item 6)	0.814	0.654	0.835
Coordination (planning) (item 7 – item 10)	0.745	0.516	0.810
Control (a sense of control) (item 11 – item 16)	0.795	0.339	0.794
Composure (anxiety) (item 17 – item 20)	0.545	0.212	0.498
Commitment (persistence) (item 21 – item 26)	0.787	0.689	0.877

Furthermore, McDonald's Omega (ω) (see Table 4) is obtained based on the equation proposed by (McDonald, 2013), which is used to estimate reliability (Hayes & Coutts, 2020; Orcan, 2023; Widhiarso & Ravand, 2014), which refers based on factor loading and variance (Dunn et al., 2014). The McDonald's Omega (ω) coefficient formula is as follows.

$$McDonald's\ \omega = \frac{(\Sigma\lambda_j)^2}{[(\Sigma\lambda_j)^2 + \sum\theta_j]}$$

In the formula above, $(\Sigma\lambda_j)^2$ is the total number of unstandardized factor loadings that are quartered from each item that makes up the dimension (McDonald, 2013). Meanwhile, the divisor is the total number of unstandardized factor loadings that are quartered from each item that makes up the dimension and the total number of residual variance items (McDonald, 2013). Several studies found that the suggested cutoff for the McDonald's ω coefficient is ≥ 0.70 (Hancock & An, 2020; McNeish, 2017; Reise et al., 2013). Meanwhile, Reise et al. (2013) stated that McDonald's ω is ≥ 0.50 is acceptable. In this study, confidence (ω = 0.814), coordination (ω = 0.745), control (ω = 0.795), composure (ω = 0.545), and commitment (ω = 0.787) indicate values that are satisfaction (above 0.800) (Goodboy & Martin, 2020) and acceptable (between 0.500 to 0.700) (Reise et al., 2013).

Furthermore, Composite Reliability (CR) is also one method of determining reliability in structural equation modeling (Raykov, 1997). In detail, the Composite Reliability (CR) formula equation is as follows below.

$$Composite\ Reliability\ (CR) = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum(1 - \lambda_i^2)}$$

The Composite Reliability (CR) equation proposed by Raykov (1997) involves standardized factor loading of both latent constructs and indicators of the items that make up CARS. Hair et al. (2019) state that the CR value can be used to state good reliability if it is above 0.70. This study found that composure (Composite Reliability (CR) = 0.498) shows poor reliability due to Composite Reliability (CR) below 0.70. Then, confidence (Composite Reliability (CR) = 0.835), coordination (Composite Reliability (CR) = 0.810), control (Composite Reliability (CR) = 0.794), and commitment (Composite Reliability (CR) = 0.877) were found with good reliability due to Composite Reliability (CR) above 0.70.

The reliability index and separation of persons obtained from the results of the analysis using the help of jMetric software, it was found that the 'reliability of person' index was 0.87, and the value of separation of persons measured was 2.50. From the results of these two reliability values are classified as good, this indicates that the variability of student abilities in this study is quite adequate. This is an indication that the resilience ability of each student is well tested, and there are three different groups of students, namely students with low, medium, and high abilities. The results of the Rasch model analysis also indicate that the item reliability and item separation index are 0.93 and 3.73. These values indicate that the reliability of the items in the developed Resilience Test is very good and that the sample of people is large enough to confirm the hierarchy of difficulty levels of the test items.

Figure 1 provides information that the person density table shows the distribution of respondents is normally distributed, and in the item number table, the distance between all items is the same because the threshold value is made the same, but the position is different because it depends on the item difficulty of each item. Difficult items will be at the highest position. Figure 1 can be interpreted that students who have low academic resilience, with a value on the X axis of -0.5, are 50% likely to answer strongly disagree and 50% to answer strongly agree.

Figure 2 provides information on the normal distribution of items by meeting the criteria can be seen in table 2 with the limits of items declared fit with the model if they meet one or both of the MNSQ Outfit between 0.5 - 1.5 and ZSTD Outfit between -0.2 to +2.0 and the item correlation value with the total score (point measure correlation) ranging from 0.4 - 0.85. Thus, to maintain any item in a test, it should satisfy the following conditions as provided by (Bond et al., 2021), (1) PTMEA CORR is positive and not 0 or close to it, (2) The INFIT and OUTFIT MNSQ index fall within the acceptable range for Multiple choice Questions, i.e., 0.7 ≤ MNSQ ≤ 1.3, (3) The Z standard (ZSTD) values fall within the acceptable range of -2.0 ≤ Z ≤ 2.0. The result shows that items 11, 3,17, and 21 Outfit MNSQ are out of the acceptable range and have very low PTMEA CORR close to zero.

Figure 3 shows the measurement information obtained from the College Academic Resilience Scale. The X axis shows the level of student ability in answering the academic resilience instrument, while the Y axis shows the magnitude of the Probability information function. At a high level of academic resilience, the information obtained by measurement is very high, meaning that very much information is obtained to provide a high reliability value. Therefore, the development of academic resilience test instruments is optimal for knowing the ability of students who have high academic resilience.

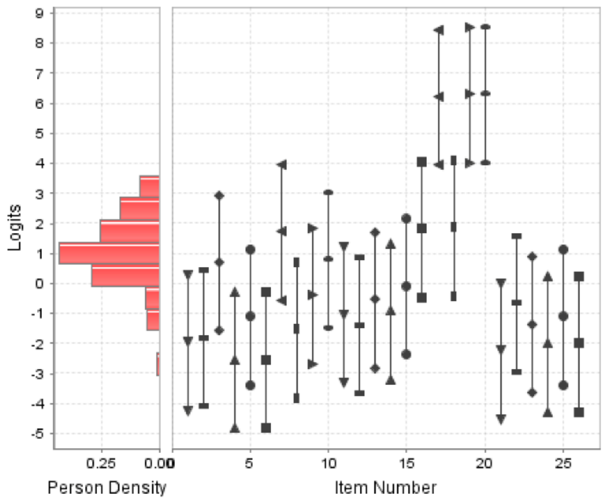

Figure 1. <Item Map of the Academic Resilience Scale (CARS)>

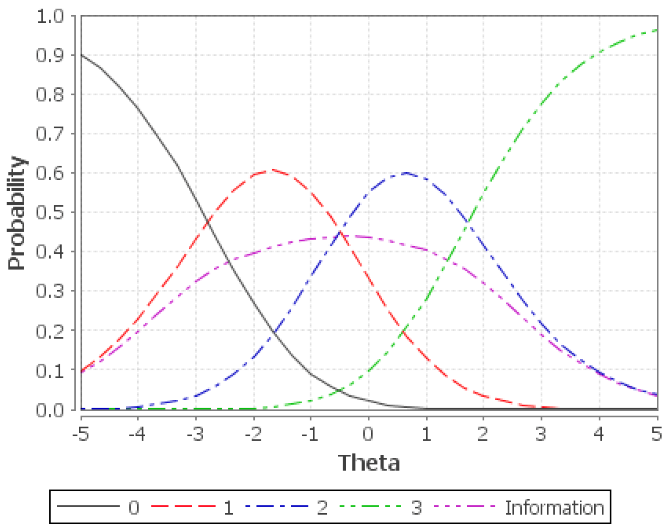

Figure 2. <CARS item information>

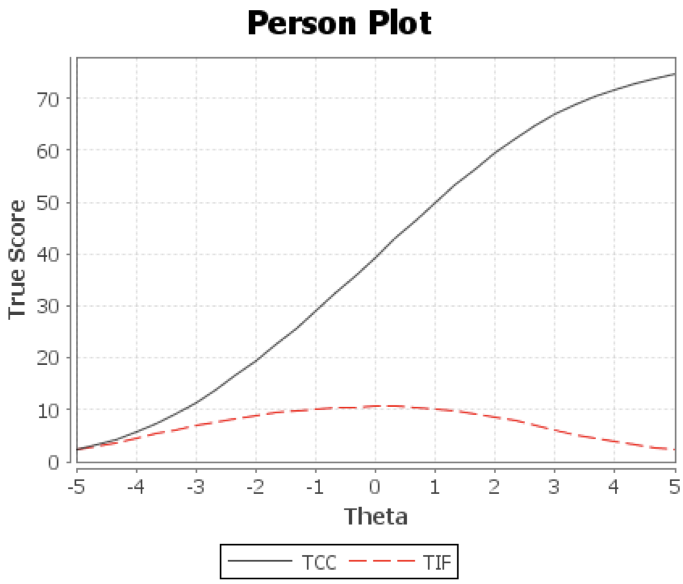

Figure 3. <CARS person plot information>

To ensure that the resilience test on the CARS scale measures the desired five factors of Confidence, Coordination, Control, Composure, and Commitment, assessing unidimensionality is essential. To determine unidimensionality in this study, PCA of the Rasch residuals was performed. The raw variance explained by size was 25.9%, which closely matched the expected variance of 25.7%. The raw variance explained by person was 5.7%, and the variance explained by item was 20.89%. The results show that the explained variance of 25.9% is higher than the minimum requirement of unidimensionality, which is 20%. this means that, unidimensionality of each factor is accomplished.

Based on the results of the confirmatory factor analysis and polytomous Rasch model test, of the 29 items, 3 items were eliminated due to the factor loading t-value (on confirmatory factor analysis) and the unweighted mean square value on the Rasch model. Therefore, based on the results of the item analysis, 26 items explain the five factors/dimensions that measure academic resilience. However, in the differential item functioning (DIF) analysis, items 5 and 19 did not meet the statistical requirements that had a their values exceeded 0.05, so the items needed to be revised. The instruments used in this study meet the criterion for unidimensionality, demonstrating their capacity to measure what is expected. DIF testing based on gender demonstrates that using gender as a differentiator in this evaluation does not cause a bias in determining the amount of student academic resilience. However, at this point, it cannot be determined and requires more study to learn more about the different factors that might influence the evaluation of students' academic resilience levels, some of which can be attributed to ethnicity, parents' educational backgrounds, and so on.

The College Academic Resilience Inventory (CARS) is a multidimensional construct based on Martin and Marsh (2003, 2006) 5-C model of academic resilience, which includes confidence (self-efficacy), coordination (planning), control, composure (low anxiety), and commitment. The multidimensional notion of academic resilience implies that it includes dimensions that interact distinctly for each undergraduate student. The Academic Resilience Scale (ARS-30) is another multidimensional construct measurement that provides insights into adaptive reactions, emphasizing how students navigate adversity in their educational journeys (Cassidy, 2016). Understanding the complex nature of academic resilience, as well as cultural variations, allows educators and institutions to conduct targeted interventions that improve students' ability to overcome difficulties and prosper in their academic endeavours.

CONCLUSIONS

This report discusses findings from the development and validation of The College Academic Resilience Inventory (CARS) in undergraduate students. The College Academic Resilience Inventory (CARS) is a multidimensional construct based on Martin and Marsh (2003, 2006) 5-C model of academic resilience, which comprises confidence (self-efficacy), coordination (planning), control, composure (low anxiety), and commitment. The results indicate that the 26 items in The College Academic Resilience Inventory (CARS) have good validity and reliability when tested using confirmatory component analysis and the polytomous rash model. Thus, this test can be used to evaluate academic resilience in undergraduate students. However, because this study solely focuses on evaluating academic resilience in undergraduate students, further studies should be conducted in different countries and cultures to broaden the validation of the tool and generalize the findings.

ACKNOWLEDGMENTS

We would like to thank the students and the entire academic community at universities in South Sumatra for their participation and contribution to this research.

AUTHOR CONTRIBUTION STATEMENT

SDF conceptualizes and writes in English. KKHD and JM analyze and report the findings based on a psychometric approach. TSZ writes and criticizes the content of both theoretical perspectives and accurate English. MW, IL, KJL, LT, ASA, and SA contribute to data material, writing, citations, and references.

REFERENCES

Andrich, D. (1978). A rating formulation for ordered response categories. *Psychometrika*, *43*(4), 561–573. https://doi.org/10.1007/BF02293814

Andrich, D., & Marais, I. (2019). *A Course in Rasch Measurement Theory*. Springer Nature Singapore. https://doi.org/10.1007/978-981-13-7496-8

Anon. (1979, 1979). *National commission for the protection of human subjects of biomedical and behavioral research* 16th Meeting Transcript of Proceedings, United States of America.

Association, A. P. (2019). *Publication manual of the American Psychological Association*. American Psychological Association.

Association, W. M. (2013). Declaration of helsinki. *Review of Psychology*, *21*(2), 111–121.

Babakova, L. (2019). Initial adaptation and validation for Bulgarian conditions of a scale measuring the academic resilience among students. *KNOWLEDGE-International Journal*, *30*(5), 1267–1272.

Bond, T., Yan, Z., & Heene, M. (2020). *Applying the Rasch Model* (4th Edition ed.). Routledge. https://doi.org/10.4324/9780429030499

Cassidy, S. (2015). Resilience Building in Students: The Role of Academic Self-Efficacy. *Front Psychol*, *6*, 1781. https://doi.org/10.3389/fpsyg.2015.01781

Cassidy, S. (2016). The academic resilience scale (ars-30): A new multidimensional construct measure. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01787

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, *41*(2), 745–783. https://doi.org/10.1007/s10490-023-09871-y

Cho, G., Hwang, H., Sarstedt, M., & Ringle, C. M. (2020). Cutoff criteria for overall model fit indexes in generalized structured component analysis. *Journal of Marketing Analytics*, *8*(4), 189–202. https://doi.org/10.1057/s41270-020-00089-1

Colp, S. M. (2015). *Examining Academic Resilience as a Mediator of Post-Secondary Achievement and Retention* http://dx.doi.org/10.11575/PRISM/26012

Covington, M. V. (1992). *Making the grade: A self-worth perspective on motivation and school reform*. Cambridge University Press.

Cui, T., Wang, C., & Xu, J. (2023). Validation of academic resilience scales adapted in a collective culture. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1114285

Dos Santos, P. M., & Cirillo, M. Â. (2023). Construction of the average variance extracted index for construct validation in structural equation models with adaptive regressions. *Communications in Satistics - Simulation and Computation*, *52*(4), 1639–1650. https://doi.org/10.1080/03610918.2021.1888122

Dunn, T. J., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology*, *105*(3), 399–412. https://doi.org/10.1111/bjop.12046

Dwiastuti, I., Hendriani, W., & Andriani, F. (2022). The impact of academic resilience on academic performance in college students during the covid-19 pandemic. *KnE Social Sciences*. https://doi.org/10.18502/kss.v7i1.10198

Flora, D. B. (2020). Your coefficient alpha is probably wrong, but which coefficient omega is right? A tutorial on using R to obtain better reliability estimates. *Advances in Methods and Practices in Psychological Science*, *3*(4), 484–501. https://doi.org/10.1177/25152459209517

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Goodboy, A. K., & Martin, M. M. (2020). Omega over alpha for reliability estimation of unidimensional communication measures. *Annals of the International Communication Association*, *44*(4), 422–439. https://doi.org/10.1080/23808985.2020.1846135

Gravetter, F., & Forzano, L. A. B. (2018). *Research methods for the behavioral sciences*. Cengage.

Gravetter, F. J., Wallnau, L. B., Forzano, L. A. B., & Witnauer, J. E. (2021). *Essentials of statistics for the behavioral sciences* (10th ed.). Cengage Learning.

Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hancock, G. R., & An, J. (2020). A closed-form alternative for estimating ω reliability under unidimensionality. *Measurement: Interdisciplinary Research and Perspectives*, *18*(1), 1–14. https://doi.org/10.1080/15366367.2019.1656049

Hayes, A. F., & Coutts, J. J. (2020). Use omega rather than cronbach's alpha for estimating reliability. *But. . . . Communication Methods and Measures*, *14*(1), 1–24. https://doi.org/10.1080/19312458.2020.1718629

He, Z. (2014). Examining the academic resilience in mathematics performance for the underprivileged ninth graders using the national data from the High School Longitudinal Study.

Homaedi, R., Mafruhah, M., & Yuliana, A. T. (2022). Profil Mahasiswa Dengan Tugas Ganda Kuliah Dan Bekerja. *Shine: Jurnal Bimbingan Dan Konseling*, *2*(2), 125-137. https://doi.org/10.36379/shine.v2i2.217

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jamovi. (2022). *The jamovi project*. Computer Software. https://www.jamovi.org

Kumalasari, D. (2023). Academic resilience among Indonesian college students during the COVID-19 pandemic: The role of future orientation and peer support. *Electronic Journal of Research in Education Psychology*, *21*(61), 541–558. https://doi.org/10.25115/ejrep.v21i61.7945

Li, C., Li, S., & Wei, C. (2019, 2019). *The development and validation of academic resilience scale for undergraduates in Taiwan: Rasch analysis* Proceedings of the 2nd International Conference on Humanities Education and Social Sciences (ICHESS 2019, https://doi.org/10.2991/ichess-19.2019.41

http://dx.doi.org/10.2991/ichess-19.2019.41

Loehlin, J. C., & Beaujean, A. (2017). *Latent variable models: An introduction to factor, path, and structural equation analysis* (5th ed.). Psychology Press.

Martin, A. J., & Marsh, H. W. (2003). *Academic resilience and the four cs: Confidence, control, composure, and commitment*. NZARE AARE.

Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: A construct validity approach. *Psychology in the Schools*, *43*(3), 267–281. https://doi.org/10.1002/pits.20149

McDonald, R. P. (2013). *Test theory: A unified treatment*. Psychology Press.

McNeish, D. (2017). Thanks coefficient alpha, we'll take it from here. *Psychological Methods*, *23*(3), 412–433. https://doi.org/10.1037/met0000144

Mills, K. J. (2021). Black students' perceptions of campus climates and the effect on academic resilience. *Journal of Black Psychology*, *47*(4–5), 354–383. https://doi.org/10.1177/00957984211001195

Muthén, B., & Muthén, L. (2017). Mplus. In *In handbook of item response theory* (pp. 507–518). Chapman and Hall/CRC.

Orcan, F. (2023). Comparison of cronbach's alpha and McDonald's omega for ordinal data: Are they different? *International Journal of Assessment Tools in Education*, *10*(4), 709–722. https://doi.org/10.21449/ijate.1271693

Raykov, T. (1997). Estimation of composite reliability for congeneric measures. *Applied Psychological Measurement*, *21*(2), 173–184. https://doi.org/10.1177/01466216970212006

Raykov, T., & Marcoulides, G. A. (2011). *Introduction to psychometric theory*. Routledge.

Reise, S. P., Bonifay, W. E., & Haviland, M. G. (2013). Scoring and modeling psychological measures in the presence of multidimensionality. *Journal of Personality Assessment*, *95*(2), 129–140. https://doi.org/10.1080/00223891.2012.725437

Ricketts, S. N., Engelhard, G., & Chang, M. L. (2017). Development and validation of a Scale to measure academicrResilience in mathematics. *European Journal of Psychological Assessment*, *33*(2), 79–86. https://doi.org/10.1027/1015-5759/a000274

Tabachnick, B. G., & Fidell, L. S. (2021). *Using multivariate statistics* (7th ed.).

Urbina, S. (2014). *Essentials of psychological testing*. John Wiley & Sons.

Widhiarso, W., & Ravand, H. (2014). Estimating reliability coefficient for multidimensional measures: A pedagogical illustration. *Review of Psychology*, *21*(2), 111-121.

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods*, *51*(1), 409–428. https://doi.org/10.3758/s13428-018-1055-2

Zulfikar, M., Wadud, M., & Kurniawan, M. (2022). Pengaruh Keselamatan dan Kesehatan Kerja Karyawan terhadap Produktivitas Kerja Karyawan Bagian Gudang PT Muara Dua Kota Palembang. *Jurnal Nasional Manajemen Pemasaran & SDM*, *3*(1), 19-25. https://doi.org/10.47747/jnmpsdm.v3i1.674

APPENDIX

1 *(Sangat Setuju)* 3 *(Setuju)*

2 *(Tidak Setuju)* 4 *(Sangat Tidak Setuju)*

No.	Items
1.	Saya mampu mengerjakan tugas yang diberikandosen dengan sangat baik.
2.	Saya sangat yakin terhadap kemampuan yang dimiliki untuk menyelesaikan tugas yang diberikan.
3.	Jika mendapatkan nilai buruk, saya tidak akan merasa rendah diri.
4.	Saya selalu berusaha keras untuk mencapai prestasi yang terbaik.
5.	Saya menciptakan hal-hal yang baru untukmeningkatkan keberhasilan tugas.
6.	Saya memotivasi diri sendiri untuk terusberupaya melakukan yang terbak, terutama dalam situasi sulit.
7.	Saya merangkum materi pada malam hari yangakan dipelajari besok.
8.	Saya mengerjakan tugas sebelum batas waktu.
9.	Saya mampu mengembangkan materi pembelajaran yang relevan sesuai tujuan pembelajaran.
10.	Saya mengulang materi yang telah dijelaskandosen dari sumber lain.
11.	Saya yakin bisa mengendalikan diri dalam menghadapi situasi yang sulit dalamperkuliahan.
12.	Saya yakin tugas kuliah yang dikerjakan sudah baik.
13.	Saya yakin dosen akan puas terhadap tugasyang saya kerjakan.
14.	Saya bisa mengontrol diri meskipun sedangbanyak tuntutan belajar.
15.	Saya senang belajar meskipun ada tuntutanyang mengharuskan untuk belajar.
16.	Saya tidak merasa tertekan atas banyaknyatugas yang dosen berikan.
17.*	Terkadang saya merasa gugup saat ditanya dosen terkait materi yang sedang dibahas.
18.	Saya cemas saat presentasi di hadapan banyak orang.
19.*	Badan saya keringat dingin saat melaksanakan ujian.
20.*	Saya yakin dan mampu mengendalikan rasa cemas pada saat dihadapkan dengan banyak tugas.
21.	Saya berusaha untuk menyelesaikan tugas kuliah walaupun sulit.
22.	Saya terbiasa untuk menyelesaikan tugas sayasendiri tanpa bantuan orang lain.
23.	Saya terus mencari cara untuk tugas kuliah yang tidak saya pahami sampai menemukan caranya.
24.	Saya tidak akan menyerah walaupun banyak tantangan dalam perkulihan.
25.	Saya akan tetap semangat berangkat kuliah walaupun dalam keadaan yang tidak baik.
26.	Saya tidak akan membiarkan diri untuk terpurukmeskipun ada banyak permasalahan di perkuliahan.

*Reversed items