Jurnal Penelitian dan Evaluasi Pendidikan
Volume 28, No. 1, June 2024 (32-42)
Online: http://journal.uny.ac.id/index.php/jpep

Increasing measurement accuracy: Scaling effect on academic resilience instrument using Method of Successive Interval (MSI) and Method of Summated Rating Scale (MSRS)

Beta Wulan Febriana[12]* and Farida Agus Setiawati[1]
[1]Universitas Negeri Yogyakarta, Indonesia
[2]Universitas Islam Indonesia, Indonesia
*Corresponding Author. E-mail: betawulan.2022@student.uny.ac.id/betawulanfebriana@uii.ac.id

ARTICLE INFO

Article History
Submitted:
18 December 2023
Revised:
23 May 2024
Accepted:
07 June 2024

Keywords
Method of successive intervals; summed rating scale; confirmatory factor analysis; academic resilience

Scan Me:

ABSTRACT

A research instrument is crucial and must meet the requirements to be valid and reliable in content and construction. Not infrequently, various methods are tried to increase the accuracy of research instruments, one of them being a simple method such as the scaling technique. This research aims to improve measurement accuracy by using scaling techniques through the process of successive intervals and summated rating scale in confirmatory factor analysis of the Academic Resilience (ARS) instrument. This research is a descriptive exploratory study using a questionnaire consisting of five answer choices (5-point Likert scale) as the research instrument. Participants in this research were 300 students. Data analysis was conducted using Microsoft Excel and R programs. The research results showed that there was a significant difference in the results of the reliability and validity of the constructs as well as the parameters in the confirmatory factor analysis of the ARS instrument before and after transformation with the method of successive intervals and summated rating scale. This research contributes to implementing quantitative data scaling practices in measurement research, and it has been proven that there was an increase in measurement accuracy after scaling.

To cite this article (in APA style):
Febriana, B. W., & Setiawati, F. A. (2024). Increasing measurement accuracy: Scaling effect on academic resilience instrument using Method of Successive Interval (MSI) and Method of Summated Rating Scale (MSRS). *Jurnal Penelitian dan Evaluasi Pendidikan, 28(1)*, 32-42 doi: http://dx.doi.org/10.21831/pep.v28i1.69334

INTRODUCTION

Technology can no longer be separated from student life. Rapid technological progress has led to significant societal changes, intertwining technology with people's lives, particularly students The use of technology, in this case, the Internet, significantly impacts students. The Internet provides unlimited knowledge and unlimited opportunities for students. The Internet also causes stress and anxiety, which triggers mental health disorders in students (Pawar, 2021; Trigueros, 2020).

The Covid-19 pandemic has significantly impacted the use of technology in Indonesia. Learning activities that cannot carried out at school have resulted in a shift from the learning model to a distance method carried out online (Ramadhana et al., 2021). It causes a lack of understanding about adapting, making students feel stressed. The pressure that students continuously face causes students' mental health problems. This mental health disorder is what makes it difficult for students to develop, and their learning achievement declines. Students who can adapt and excel when faced with life's difficulties (with limitations) are strong students considered to have good academic resilience (Cassidy, 2016; Shengyao et al., 2024).

Academic resilience is related to students' ability to face challenges and achieve success in academic success (García-Crespo et al., 2021; Romano et al., 2021; Shengyao et al., 2024). Based on systematic literature review research, research on academic resilience is research that researchers often carry out because academic resilience can potentially improve the learning outcomes of students at risk of school failure (Rudd et al., 2021). Rudd et al. (2021) stated that most research on academic resilience is research related to calculating students' academic resilience scores based on their academic resilience abilities using academic resilience measurement instruments.

Measuring students' academic resilience abilities is carried out using various academic resilience instruments, such as the Academic Resilience Scale (ARS) (Martin & Marsh, 2006), the Academic Resilience in Mathematics scale (ARMS) (Ricketts et al., 2017), and the Academic Resilience Scale (ARS-30) (Cassidy, 2016). The instrument for measuring academic resilience abilities that researchers most widely use is the ARS-30 instrument developed by Cassidy (2016) because this instrument is considered to have the ability to measure the academic resilience of students from various student backgrounds. Several measurement scales, such as the Thurstone, Guttman, and Likert scales, can be used to measure behavioral-based academic resilience abilities. The ARS-30 instrument is a measurement instrument that uses a Likert scale containing five student answer choices (1 = very unsuitable, 2 = not suitable, 3 = not suitable, 4 = suitable, and 5 = very unsuitable).

The Likert scale is widely used by researchers in agriculture, psychology, education, and society (Sumin et al., 2022). The Likert scale is an ordinal scale with ordinal data where the data must be analyzed nonparametrically (Waryanto & Millafati, 2006). Although Rensis Likert (the inventor of the Likert scale) believes that the Likert scale has the quality of an interval scale, many experts consider the Likert scale to be an ordinal scale because it requires an interval scale that the difference between two consecutive scales reflects the same difference in the variables being measured (Sumin et al., 2022). Non-parametric is an analysis method that does not require certain assumptions, which results in the analysis being less sensitive and less potent than data analysis using parametric (Jamieson, 2004). For this reason, ordinal data must be converted into interval data for the analysis to be applied (Setiawati et al., 2013). One effort to make data into interval data on psychological measurement results is a scaling process (Setiawati et al., 2013).

The scaling process is an effort to place attributes or characteristics on a continuum range, which involves changing values or transforming scores from ordinal data to interval data (Setiawati et al., 2013). In this research, transformation was carried out using the Method of Successive Interval (MSI) and the Method of Summated Rating Scale (MSRS). Both methods transform data into the z-score form using a normal distribution to produce the same units for distance from each other (Kosherbayeva et al., 2024). However, the difference between the two is that MSI is done by looking for a standardized score for each response on each item, while MSRS is done by changing the cumulative proportion of each response in a category into a standard normal curve value (Ningsih & Dukalang, 2019; Asdar, 2011). Scaling is considered capable of supporting the use of measurement instruments and increasing several scales' reliability and discriminant validity (Musa et al., 2021). Through this research, it is hoped that we can find out the differences in the effects of psychometric characteristics on the ARS instrument before and after transformation using MSI and MSRS through confirmatory factor analysis.

RESEARCH METHOD

This research is quantitative research, involving 300 students at university level to fill out a questionnaire about ARS. The instrument used in this research was developed based on the ARS instrument by Cassidy (2016), which consists of three dimensions, namely perseverance, reflecting and adaptive help-seeking, and negative affect and emotional response.

10.21831/pep.v28i1.69334

The questionnaire was given online using Google Forms, which was open for two weeks. The questionnaire uses a Likert scale with five options, namely 1 = very unsuitable, 2 = not appropriate, 3 = less appropriate, 4 = appropriate, and 5 = very appropriate. Before use, the ARS instrument is first tested for content validity to ensure the correctness of the instrument by eliminating ambiguous words and double-barreled questions.

The data analysis technique used in this research is using MS Excel and the R Program. The MS Excel program is used to transform the scale based on students' responses using MSI and MSRS. Meanwhile, the R program tests validity and estimates construct reliability using a Confirmatory Factor Analysis (CFA) approach on data before and after scaling with MSI and MSRS. CFA was carried out to test construct validity because, in developing this instrument, the author adapted a frequently used instrument, the ARS-30. MSI and MSRS transform data into the z-score form using a normal distribution to produce the same units for distance from each other (Kosherbayeva et al., 2024). However, the difference between the two is that MSI is done by looking for a standardized score for each response on each item, while MSRS is done by changing the cumulative proportion of each response in a category into a standard for normal curve value (Ningsih & Dukalang, 2019; Asdar, 2011).

Before testing using CFA, it is necessary to determine the adequacy of the sample using Kaiser-Meyer-Olkin (KMO). The KMO test is applied to assess the adequacy of sampling for each variable in the structure, while the Bartlett test is used to determine the significance of the correlation between research variables. The sample adequacy measure is met if the KMO value is> 0.6 and the significance of Bartlett's Test of Sphericity is <0.05 (Watkins, 2018).

The overall model fit test in CFA is associated with a standard fit index or goodness-of-fit (GOF), which refers to three fit type parameters, namely, Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Standard Root Mean Square Residual (SRMR) and root Mean Square Error of Approximation (RMSEA). Overall model suitability is met if CFI and TLI≥0.90, SRMR≤0.08, and RMSEA<0.08 (Gana & Broc, 2019). This index provides evidence of how well the ARS three-factor model is based on empirical data. In addition, it is possible to improve model fit through simultaneous modification of indices and correlation coefficients during variable analysis.

FINDINGS AND DISCUSSION

Findings

This research aims to analyze the effects of scale transformation (scaling) using MSI and MSRS in confirmatory factor analysis. This scale transformation is carried out on the Academic Resilience (ARS) instrument by changing the score from a raw score whose range/distance is

Table 1. ARS Instrument Indicator

Dimensions	Example of Items
Perseverance	I would try to think of new solutions
	I would do my best to stop thinking negative thoughts
Reflecting and adaptive help-seeking	I would try to think more about my strengths and weaknesses to help me work better
	I would try different ways to study
Negative affect and emotional response	I would probably get depressed
	I would feel like everything was ruined and was going wrong

ISSN (print) 2685-7111 | ISSN (online) 2338-6061

10.21831/pep.v28i1.69334

unknown into a z-score to produce the same units for the distance from each other, then comparing the psychometric characteristics of the prior data and the scaling results data using an approach classic.

The development of the ARS instrument was carried out by examining the ARS concept and theory according to Cassidy (2016), with three constructs as in Table 1. The data resulting from testing the ARS instrument is from now on referred to as prior data. The priority data obtained is a response, which is then transformed into a z-score via MSI and MSRS.

Method of Successive Interval (MSI)

The Likert-type instrument scaling process with MSI was carried out using "add-ins" in Microsoft Excel. In general, the steps in MSI (Mondiana et al., 2018) are calculating the number of frequencies (f) of the subject's responses to each criterion for each item, calculating the proportion in each category, which is then converted into a proportion score (p) and cumulative proportion. The proportion score is calculated by dividing the frequency (f) by the number of respondents (N) while the cumulative proportion (pk) is obtained from the proportion in each category plus the proportion from the previous category. Then, calculate the Z value for each cumulative proportion obtained (using the normal distribution table) and determine the Z limit value (the value of the probability density function on the Z abscissa) for each category using the Formula 1.

$$\delta\ (Z) = \frac{1}{\sqrt{2\pi}}\ e^{\left[\frac{z^2}{2}\right]} \qquad -\infty < Z < +\infty \tag{1}$$

and finally calculate the scale value (average interval) for each category, with a Formula 2.

$$\text{Scale} = \frac{\textit{lower limit density} - \textit{upper limit density}}{\textit{the area under the upper limit} - \textit{the area under the lower limit}} \tag{2}$$

The results of MSI scaling in item 2 can be seen in Table 2.

Table 2. Results of Successive Interval Method Scaling on One Item

No. Items	Categories	F	Prop	Cum	Density	Z	Scale
2	1	6,000	0.02	0.02	0.05	-2.05	1.00
	2	45,000	0.15	0.17	0.25	-0.95	2.06
	3	90,000	0.30	0.47	0.40	-0.08	2.94
	4	103,000	0.34	0.81	0.27	0.89	3.80
	5	56,000	0.19	1.00	0.00	8.21	4.86

The results of MSI scaling obtained a z score for each response on each item. These results show that with the scaling process, the response score for each item is different from the response score without scaling (category). In Table 2, there are changes in the scale, especially in category 3, which changed to 2.94; category four which changed to 3.80; and category five which changed to 4.86. This difference is due to differences in density in each category, where the greatest density is in category three, and the smallest density is in category 5.

Method of Summated Rating Scale (MSRS)

Scaling Likert-type instruments using MSRS was carried out with the help of the Microsoft Excel program. This scaling calculation begins by calculating the number of

ISSN (print) 2685-7111 | ISSN (online) 2338-6061

10.21831/pep.v28i1.69334

frequencies (f) of the subject's responses to each criterion for each item. This frequency score is converted into a proportion score (p) and cumulative proportion. The proportion score is calculated by dividing the frequency (f) by the number of respondents (N). Cumulative proportion (pk) is obtained from the proportion in each category plus the proportion in the previous category. The following process is calculating the middle pk, namely the midpoint of the cumulative proportion, which is calculated from half the proportion in the category plus the pk of the previous category or can be formulated as follows: middle pk= ½p + pkb. The next process calculates the deviation value (z) by converting the middle pk score into a z score by referring to the normal curve z score table. The results of the summated rating scale calculation in item 2 can be seen in Table 3.

The MSRS scaling results obtained a z score for each response on each item. These results show that with the scaling process, the response score for each item is different from the response score without scaling (category).

Table 3. Scaling Results of the Summated Rating Scale Method on One Item

No. Items	Categories	F	Prop	Cum	Density	Z	Scale
2	1	6,000	0.02	0.02	0.01	-2.33	0.00
	2	45,000	0.15	0.17	0.10	-1.31	1.02
	3	90,000	0.30	0.47	0.32	-0.47	1.86
	4	103,000	0.34	0.81	0.64	0.36	2.69
	5	56,000	0.19	1.00	0.91	1.32	3.65

Sample Adequacy Test

The steps taken before carrying out CFA are the Kaiser-Meyer-Olkin (KMO) sampling adequacy test and iteration with the Bartlett Sphericity test. The test results show that the KMO and Bartlett test values for the three data (prior data, MSI data, and MSRS data) show the same results, namely 0.91 and 0.00, respectively. It indicates very high sample adequacy, and the p-value significance level shows sufficient correlation between variables (Watkins, 2018), so the three data can be analyzed using CFA.

Determination Goodness-of-fit

Next, calculations are carried out to determine the goodness-of-fit criteria for each data using three fit types: incremental, parsimonious, and absolute. The results of calculating the goodness-of-fit indices are shown in Table 4.

Table 4. Calculation of goodness-of-fit criteria

Fit Type	Index	Data		
		Prior Data	MSI Data	MSRS Data
Incremental	CFI	0.827*	0.950	0.943
	TLI	0.791*	0.939	0.931
Parsimonious	RMSEA	0.130*	0.067	0.073
Absolute	SRMR	0.129*	0.057	0.053

The results of the goodness-of-fit indices calculation show that the MSI and MSRS data meet a fit model (CFI and TLI≥0.90, SRMR≤0.08, and RMSEA<0.08) (Gana & Broc, 2019). However, all goodness-of-fit indices cannot be met in data that has not been transformed.

Validity Analysis

In CFA, a variable is said to be good if one of the indicators is a factor loading greater than 0.6 (Gana & Broc, 2019). Table 5 shows the calculation of loading factors in ARS for prior data, MSI data, and MSRS data.

10.21831/pep.v28i1.69334

Table 5. Calculation of loading factors for each item

Items	Loading Factor		
	Prior Data	MSI Data	MSRS Data
RA1	0.623	0.665	0.660
RA2	0.748	0.748	0.746
RA3	0.589*	0.806	0.812
RA4	0.749	0.765	0.765
RA5	0.674	0.773	0.774
RA6	0.729	0.796	0.796
RA7	0.772	0.684	0.684
RA8	0.675	0.725	0.725
RA9	0.274*	0.670	0.711
RA10	0.782	0.736	0.685
RA11	0.823	0.813	0.813
RA12	0.794	0.785	0.773
RA13	0.716	0.691	0.716
RA14	0.883	0.864	0.886
RA15	0.782	0.732	0.773

The calculation results show that each indicator (item) in the MSI data and MSRS data has a loading factor value > 0.6, which means it is valid and can reflect the ARS. However, the loading factors on items RA3 and RA9 (prior data) are below 0.6, 0.589, and 0.274. It shows that the construction of the ARS instrument on prior data cannot be said to be valid and does not adequately reflect the ARS. Generally, the instrument construction for the three data can be seen in Figure 1, Figure 2, and Figure 3.

Reliability Analysis

This study used three approaches to calculate reliability: Cronbach Alpha, composite reliability, and omega reliability. The aim of using these two types of reliability is to compare data reliability before and after being transformed using MSI and MSRS. The Cronbach alpha is used to determine the lower limit of the reliability value of a construct, while composite reliability estimates the reliability value of each indicator on a variable, and omega reliability estimates the reliability of a construct (Hair et al., 2017). Reliability estimates are carried out to prove the instrument's accuracy, consistency, and precision in measuring the construct. To achieve good reliability, the Cronbach Alpha, composite reliability, and omega values must be greater than 0.70 (Chin, 1998). The results from Table 6 show that all data meets good reliability, namely more than 0.7, regarding statement items and constructs.

Table 6. Estimates Reliability

Reliability	Dimensions	Reliability		
		Prior Data	MSI Data	MSRS Data
Cronbach Alpha		0.90 8	0.90 8	0.90 8
Omega	PRS	0.765	0.834	0.834
	REF	0.803	0.832	0.832
	NEG	0.903	0.904	0.909
Composite	PRS	0.780	0.780	0.780
	REF	0.813	0.813	0.813
	NEG	0.913	0.913	0.913

10.21831/pep.v28i1.69334

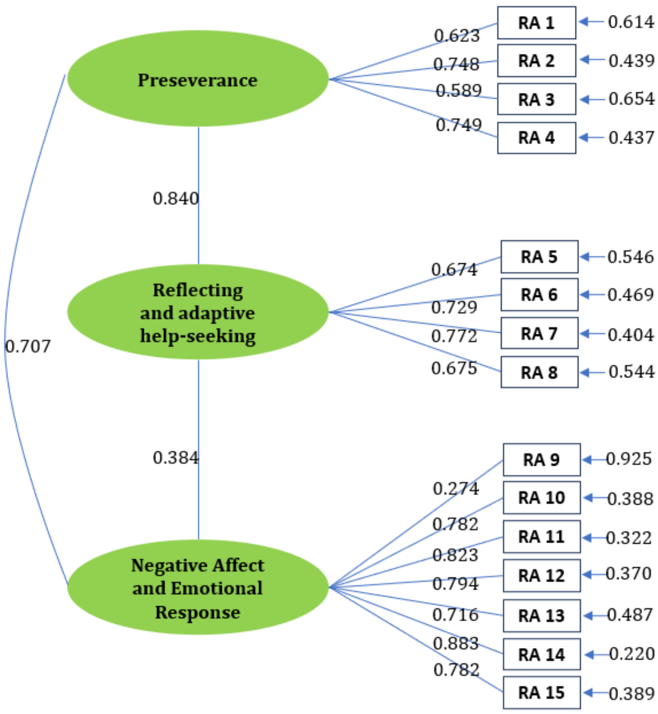

Figure 1. CFA for prior data in ARS

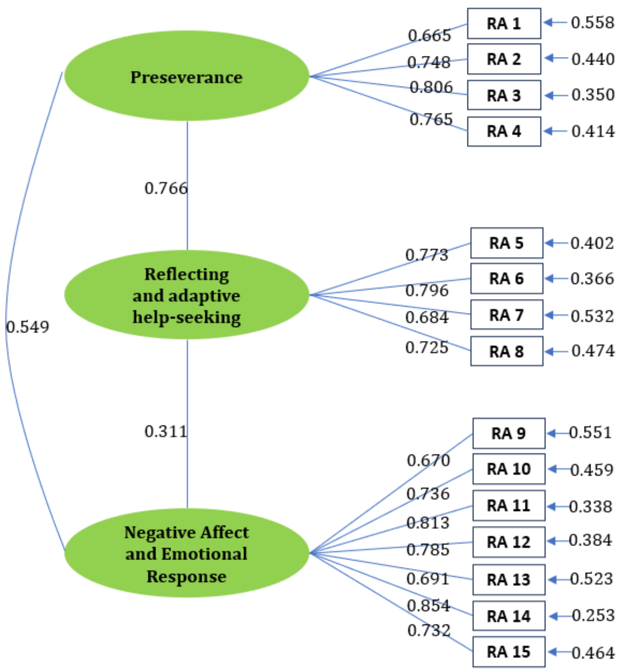

Figure 2. CFA for MSI data in ARS

ISSN (print) 2685-7111 | ISSN (online) 2338-6061

10.21831/pep.v28i1.69334

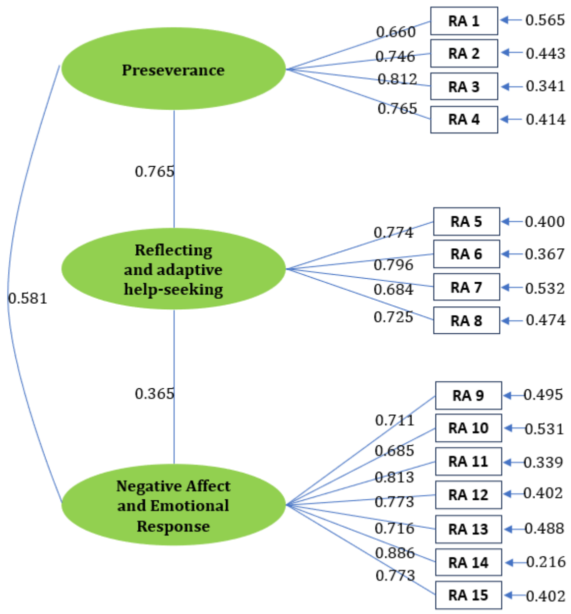

Figure 3. CFA for MSRS data in ARS

Discussion

The academic resilience assessment instrument that has been developed is expected to have good instrument characteristics after transformation. The characteristics of a good instrument produce validity and reliability both in content and construct. Constructively, the validity of the instrument is proven through confirmatory factor analysis. In this study, CFA was used, where the validity evidence met the statistical model, namely CFI and TLI≥0.90, SRMR≤0.08, and RMSEA<0.08) (Gana & Broc, 2019). Before construct testing, CFA requires tests that have been fulfilled, namely the sample adequacy test (KMO) and the Bartlet test.

The construct validity parameters can also be seen from the factor loading, which meets the value >0.6. Table 5 shows that as many as two statement items, namely RA3 and RA9 in the prior data, have a factor loading of less than 0.6, meaning that the construct in the prior data has not been proven to be construct valid. On the other hand, all items in the MSI data and MSRS data show a loading factor of more than 0.6, which means that the MSI data and MSRS data have been proven to be construct valid.

Determining the criteria for obtaining a quality instrument is by testing its reliability. The reliability estimate for this instrument uses Cronbach Alpha, which must be greater than 0.70, namely 0.908. Apart from using Cronbach Alpha, reliability is estimated using composite reliability and omega reliability. Table 6 shows that reliability estimates using different techniques produce good reliability (> 0.7). High construct reliability indicates internal consistency, so all measurement steps consistently represent the same latent construct (Pada et al., 2018). These estimates are comparable to those found in studies using the same scale and thus are considered satisfactory (Trinidad et al., 2005). In conclusion, the ARS instrument, which has been transformed into the MSI and MSRS scales, meets the requirements for good reliability.

In general, based on research that has been conducted, the effect of transformation/scaling that has been carried out using MSI and MSRS shows that ARS instrument data that has been transformed produces better instrument constructs than data that has not been transformed. This result can occur because the distance between value entries is not the same in the prior data, resulting in a mismatch between the conclusions drawn and the actual data. To produce the same scale, the data needs to be converted into the same units (scale) into a z-score using a normal distribution (Kosherbayeva et al., 2024). The scaling results show

ISSN (print) 2685-7111 | ISSN (online) 2338-6061

10.21831/pep.v28i1.69334

differences in categories (scores); for example, in item number 2, the prior data category is 2, but in MSI, it is 2.06, while in MSRS, it is 1.02. This difference is due to differences in density in each category. Differences in score categories result in differences in instrument constructs between prior data, MSI, and MSRS, such as validity (loading factor), goodness of fit, and reliability.

This finding also strengthens research conducted by Setiawati (2014), where after scaling, there were changes in scores before and after the scaling process, which was possible for changes in psychometric characteristics. In line with what was stated by Bahar et al. (2021), scores resulting from scaling using different methods will produce different psychometric scores. The results are similar to research conducted by Solimun et al. (2017), which used MSI and MSRS transformations to view latent data parameters in path analysis. This research shows that analysis using MSI and MSRS transformations is efficient. This research shows that with good construct results from the transformation process, it can be said that data transformation using MSI and MSRS can increase the accuracy of a measurement, especially in CFA construct variables.

On the other hand, the findings that have been produced differ from research conducted by Kusuma et al. (2023), which states that scaling using the MSRS shows an insignificant effect on the community of inquiry instruments. Differences in results may occur due to many factors, for example, the number of scoring criteria used in the Likert scale, the test taker's abilities, the statement items in the instrument, or the suitability of the statement items with the theory taken. This research recommends that the transformation of scores to the same range or scale (scaling) increases measurement accuracy by minimizing measurement errors and drawing conclusions from actual data (Huang et al., 2020; Kosherbayeva et al., 2024). However, researchers also need to ensure the qualitative quality of the instruments used.

CONCLUSION

Scaling using the Method of Successive Interval (MSI) and Method of Summated Rating Scale (MSRS) provides changing effects on the psychometric characteristics of the academic resilience instrument that has been developed. These changes include differences in the z-score scale resulting from prior data and data from scaling results using the two methods, even though the order from smallest to largest is the same.

Scaling provides a dominant change in the instrument construct, namely goodness of fit which consists of CFI/TLI, RMSEA, SRMR, and loading factor where all goodness of fit requirements are met on all scaled data. In general, the scaling that has been carried out can influence the instrument's characteristics for the better.

Conflict of interests

There are no known conflicts of interest associated with this publication.

REFERENCES

Asdar, B. (2011). Method of successive interval in community research: Ordinal transformation data to interval data in Mathematic Education Study. International Journal of Social Science and Humanities Research, 4(2), 356-363.

Bahar, R., Setiawati, F. A., Sutarji, A., Hidayat, O., & Sudarna, N. (2021). Perbandingan metode Skala Thurstone dalam mengukur kompetensi kepribadian guru. Measurement In Educational Research, 1(2), 97-103. doi: 10.33292/meter.v1i2.162

Cassidy, S. (2016). The Academic Resilience Scale (ARS-30): A new multidimensional construct measure. Frontiers in psychology, 7, 1787. doi: 10.3389/fpsyg.2016.01787

10.21831/pep.v28i1.69334

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. MIS quarterly, vii-xvi. https://www.jstor.org/stable/249674

Gana, K. & Broc, G. (2019). Structural equation modeling with lavaan. John Wiley & Sons. doi: 10.1002/9781119579038

García-Crespo, F. J., Fernández-Alonso, R., & Muñiz, J. (2021). Academic resilience in European countries: The role of teachers, families, and student profiles. Plos one, 16(7), e0253409. doi: 10.1371/journal.pone.0253409

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial management & data systems, 117(3), 442-458. doi: 10.1108/imds-04-2016-0130

Huang, F., Wang, H., Wang, Z. et al. (2020). Psychometric properties of the perceived stress scale in a community sample of Chinese. BMC Psychiatry, 20, p. 130. doi: 10.1186/s12888-020-02520-4

Jamieson, S. (2004). Likert scales: How to (ab) use them? Medical education, 38(12), 1217-1218. doi: 10.1108/imds-04-2016-0130

Kusuma, M., Wilujeng, I., Susongko, P., Setiawati, F. A., & Yuenyong, C. (2023). Efek summated rating scale pada instrumen Community of Inquiry dalam pembelajaran daring selama masa pandemi. Measurement In Educational Research, 3(1), 17-26. doi: 10.33292/meter.v3i1.232

Kosherbayeva, A. N., Issaliyeva, S., Begimbetova, G. A., Kassymova, G. K., Kosherbayev, R., & Kalimoldayeva, A. K. (2024). An overview study on the educational psychological assessment by measuring students 'stress levels. Cakrawala Pendidikan: Jurnal Ilmiah Pendidikan, 43(1), 1-18. doi: 10.21831/cp.v43i1.66276

Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: A construct validity approach. Psychology in the Schools, 46(1), 53–83. https://doi.org/10.1002/pits.20149.

Mondiana, Y. Q., Pramoedyo, H., & Sumarminingsih, E. (2018). Structural equation modeling on Likert scale data with transformation by successive interval method and with no transformation. Int. J. Sci. Res. Publ, 8(5), 398-405. doi: 10.29322/ijsrp.8.5.2018.p7751

Musa, A. F., Yasin, M. S. M., Smith, J., Yakub, M. A., & Nordin, R. B. (2021). The Malay version of SF-36 health survey instrument: testing data quality, scaling assumptions, reliability, and validity in post-coronary artery bypass grafting (CABG) surgery patients at the National Heart Institute (Institut Jantung Negara—IJN), Kuala Lumpur. Health and quality of life outcomes, 19, 1-11. doi: 10.1186/s12955-020-01658-9

Ningsih, S., & Dukalang, H. H. (2019). Penerapan metode suksesif interval pada analsis regresi linier berganda. Jambura Journal of Mathematics, 1(1), 43-53. doi: 10.34312/jjom.v1i1.1742

Pawar, Y. (2021). Impact of digitalization on mental wellness of students. *International Journal of Social Science and Economic Research*, 6 (6), 1807- 1816. doi: 10.46609/ijsser.2021.v06i06.014

Pada, A. U. T., Mustakim, S. S., & Subali, B. (2018). Construct validity of creative thinking skills instrument for biology student teachers in the subject of human physiology. Jurnal Penelitian dan Evaluasi Pendidikan, 22(2), 119-129. doi: 10.21831/pep.v22i2.22369

Ramadhana, M. R., Putra, A., Pramonojati, T. A., Haqqu, R., Dirgantara, P., Ismail, O. A., &; Wijaksono, D. S. (2021). Learning Readiness as a Predictor of Academic Resilience in

10.21831/pep.v28i1.69334

Online Learning during School from Home. Library Philosophy and Practice(ejournal). 5362. https://digitalcommons.unl.edu/libphilprac/5362

Ricketts, S., Engelhard, G., Jr., & Chang, M. (2017). Development and validation of a scale to measure academic resilience in mathematics. European Journal of Psychological Assessment, 33(2), 79–86. doi: 10.1027/1015-5759/a000274.

Romano, L., Angelini, G., Consiglio, P., & Fiorilli, C. (2021). Academic resilience and engagement in high school students: The mediating role of perceived teacher emotional support. European journal of investigation in health, psychology, and education, 11(2), 334-344. doi: 10.3390/ejihpe11020025

Rudd, G., Meissel, K., & Meyer, F. (2021). Measuring academic resilience in quantitative research: A systematic review of the literature. Educational Research Review, 34, 100402. doi: 10.1016/j.edurev.2021.100402

Setiawati, F. A. (2014). Perbandingan berbagai metode penskalaan yang dikembangkan Thurstone. Jurnal Penelitian Ilmu Pendidikan, 7(1). doi: 10.21831/jpipfip.v7i1.3114

Setiawati, F. A., Mardapi, D., & Azwar, S. (2013). Penskalaan teori klasik instrumen multiple intelligences tipe Thurstone dan Likert. Jurnal Penelitian dan Evaluasi Pendidikan, 17(2), 259-274. doi: 10.21831/pep.v17i2.1699

Shengyao, Y., Salarzadeh Jenatabadi, H., Mengshi, Y., Minqin, C., Xuefen, L., & Mustafa, Z. (2024). Academic resilience, self-efficacy, and motivation: The role of parenting style. Scientific reports, 14(1), 5571. doi: 10.1038/s41598-024-55530-7

Solimun, S., Fernandes, A. A. R., & Arisoesilaningsih, E. (2017, December). The efficiency of parameter estimation of latent path analysis using summated rating scale (SRS) and method of successive interval (MSI) for transformation of score to scale. In AIP Conference Proceedings (Vol. 1913, No. 1). AIP Publishing. doi: 10.1063/1.5016671

Sumin, Sukmawati, F., Setiawati, F.A., Asmawi, S. (2022). The Impact of Z-Score Transformation Scaling on the Validity, Reliability, and Measurement Error of Instrument SATS-36. JP3I (Jurnal Pengukuran Psikologi dan Pendidikan Indonesia), 11(2), 166-180. doi: 10.15408/jp3i.v11i2.26591

Taqwa, M. (2021, January). Metode suksesif interval pada motivasi belajar matematika selama Covid-19 berbasis MSLQ dengan Software R. In Prosandika UNIKAL (Prosiding Seminar Nasional Pendidikan Matematika Universitas Pekalongan) (Vol. 2, pp. 29-40). https://proceeding.unikal.ac.id/index.php/sandika/article/view/506/410

Trigueros, R., Magaz-González, A. M., García-Tascón, M., Alias, A., & Aguilar-Parra, J. M. (2020). Validation and adaptation of the academic-resilience scale in the Spanish context. *International Journal of Environmental Research and Public Health*, 17(11), 3779. doi: 10.3390/ijerph17113779

Trinidad, S., Aldridge, J., & Fraser, B. (2005). Development, validation, and use of the Online Learning Environment Survey. Australasian Journal of Educational Technology, 21(1). doi: 10.14742/ajet.1343

Waryanto, B., & Millafati, Y. A. (2006). Transformasi data skala ordinal ke interval dengan menggunakan makro Minitab. Informatika Pertanian, 15, 881-895.

Watkins, M. W. (2018). Exploratory factor analysis: A guide to best practice. Journal of Black Psychology, 44(3), 219-246. doi: 10.1177/0095798418771807

ISSN (print) 2685-7111 | ISSN (online) 2338-6061