

Jurnal Penelitian Pendidikan IPA

JPPIPA

http://jppipa.unram.ac.id/index.php/jppipa/index

Development Instrument Independence Study in Chemistry Learning Using Exploratory Factor Analysis (EFA) and Factor Analysis Confirmatory (CFA)

Aurelia Revi Pusbelina^{1*}, Hari Sutrisno²

- ¹ Magister Pendidikan Kimia, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia.
- ² Pendidikan Kimia, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia.

Received: November 21, 2024 Revised: March 11, 2025 Accepted: May 25, 2025 Published: May 31, 2025

Corresponding Author: Aurelia Revi Pusbelina aureliarevi.2021@student.uny.ac.id

DOI: 10.29303/jppipa.v11i5.9790

© 2025 The Authors. This open access article is distributed under a (CC-BY License)



Abstract: This study examines the early development of student learning independence instruments in chemistry learning using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The purpose of this study is to develop a learning independence instrument that specifically measures chemistry learning independence. A quantitative survey approach was used in this investigation. The research sample used was 642 students of class XI MIPA 1 from 10 State Senior High Schools in Bantul Regency, then the sample determination was carried out using a random sampling technique. The instrument used was a questionnaire consisting of 16 items. Sixteen items on a 5-point Likert scale representing students' perceptions of themselves were used to collect data. Exploratory Factor Analysis (EFA) is the data analysis method used. The learning independence questionnaire filled out by 642 respondents was analyzed using the JASP for Windows 10 application. All items from the EFA analysis results were acceptable because they had a factor value of >0.3. While the results of the CFA test showed that all items were valid with a p value <0.05; *** significance and SLF value ≥ 0.5 and reliable with CR value ≥ 0.70 and AVE value of at least 0.5. The results obtained prove that the instrument is valid and can be used to measure the independence of learning chemistry.

Keywords: Confirmatory factor analysis (CFA); Exploratory factor analysis (EFA); Independence learning; Learning chemistry

Introduction

At the high school level or equivalent to university level, chemistry is first introduced. Chemistry is one of the subjects that is less popular with most high school students (Subagia, 2014). Chemistry is often considered a difficult subject and students do not want to study it further. Students' difficulties in understanding chemistry are characterized by their inability to understand chemical concepts correctly (Beerenwinkel et al., 2011; Rogers et al., 2000). Shadreck et al. (2017) also stated that chemistry has a high level of difficulty, making it diffi-

cult for students to understand. This is because chemistry has concepts that are related to each other (Üce et al., 2019).

This learning does not only focus on knowledge but also on learning activities in schools that are held to develop students' attitudes, knowledge, and skills (Aulia et al., 2019). This is in accordance with the opinion of Fadhillah et al. (2016), one of the attitudes that is expected to develop through the implementation of education is independence. According to Fadhillah et al. (2016), learning independence includes students' abilities in planning goals, choosing effective strategies, managing time, and evaluating learning outcomes.

Learning independence is a requirement that must be possessed by students considering the increasingly complex challenges of the future (Ana et al., 2017). Independent learning has a major impact on students' academic success (Dent, 2013; Kistner et al., 2015) and is an important skill for lifelong learning (Cornford, 2002). Students who have high learning independence are expected to be able to learn well so that they master the subject matter and improve their chemistry learning outcomes. However, in reality, students have difficulty realizing independent learning due to the lack of a sense of competition to effectively activate students' SRL (Peeters et al., 2014).

This study aims to develop a validated learning independence instrument that can be widely used to measure student independence. This study is very important because it is a pioneering study that develops an instrument for learning independence for students. The chemistry learning instrument for student independence used in this study was then tested for validity and reliability using EFA and CFA. Factor analysis evaluates the validity of a measurement through EFA or CFA of an item in a construct (Natalya et al., 2018). As mentioned above, there are two types of factor analysis, CFA and EFA. CFA evaluates latent constructs that are developed a priori from a particular theory (Byrne, 1998).

CFA is used to confirm whether the design of a measurement is appropriate and whether items are grouped appropriately, while EFA is used to determine grouping patterns based on the data obtained (Yong et al., 2013). EFA is used to find several factors that influence items that will be analyzed simultaneously (Yong et al., 2013). Although these two types of factor analysis have different purposes, both can be used to support each other and justify the evaluation of the validity of a measurement. Currently, there is no theory that states that one type of analysis is better than the other (Wiktorowicz, 2016). This study uses EFA and CFA simultaneously to ensure that all items are grouped appropriately through double-check analysis. This is in line with the opinion of Netemeyer et al. (2003), that there are three steps needed to carry out the validation process: EFA, item analysis, and CFA. If the EFA results show that each item is grouped appropriately and supported by the CFA results indicating a suitable model, then it can be concluded that the items in the grouping can measure the intended construct accurately.

Method

Research Design

This type of research is quantitative research with a survey method. A survey is a research method used to provide information related to the prevalence, distribution and relationships between variables in a population. Survey research collects data by distributing questionnaires, tests, interviews, and so on from certain places. The survey method is used to obtain data naturally and does not provide any treatment (Subakti et al., 2021). This research was conducted in the even semester of the 2022/2023 academic year, namely in February with 642 participants from 10 in State High Schools in Bantul Regency at the XI grade level majoring in Mathematics and Natural Sciences. Exploratory Factor Analysis (EFA) is used in this study to evaluate the validity and reliability of the instrument with the of the JASP application version 0.14.1.0. Confirmatory Factor Analysis (CFA) is applied with the help of the application in AMOS to determine or confirm a good model empirically in describing the relationship between the constructs in the instrument and its dimensions or factors.

Research Instruments

The research variables were measured using instruments. The questionnaire must be developed properly to be an efficient tool for collecting data and to ensure that the results obtained are valid and reliable. To collect information about the elements that influence students' independence in learning chemistry, the researcher used a questionnaire. To assess student responses, a 5-point Likert scale was used (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree).

Table 1. Learning Independence Instrument

rabie i.	. Learning independen	ce instrument
Item	Dimensions	Statement
KB1	Planning	Setting target grades to be achieved for chemistry subjects
KB2		Determine a specific learning strategy in completing tasks
KB3		Setting a chemistry study schedule independently
KB4		Not making a special study schedule when facing a chemistry exam
KB5	Motivation study	Can maintain motivation to study chemistry by remembering the target grades that I set
KB6		The desire to make parents proud can maintain motivation to study chemistry.
KB7		Difficulty in maintaining motivation to learn chemistry
KB8		Studying chemistry in groups or with friends can increase learning motivation.
KB9	Performance	Difficulty completing chemistry assignments well if done alone
KB10		Can do chemistry exams well without cheating

Item	Dimensions	Statement
KB11		Confidence to be actively involved in chemistry learning
KB12		Get the chemistry exam score according to the planned target
KB13	Self reflection	Initiative to seek additional references (direct reference sources or the internet) when having diffi-
		culty understanding chemistry lesson material
KB14		Have a special trick to overcome the disappointment of getting a chemistry exam score that is not
		up to target
KB15		Not checking the chemistry exam sheets repeatedly before collecting them
KB16		Re-study the chemistry material that you don't understand by summarizing it again in your note-
		book.

The questionnaire consisted of 16 items developed by the researcher in accordance with the theory underlying the research and the available literature (Schunk, 2011; Sulisworo et al., 2020; Woolfolk et al., 2024; Zimmerman et al., 1990). Because the instrument was modified by the researcher himself, the error factor is very likely to occur (Periantalo, 2015). Therefore, the appropriate data collection technique for psychological evaluation is by questionnaire. The questions consist of 4 sub-aspects consisting of: planning, self-motivation, performance, and self-reflection. The revised and validated questionnaire was then distributed to 642 students from 10 selected schools tested. At the time of data collection, students were informed participation was voluntary and did not affect their grades. Data collection was carried out web-based via google form, because generally the response rate of webbased students is very large (Mulyono, 2020).

Data Analysis Techniques Data Analysis Prerequisite Test

This test is conducted before conducting statistical tests for each change in data, both empirical trial data and field data. This is done in order to obtain statistically good data, the prerequisite tests conducted above are two, namely:

Research Data Outlier Test

Outliers are observations that have extreme values or are very different from other values (Hair et al., 2010). Outlier tests are conducted by eliminating data that is considered too extreme based on calculations. Univariate outlier tests are conducted using Box Plot statistics which describe the distribution of data depicted in graphical form from several data groups containing data summaries, namely median (me), Q1, Q3, minimum, and maximum. Data is said to be outliers if it is outside the graphic area marked with a circle (o) meaning the data is slightly approaching the outlier acceptance limit and an asterisk (*) meaning the data is very extreme. Furthermore, data that has been free of outliers is tested for normality.

Research Data Normality Test

The normality test aims to test whether in the regression model, the confounding variables or residuals have a normal distribution. If the residual value does not follow a normal distribution, the statistical test is invalid (Ghozali, 2011). The method used in this study to conduct a normality test is the One Sample Kolmogorov-Smirnov statistical analysis. The test criteria are when the resulting significant value is > 0.05, then the data is normally distributed.

Homogeneity Test of Research Data

The univariate homogeneity test is used to determine whether several population variants are the same or not, namely by comparing the two variances (Usmadi, 2020). One statistical test that can be used is the Levene Test. The test criteria are when the Levene Test significance value is greater than or equal to 0.05; then it can be concluded that the data is univariately homogeneous. However, when the significance value is less than 0.05; then it can be concluded that the data is not univariately homogeneous (Parra-Frutos, 2013). The homogeneity test can be carried out if the data group is in a normal distribution. The homogeneity test was processed using SPSS 16.0 software.

Field test

Exploratory Factor Analysis (EFA)

The field data that has been free from outliers and normal is tested for validity using factor analysis. Factor analysis is used in this study to evaluate the validity of the instrument by applying exploratory factor analysis (EFA) with the help of the JASP application version 0.14.1.0. General guidelines include a rule of thumb (Tabachnick et al., 2007) which states that at least 300 samples are needed for factor analysis. Flury et al. (1988) suggest that the sample size should be 100 or larger. In this study, the EFA requirements have been met with a sample of 642 respondents.

The overall Bartlett and Kaiser-Meyer-Olkin MSA values and the per-variable and per-item instruments in the instrument are used as an evaluation in determining the validity of the instrument. KMO-MSA value of more than 0.5 is acceptable and the Bartlett's Test of Sphericity coefficient value must be less than 5% or 0.05 as the level

of significance acceptance (Hair et al., 2010). In addition, EFA is used for re-mapping of items in variables. If it does not match the theoretical variable, then a redefinition of the variable that has changed dimensions or factors is carried out based on the factor loading value. The factor loading value is considered to redefine items or determine the dimension map and items in each variable. This allows for changes in dimensions or factors from the initial instrument developed. EFA uses the varimax rotation method, parallel FA analysis and maximum likelihood estimation

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis is applied with the help of applications in AMOS to determine or confirm a good empirical model in describing the relationship between constructs in the instrument and its dimensions or factors. The suitability of the relationship model between constructs in one variable is evaluated in terms of the overall suitability of the validity model and dimensional reliability. At this stage, a structural equation model is produced which states the relationship between dimensions and items in each variable.

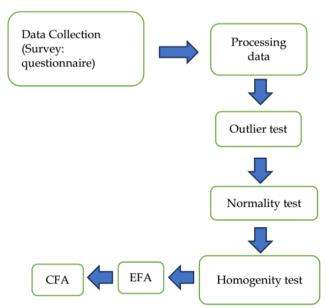


Figure 1. Research flow

Results and Discussion

Outlier Test of Research Data

At the univariate outlier test stage, no extreme data (outliers) were found. The results of the univariate outlier test analysis of research data can be seen in more detail in Figure 2.

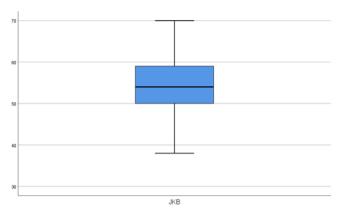


Figure 2. Data outlier test

Normality Test

The results of the normality test indicate that the data is normally distributed. This can be seen in table 2 which has an Asymp. Sig value of 0.052 (Asymp. Sig > 0.05) (Riong et al., 2024).

Table 2. Univariate Normality Test

N	•	574
Normal Parameters	Mean	0.00
	Std. Deviation	5.32
Most Extreme Differences	Absolute	0.03
	Positive	0.03
	Negative	-0.03
Test Statistic		0.03
Asymp.Sig.(2-tailed)		0.05

Homogeneity Test

The homogeneity test was analyzed using the Levene test with a significance value of 5%. The results of the homogeneity test of variance with the acceptance criteria of H0 if the output sig> 0.05. The results of the data analysis showed that the Levene significance value of learning independence was 0.772> 0.05. Therefore, the samples came from the same or homogeneous population.

Table 3. Results of the Homogeneity Test of Two Variances

	Levene Statistics	df1	df2	Sig.
Based on mean	0.08	1	640	0.77
Based on median	0.13	1	640	0.71
Based on median and	0.13	1	639.68	0.71
with adjusted df				
Based on trimmed mean	0.09	1	640	0.76

Exploratory Factor Analysis (EFA)

The learning independence instrument in general has a Kaiser-Meyer-Olkin MSA validity value of 0.913 and is significant for use with a Bartlett value <0.001, which means that the instrument is proven to be significant for use (Gülay et al., 2022). The results of the

validity of the learning independence variable per item are presented in table 4.

Table 4. Validity Independence Item Study

Item	KMO	Interpretation
KB1	0.91	Valid
KB2	0.91	Valid
KB3	0.95	Valid
KB4	0.91	Valid
KB5	0.91	Valid
KB6	0.93	Valid
KB7	0.91	Valid
KB8	0.93	Valid
KB9	0.92	Valid
KB10	0.95	Valid
KB11	0.93	Valid
KB12	0.89	Valid
KB13	0.91	Valid
KB14	0.83	Valid
KB15	0.92	Valid
KB16	0.86	Valid

The Bartlette test results show that there is a fairly large correlation between variables and the data is suitable for exploratory component analysis (p<0.001; Table 5). If the probability value is less than 0.001, then the sample size and normality are sufficient to perform PCA (Yamin et al., 2009).

Table 5. Bartlett's Test Value Output in JASP Software

X2	df	P
4875.13	120.00	< 0.001

These variables are represented by the four factors using a normal Eigenvalue of 1. Eigenvalues > 1 for the four factors indicate that there are more components than the number of existing ones. Thus, the variations of

41.3%, 5.8%, 4.8% and 3.2% can be explained by factor 1, factor 2, factor 3, factor 4 and factor 5. This means that 55.1% of the variance can be explained by the four factors.

Table 6. Total Variance Explained JASP Output

Factor	Sq Loading Amount	Proportion var	Cumulative
1	5.04	0.41	0.41
2	0.69	0.05	0.47
3	0.59	0.04	0.52
4	0.43	0.03	0.55
5	0.30	0.02	0.58

Based on the results of the EFA analysis, it revealed changes in dimensions and changes in items in one dimension of the original instrument. This is due to differences in the relationship between items and dimensions/factors of the instrument that were originally developed as a result of the EFA analysis (Netemeyer et al., 2003). Based on the results of the researcher's synthesis, learning independence has four dimensions. However, according to the results of the analysis, learning independence has dimensions according to each of the largest factor values. There is one additional split variable from the "planning" variable, namely the "internal planning" variable and the "external planning-response" variable. All items from the EFA analysis are acceptable because they have a factor value >0.3 according to the recommendations of Floyd et al. (1995). Four items (KB4, KB7, KB9, KB15) have negative factor values because they are negative items with values that are still within the acceptance limit. The description of the EFA results can be seen in Table 7 In addition, the exploration components of the learning independence instrument are displayed in the scree plot in Figure 3.

Table 7. JASP Factor Loadings

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
	(Internal planning)	(Planning External Response)	(Motivation to learn)	(Performance)	(Self-Reflection)
KB1	0.50				
KB2	0.54				
KB3		0.40			
KB4		-0.55			
KB7		-0.54			
KB9		-0.53			
KB15		-0.45			
KB10			0.41		
KB11			0.52		
KB12			0.75		
KB13				0.47	
KB14				0.74	
KB16				0.61	
KB5					0.69
KB6					0.47
KB8					0.47

After that, a scree plot is created by mapping the derived eigenvalues. Figure 3, which depicts the development of the four principal components, shows this.

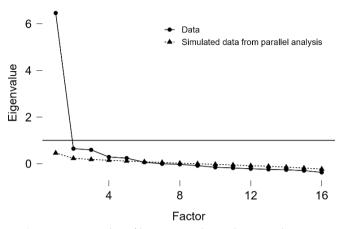


Figure 3. Scree plot of learning independence in the EFA model

Confirmatory Factor Analysis (CFA)

The learning independence variable consisting of five dimensions with 16 items is described in the form of a CFA test result measurement model as follows:

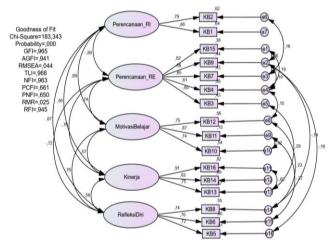


Figure 4. CFA result fit model for the learning independence variable

Overall, the model is concluded to be fit because 90% of the 10 parameters state the good fit category for the Goodness of Fit parameter with details in table 8. All items in the learning independence variable are valid and the results of the construct validity test (CFA test) show appropriate data and can be continued in testing the hypothesis of the SEM model. The acceptance criteria for the validity test with a p value <0.05; *** significance and SLF value \geq 0.5 (Bentler, 1990; Bagozzi & Yi, 1998; Hair et al., 2007). Clearer results can be seen in Table 9.

Table 8. Overall Model Fit for Variable Independence Study on the CFA Test

Goodness of Fit Parameters	Results Measurement	Interpretation
Chi-square/degree of freedom	183.34	Poor fit
Probability	0.00	Poor fit
GFI	0.96	Good fit
AGFI	0.94	Good fit
RMSEA	0.04	Good fit
TLI	0.96	Good fit
NFI	0.93	Good fit
RMR	0.02	Good fit
RFI	0.94	Good fit

Table 9. Results of Construct Validation Analysis for the Learning Independence Variable in the CFA Test

Item	Probability (P)	Convergence Validity:	Interpretation
		Std. Load Factor (SLF)	
KB2	< 0.001	0.78	Valid
KB1	< 0.001	0.79	Valid
KB15	< 0.001	0.61	Valid
KB9	< 0.001	0.66	Valid
KB7	< 0.001	0.65	Valid
KB4	< 0.001	0.61	Valid
KB3	< 0.001	-0.65	Valid
KB12	< 0.001	0.75	Valid
KB11	< 0.001	0.86	Valid
KB10	< 0.001	0.73	Valid
KB16	< 0.001	0.90	Valid
KB14	< 0.001	0.83	Valid
KB13	< 0.001	0.75	Valid
KB8	< 0.001	0.74	Valid
KB6	< 0.001	0.70	Valid
KB5	< 0.001	0.71	Valid

Table 10. Results of reliability analysis for learning independence variables in the CFA test

independence variables in the CFA test					
Variable	Compo-	Average	Conclusion		
	site Relia-Va	site Relia-Variance Ex-			
	bility	tracted			
	(CR)	(AVE)			
Planning	0.775	0.408	Reliable		
_RE					
Planning _RI	0.772	0.628			
Motivation Study	0.828	0.618	Reliable		
Performance	0.870	0.700	Reliable		
Self Reflection	0.764	0.520	Reliable		

All dimensions or overall learning independence variables are considered reliable with results showing appropriate data and can be used in hypothesis testing of the SEM model. The acceptance criteria for reliability testing with a CR value ≥ 0.70 are said to be reliable (Ghozali, 2011; Hair et al., 2010) and $0.60 \leq \text{CR} \leq 0.70$ with the Acceptable category (Ghozali, 2011). Meanwhile, the minimum recommended AVE value is 0.5, but 0.4 is acceptable because if AVE is less than 0.5, but the

composite reliability is higher than 0.6 (Huang et al., 2013). Clearer results can be seen in Table 10.

Conclusion

Based on the results of the study it can be concluded that the learning of learning independence developed in the buffer solution material meets the criteria is very feasible and can be used. This is evidenced by the results of the assessment of the quality of the learning instrument of learning all items of item valid. Student responses to the learning independence questionnaire instrument developed are very good.

Acknowledgments

Thanks to the Chemistry Education Study Program, Faculty of Mathematics and Natural Sciences, Yogyakarta State University for providing the opportunity for researchers to conduct this research. Thanks to the schools in Bantul district who have been willing to provide service facilities during the research and thanks to the supervisor who has guided in completing this article.

Author Contributions

In completing this research, there are two authors who contributed, namely A.R.P contributed in conducting research, developing products, analyzing data, and writing articles. H.S acted as a supervisor during research activities and writing articles.

Funding

This research was funded by the researcher's private funds and did not receive external funding.

Conflict of Interest

The authors declare no conflict of interest.

References

- Ana, A., & Achdiani, Y. (2017). Penerapan Self Regulated Learning Berbasis Internet Untuk Meningkatkan Kemandirian Belajar Mahasiswa. *Innovation of Vocational Technology Education*, 11(1), 15–22. https://doi.org/10.17509/invotec.v11i1.4835
- Aulia, L. N., Susilo, S., & Subali, B. (2019). Upaya peningkatan kemandirian belajar siswa dengan model problem-based learning berbantuan media Edmodo. *Jurnal Inovasi Pendidikan IPA*, 5(1), 69–78. https://doi.org/10.21831/jipi.v5i1.18707
- Beerenwinkel, A., Parchmann, I., & Gräsel, C. (2011).

 Conceptual Change Texts In Chemistry Teaching:
 A Study On The Particle Model Of Matter.

 International Journal of Science and Mathematics
 Education, 9(5), 1235–1259.

 https://doi.org/10.1007/s10763-010-9257-9
- Cornford, I. R. (2002). Learning-to-learn strategies as a basis for effective lifelong learning. *International*

- *Journal of Lifelong Education*, 21(4), 357–368. https://doi.org/10.1080/02601370210141020
- Dent, A. L. (2013). The relation between self-regulation and acadamic achievement: a meta-analysis exploring variation in the way constructs are labeled, defined and measured. Duke University.
- Fadhillah, N., & Faradina, S. (2016). Hubungan kelekatan orang tua dengan kemandirian remaja sma di banda aceh. *Jurnal Ilmiah Mahasiswa Psikologi*, 1(4), 44–51. Retrieved from http://jim.unsyiah.ac.id/Psikologi/article/view/1429.
- Flury, B., Murtagh, F., & Heck, A. (1988). Multivariate Data Analysis. In *Mathematics of Computation* (7th ed., Vol. 50, Issue 181). Pearson Education Limited. https://doi.org/10.2307/2007941
- Ghozali, I. (2011). *Aplikasi analisis multivariat dengan program SPSS*. Semarang: Badan Penerbit Universitas Diponegoro.
- Gülay, E., & Ungan, S. (2022). Development of Academic Writing Block Scale (AWBS): A Validity and Reliability Study. *Participatory Educational Research*, 9(2), 178–198. https://doi.org/10.17275/per.22.35.9.2
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis a global perspective* (7th ed.). Prentice Hall.
- Kistner, S., Rakoczy, K., Otto, B., & Klieme, E. (2015).

 Teaching learning strategies: The role of instructional context and teacher beliefs. *Journal for Educational Research Online*, 7(1), 176–197.

 Retrieved from http://www.j-e-ro.com/index.php/jero/article/download/542/22
- Mulyono, W. D. (2020). Respon Mahasiswa Terhadap Pembelajaran Daring Pada Masa Pandemi Covid-19. *Steam Engineering*, 2(1), 23–30. https://doi.org/10.37304/jptm.v2i1.1661
- Natalya, L., & Purwanto, C. V. (2018). Exploratory and Confirmatory Factor Analysis of the Academic Motivation Scale (AMS)–Bahasa Indonesia. *Makara Human Behavior Studies in Asia*, 22(1), 29. https://doi.org/10.7454/hubs.asia.2130118
- Netemeyer, R. G., Barden, W. O., & Sharma, S. (2003). Scaling procedures: issues and applications. Sage Publications.
- Peeters, J., De Backer, F., Reina, V. R., Kindekens, A., Buffel, T., & Lombaerts, K. (2014). The Role of Teachers' Self-regulatory Capacities in the Implementation of Self-regulated Learning Practices. *Procedia Social and Behavioral Sciences*, 116, 1963–1970.
 - https://doi.org/10.1016/j.sbspro.2014.01.504
- Periantalo, J. (2015). *Penyusunan Skala Psikologi: Asyik, Mudah & Bermanfaat*. Yogyakarta: Pustaka Pelajar.

- Riong, M. B. D., Haryono, H., Supriyadi, S., & Ahmadi, F. (2024). Penguasaan konsep dan kemampuan pemecahan masalah fisika melalui model Creative Problem Solving (CPS) berbantuan Mimind. *PENDIPA Journal of Science Education*, 8(2), 131–138. Retrieved from https://ejournal.unib.ac.id/index.php/pendipa
- Rogers, F., Huddle, P. A., & White, M. D. (2000). Using a Teaching Model to Correct Known Misconceptions in Electrochemistry. *Journal of Chemical Education*, 77(1), 104. https://doi.org/10.1021/ed077p104
- Schunk, D. H. (2011). Handbook of Self-Regulation of Learning and Performance. In *Handbook of Self-Regulation of Learning and Performance*. Routledge. https://doi.org/10.4324/9780203839010
- Shadreck, M., & Chukunoye Enunuwe, O. (2017). Problem Solving Instruction for Overcoming Students' Difficulties in Stoichiometric Problems. *Acta Didactica Napocensia*, 10(4), 69–78. https://doi.org/10.24193/adn.10.4.8
- Subagia, I. W. (2014). Paradigma Baru Pembelajaran Kimia SMA. *Seminar Nasional FMIPA UNDIKSHA IV*, 152–163. Retrieved from https://ejournal.undiksha.ac.id/index.php/semnasmipa/article/view/10479
- Sulisworo, D., Kusumaningtyas, D. A., & Handayani, T. (2020). Self-Regulated Learning of Junior High School Students to Predict Online Learning Achievement. *Proceedings of the International Conference on Community Development (ICCD 2020)*, 477, 203–207.
 - https://doi.org/10.2991/assehr.k.201017.045
- Tabachnick, B. G., & Fidell, L. S. (2007). Using multivariate statistics. Northridge. In *Cal.: Harper Collins* (Vol. 1, Issue 2). Pearson Education, Inc.
- Üce, M., & Ceyhan, İ. (2019). Misconception in Chemistry Education and Practices to Eliminate Them: Literature Analysis. *Journal of Education and Training Studies*, 7(3), 202. https://doi.org/10.11114/jets.v7i3.3990
- Usmadi, U. (2020). Pengujian Persyaratan Analisis (Uji Homogenitas Dan Uji Normalitas). *Inovasi Pendidikan*, 7(1). https://doi.org/10.31869/ip.v7i1.2281
- Wiktorowicz, J. (2016). Exploratory factor analysis in the measurement of the competencies of older people. *Ekonometria*, 4(54), 48–60. Retrieved from https://dbc.wroc.pl/Content/36540/Wiktorowic z_Exploratory_Factor_Analysis_In_The_Measure ment.pdf
- Woolfolk, A., & Usher, E. L. (2024). *Educational Psychology Active Learning* (Fifteenth). Allyn & Bacon.
- Yamin, S., & Kurniawan, H. (2009). Structural equation modeling: Belajar lebih mudah teknik analisis data

- kuesioner dengan Lisrel-PLS. Jakarta: Salemba Infotek.
- Yong, A. G., & Pearce, S. (2013). A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, 9(2), 79–94. https://doi.org/10.20982/tqmp.09.2.p079
- Zimmerman, B. J., & Martinez-Pons, M. (1990). Student Differences in Self-Regulated Learning: Relating Grade, Sex, and Giftedness to Self-Efficacy and Strategy Use. *Journal of Educational Psychology*, 82(1), 51–59. https://doi.org/10.1037/0022-0663.82.1.51