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Predicting students' achievement during COVID-19 mitigation through self-regulated learning profiles: Indonesian context

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Abstract:
The study of the various impacts of the spread of COVID-19 in multiple fields is significant now, including in education. This study aims to predict the success of online learning conducted during the COVID-19 mitigation period. Predictions were made using data from the self-regulated learning profile of students in grades 1 through 12. Data was taken using an online questionnaire on aspects of SRL (Panning, Monitoring, Controlling, and Reflecting). The scale used is 1 (Strongly Disagree) to 5 (Strongly Agree). The analysis used is cluster analysis. The results show that three clusters can be identified as clusters that have the possibility of low, medium, and high learning achievement by being characterized in terms of SRL. By comparing SRL profiles, school management can prepare policies to anticipate students' performance and to improve the processes that are running in online learning.

Keywords*: achievement, COVID-19, education, internet, online learning, self-regulated learning.*

INTRODUCTION

The fact that COVID-19 influences almost all aspects of life starting in March 2020 is undeniable. Education is not an exception. Primary, secondary and tertiary levels of education are among those that have been directly getting the effects. Their management, academic and non-academic staff, students as well as stakeholders have to suddenly make the proper and necessary adjustment to remain able to take their roles in the educational context. The emerging need, along with the official statement of the Indonesian Ministry of Education and Culture, responding to the spread of the COVID-19, indeed, makes the change in the learning modes. What is clearly seen and genuinely experienced by related partiesin this field is the shift of the learning from face-to-face to fully online learning.

Existing, as well as recently established online learning platforms or applications, provide support to keep students learning. The use of social media such as Whatsapp, Instagram, Facebook, G-class, Zoom for learning is some to mention. This decision becomes the concern of almost all educational institutions from primary, secondary to the tertiary level of education, from the government to private institutions. Several relevant studies present salient evidence on the running of online learning in diverse educational settings. Moreover, what is also worth investigating is whether students' independence in online learning results in their learning success.The

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particular life setting like when COVID-19 is around, indeed, demands students to be autonomous learners, and also teachers as an independent course designer and instructor. It is challenging that the online learning design supports the accomplishment of tasks and, by the end of the learning process, facilitates students to achieve their learning objectives. Their best learning achievement must be the priority.

In this mitigation period, teachers try to use various methods to be able to teachthe students well regardless of all the limitations. The learning evaluation process starting on April 10, 2020, was attempted by utilizing several online media, although its mechanism is not secure. The way of interaction in learning that has been suddenly changing is certainly still expected to achieve excellent learning performance. In discussions like this, reviews about learning success are not easy to predict. Many research results show that internet-based learning is not going well caused by no social presence in learning (Alhomod and Shafi, 2013; Lam et al., 2012; Mawere and van Stam, 2019).

Student focus is essential in online learning, so SRL becomes a factor that needs special attention by educators to get success (Karlen, 2016; Pei-Ching et al., 2011). SRL measures some parameters that exist in students. In some literature, self-regulated learning (SRL) can be used to predict students' learning outcomes. SRL refers to how students drive their learning. The study of SRL explains that this concept is related to intentional adaptation and learning strategies to change cognitive, motivational, and learning outcomes (Persico & Steffens, 2017; Zimmerman & Schunk, 2011). Whereas in related studies to education and learning, SRL is a proactive application of self-directive, cognitive, and motivational processes to achieve goals, learn skills, and manage emotional reactions (Inan et al., 2017; Persico & Steffens, 2017). Learning strategies that are SRL-basedconfirm improving learning performance in computer-based or online learning environments (Wong et al., 2019). SRL includes cognitive, metacognitive, behavioral, motivational, and emotional aspects of learning. Therefore, it is a broad concept under which a significant number of learning variables can be predicted (Panadero, 2017). Thus, SRL can be one of the indicators to predict learning outcomes, and it is vital in education.

This critical factor will determine students in achieving their competencies. Some research shows that students with high SRL tend to be more successful in learning (Chiu et al., 2013 Mooij, 2009; Dunn & Rakes, 2015). Existing models explain that SRL is a cycle of how someone's carrying out tasks determineshis or her performance. In other words, SRL is an impetus for student goals guiding cognitive processes and some efforts in decision making based on the interaction of competencies, self-concept in the task domain, motivation, and effects, perceptions of the task, and demands of the outcome.The process of self-regulation can be expressed as an individual activity in planning, monitoring of plan, making changes to fit the path, and reflecting results for subsequent improvements (Ellis et al., 2014; Jaleel, 2016; Rahimi & Katal, 2012). Through this article, the researchers intend to present the idea of predicting the students' achievement during COVID-19 mitigation by relating it to their self-regulated learning profiles.

METHOD

Settings

This research is a survey conducted in private schools (from elementary to high schools) under the management of the Primary and Secondary Education Council of a Foundation in Yogyakarta, Indonesia. In general, Yogyakarta is a city with a good level of internet network availability, so that during the COVID-19 mitigation period, it can serve online learning activities in schools. This foundation has 35 elementary schools (12,381 students), 12 junior high schools (4,974 students), and 11 high schools (5,794 students). Before the outbreak of

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COVID-19, learning was dominated by face to face learning in the classroom. A week after Indonesia declared COVID-19 an emergency, the government, through the local Education Office, issued a policy to conduct online learning with various platforms. Three weeks after applying online learning, the SRL questionnaire was distributed via Google Form. The research sample, which was collected with an accident sampling technique, consisted of 6364 students, but only 5873 completed the form. The remainders not completely fulfilling the form were discarded and not included in further analysis. The sample distribution is as presented in Table 1.

Table 1. Distribution of Participants

Grade	Frequency	Percent	Cumulative Percent
1	374	6.4	6.4
2	224	3.8	10.2
3	378	6.4	16.6
4	407	6.9	23.5
5	322	5.5	29.0
6	318	5.4	34.4
7	572	9.7	44.2
8	434	7.4	51.6
9	445	7.6	59.2
10	813	13.8	73.0
11	777	13.2	86.2
12	809	13.8	100.0
Total	5873	100.0	

Research Instrument

The instrument to measure SRL was a questionnaire with Likert scales ranging from 1 to 5 (from Strongly Disagree toStrongly Agree). There are 4 SRL factors adopted from the Pintrich model, i.e., Planning (P, 5 items), Monitoring (M, 6 items), Controlling (M, 6 items) dan Reflecting (R, 6 items). Table 2 shows the matrix for each factor and item.

Table 2. Questionnaire Matrix

No	Factors	Item number		Total
		Positive Statements	Negative Statements	
1	Planning	1, 2, 3, 4	5	5
2	Monitoring	6, 7, 8, 9, 10	11	6
3	Controlling	12, 13, 14, 15	16, 17	6
4	Reflecting	18, 19, 20, 21	22	5

Analysis Techniques

The ex-post facto design approach was implemented in this study. There were four analytical techniques, i.e., descriptive statistics, Two-Way ANOVA, Factor Analysis, and Cluster Analysis. First, descriptive data (frequency, average, and standard deviation) were employed for each factor in the comparison of profiles among factors of SRL. Two-Way ANOVA was to find out the effect of Grade (1 to 12). Factor Analysis was utilized to decide which items gave significance loading to the variables. Further, cluster analysis was done by transforming data to Z-score, and 3 clusters were selected accordingly. The technique used in this analysis was the K-Means Cluster.

RESULTS

Descriptive Analysis

Data from all valid respondents were processed to find descriptive for each aspect. The results of this processing are shown in Table 3 for the calculation of each item. Table 3 explains that each item got a good score (more than 3) except for item C5 (2.68). Also, standard deviations tend to be high on all scores.

Table 3. Descriptive Statistics

Plan	Mean	STD	**Monitor**	Mean	STD	**Control**	Mean	STD	**Reflect**	Mean	STD
P1	4.1274	.93603	M1	3.8142	.96219	C1	3.9436	.94990	R1	3.8692	.89423
P2	3.8120	1.02260	M2	3.8342	1.01391	C2	3.8743	.99070	R2	4.3402	.88531
P3	4.2002	.90605	M3	3.8372	.95847	C3	4.2081	.86245	R3	3.9213	.90729
P4	3.6515	1.06431	M4	3.8066	1.02359	C4	4.3482	.82255	R4	4.3521	.84208

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P5	3.1507	1.17910	M5	2.8331	1.22436	C5	2.6767	1.19055	R5	4.0259	1.13016
			M6	3.3068	1.18654	C6	3.8171	1.21158			

Table 4 shows the processing results for the aggregate of each factor and its correlation, along with Cronbach's Alpha values.

Table 4. Descriptive Statistics

	Mean	Std. Deviation	AVGP	AVGM	AVGC	AVGR	Cronbach's Alpha
AVGP (5 items)	3.7884	.64801	1				.623
AVGM (6 items)	3.5720	.61550	.642**	1			.599
AVGC (6 items)	3.8113	.60864	.637**	.615**	1		.643
AVGR (5 items)	3.4181	.51099	.596**	.583**	.664**	1	.666

Notes: All mean scores are on a five-point scale; **significant at p<0.01 The Cronbach's alpha measures the internal consistency of the measurement scales for each SRL dimension; The overall SRL score for each respondent was obtained by averaging the scores of the four dimensions, i.e., Planning + Monitoring + Controlling + Reflecting

One-Way ANOVA

ANOVA analysis was conducted to see the effect of Grade variables on the SRL. This analysis was performed with the mean of Total score (scale 1 to 5) as the dependent variable and Grade as the independent variable.The descriptive statistical results for this analysis are presented in Table 5 below.

Table 5. Descriptive of Each SRL Aspect based on Grade

	Grade	N	Mean	Std. Deviation	Minimum	Maximum
AVGP	1.00	374	4.0166	.64939	1.80	5.00
	2.00	224	4.0187	.66925	1.00	5.00
	3.00	378	3.9519	.66986	1.40	5.00
	4.00	407	3.9243	.62759	1.40	5.00
	5.00	322	3.9155	.66403	2.00	5.00
	6.00	318	3.8717	.66789	1.40	5.00
	7.00	572	3.8017	.59271	1.00	5.00
	8.00	434	3.7959	.58439	2.20	5.00
	9.00	445	3.7344	.61175	1.80	5.00
	10.00	813	3.6236	.66646	1.00	5.00
	11.00	777	3.6494	.64666	1.00	5.00
	12.00	809	3.7061	.60565	1.60	5.00
	Total	5873	3.7884	.64801	1.00	5.00
AVGM	1.00	374	3.7892	.63267	1.67	5.00
	2.00	224	3.7195	.64699	1.50	5.00
	3.00	378	3.7319	.60575	1.50	5.00
	4.00	407	3.7142	.60743	2.00	5.00
	5.00	322	3.6713	.66242	2.00	5.00
	6.00	318	3.6483	.65320	1.67	5.00
	7.00	572	3.5609	.57679	1.67	5.00
	8.00	434	3.5703	.59063	1.33	5.00
	9.00	445	3.5648	.60133	1.67	5.00
	10.00	813	3.4049	.61224	1.50	5.00
	11.00	777	3.4436	.59228	1.67	5.00
	12.00	809	3.5192	.56307	1.17	5.00
	Total	5873	3.5720	.61550	1.17	5.00
AVGC	1.00	374	3.9439	.63764	1.83	5.00
	2.00	224	3.9420	.69295	1.17	5.00
	3.00	378	3.9180	.63973	1.17	5.00
	4.00	407	3.9361	.60025	2.00	5.00
	5.00	322	3.8613	.65216	1.67	5.00
	6.00	318	3.9025	.64727	1.33	5.00
	7.00	572	3.8176	.55863	1.50	5.00
	8.00	434	3.7673	.59872	2.00	5.00
	9.00	445	3.7820	.56833	1.17	5.00
	10.00	813	3.6923	.60382	1.17	5.00
	11.00	777	3.7145	.59503	1.83	5.00
	12.00	809	3.7936	.56089	1.83	5.00
	Total	5873	3.8113	.60864	1.17	5.00
AVGR	1.00	374	3.5530	.51469	1.50	4.17
	2.00	224	3.5223	.54196	1.17	4.17
	3.00	378	3.5269	.52922	1.50	4.17

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4.00	407	3.5029	.47219	1.67	4.17
5.00	322	3.4586	.54035	2.00	4.17
6.00	318	3.4434	.48922	1.50	4.17
7.00	572	3.3907	.49276	1.50	4.17
8.00	434	3.3971	.50074	1.17	4.17
9.00	445	3.3801	.47654	1.33	4.17
10.00	813	3.3372	.53364	.83	4.17
11.00	777	3.3483	.52961	1.00	4.17
12.00	809	3.4073	.47001	1.50	4.17
Total	5873	3.4181	.51099	.83	4.17

AVGP: the average of Planning items,
AVGM: the average of Monitoring items,
AVGC: the average of Controlling items,
AVGR: the average of Reflecting items,

Further, Figure 1 below is provided to make it easier to get a general description of the relation between SRL and Grade.

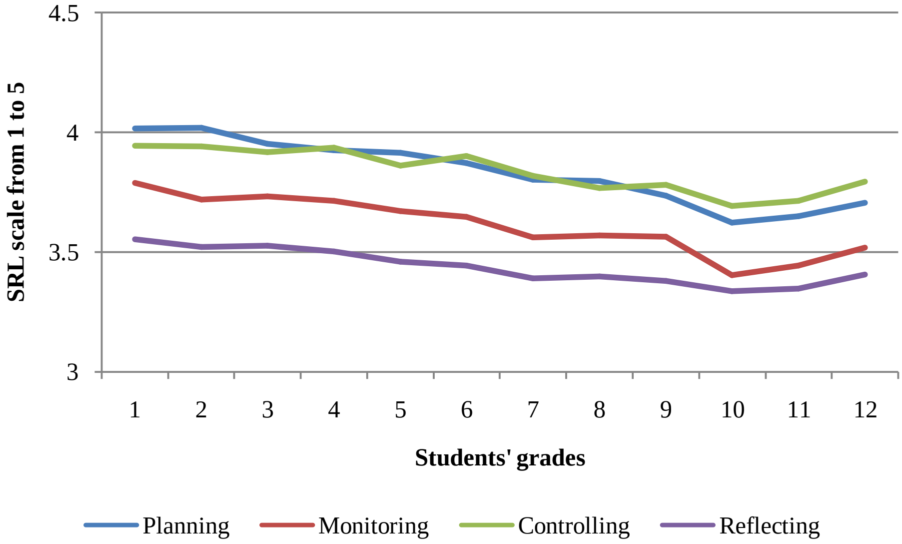

Figure 1. The comparison of each aspect of SLR

There is a consistent trend reflecting that lower grade students tend to be higher on all the indicators of SRL than all higher grades (classes). Changes occur when the students are at tenth-grade, at which the SRL increases again along with the grade level. Further analysis to determine the effect of Grade on SRL is shown by the results of the F-Test in Table 6. This table (on F value and Sig. Number) indicates that there is a significant effect of Grade on AVGP, AVGM, AVGC, or AVGR (p-value = 0.05).

Table 6. ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
AVGP	Between Groups	100.381	11	9.126	22.611	.000
	Within Groups	2365.383	5861	.404		
	Total	2465.763	5872			
AVGM	Between Groups	83.315	11	7.574	20.732	.000
	Within Groups	2141.218	5861	.365		
	Total	2224.534	5872			
AVGC	Between Groups	44.784	11	4.071	11.200	.000
	Within Groups	2130.459	5861	.363		
	Total	2175.243	5872			

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AVGR	Between Groups	27.825	11	2.530	9.848	.000
	Within Groups	1505.447	5861	.257		
	Total	1533.272	5872			

Factor Analysis

To see whether the data can be used to explain the phenomenon, extraction was done by factor analysis with the Principal Component method at Eigenvalue greater than 1, as presented in Table 7.

Table 7. Communalities

Items (Z-score)	Initial	Extraction	Items (Z-score)	Initial	Extraction
Zscore(P1)	1.000	.445	Zscore(C1)	1.000	.515
Zscore(P2)	1.000	.503	Zscore(C2)	1.000	.414
Zscore(P3)	1.000	.372	Zscore(C3)	1.000	.600
Zscore(P4)	1.000	.511	Zscore(C4)	1.000	.627
Zscore(P5)	1.000	.464	Zscore(C5)	1.000	.569
Zscore(M1)	1.000	.534	Zscore(C6)	1.000	.531
Zscore(M2)	1.000	.269	Zscore(R1)	1.000	.459
Zscore(M3)	1.000	.525	Zscore(R2)	1.000	.417
Zscore(M4)	1.000	.302	Zscore(R3)	1.000	.487
Zscore(M5)	1.000	.508	Zscore(R4)	1.000	.567
Zscore(M6)	1.000	.501	Zscore(R5)	1.000	.462

Extraction Method: Principal Component Analysis.

From Table 7, it can be seen how much a variable can explain factors. For example, P1 is 0.445, meaning that the P1 can explain the factor of 44.5%. Such an explanation also works for other variables.The following Table 8 of Total Variance Explained is useful to see the factors that can be determined.

Table 8. Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.984	31.745	31.745	6.984	31.745	31.745	4.304	19.563	19.563
2	2.352	10.690	42.434	2.352	10.690	42.434	3.789	17.222	36.785
3	1.249	5.679	48.113	1.249	5.679	48.113	2.492	11.328	48.113
4	.930	4.228	52.341						
5	.822	3.736	56.077						
Number 6 to number 21 are intentionally hidden									
22	.384	1.743	100.000						

Extraction Method: Principal Component Analysis.

Based on Table 8, the "Component" column shows that there are 22 components (of the actual items) that can represent SRL variables. The column of "Initial Eigenvalues" has been determined greater than 1 (one). The variance explained by the first factor is 6.984 / 22 x 100% = 31.745%. By the second factor, it is 2.352 / 22 x 100% = 10.690%. By the third factor it is 1.2449 / 22 x 100% = 5.679%. Thus the total of the three factors will be able to explain the variables of 31.745% + 10.690% + 5.679% = 48.113%. Hence, because the Eigenvalues value is set 1, the total value to be taken is> 1, which is components 1, 2, and 3.

The next stage is to look at the loading factor to find out which items will be loaded with which factors. There are three factors formed at maximum, the determination of each variable is associated with which factor is conducted, whether to the first, second, or third factor. How to determine that is by referring to the following Component Matrix Table (Table 9).

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Table 9. Component Matrix

Items (Z-score)	Component 1	Component 2	Component 3	Items (Z-score)	Component 1	Component 2	Component 3
Zscore(P1)	.652	-.004	.143	Zscore(C1)	.713	.024	.073
Zscore(P2)	.636	.025	.313	Zscore(C2)	.608	-.161	-.135
Zscore(P3)	.603	-.049	-.084	Zscore(C3)	.719	-.035	-.288
Zscore(P4)	.627	-.034	.342	Zscore(C4)	.713	-.009	-.344
Zscore(P5)	.133	.667	-.040	Zscore(C5)	.057	.694	.291
Zscore(M1)	.696	-.011	.222	Zscore(C6)	.308	.661	.001
Zscore(M2)	.474	-.210	.006	Zscore(R1)	.668	-.112	.025
Zscore(M3)	.705	-.017	.168	Zscore(R2)	.548	-.103	-.326
Zscore(M4)	.498	-.181	.148	Zscore(R3)	.658	-.137	-.189
Zscore(M5)	.474	-.075	.526	Zscore(R4)	.649	.065	-.375
Zscore(M6)	.091	.690	-.128	Zscore(R5)	.302	.593	-.140

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Table 9 shows the correlation between a variable and the factor to be formed. For example, P1 correlates 0.652 with factor 1, -.004 with factor 2, and .143 with factor 3. In fact, a calculation by rotating can be used to determine the members of each factor. This result can be seen in the Rotated Component Matrix table below to determine which variables are loaded to which factors (Table 10).

Table 10. Rotated Component Matrix[a]

Items (Z-score)	Component 1	Component 2	Component 3	Items (Z-score)	Component 1	Component 2	Component 3
Zscore(P1)	.379	.539	.106	Zscore(C1)	.466	.525	.146
Zscore(P2)	.249	.652	.127	Zscore(C2)	.557	.319	-.048
Zscore(P3)	.501	.343	.060	Zscore(C3)	.721	.267	.099
Zscore(P4)	.232	.673	.066	Zscore(C4)	.750	.219	.126
Zscore(P5)	.024	-.005	.680	Zscore(C5)	-.257	.188	.684
Zscore(M1)	.359	.628	.105	Zscore(C6)	.125	.141	.704
Zscore(M2)	.372	.340	-.124	Zscore(R1)	.485	.473	.005
Zscore(M3)	.402	.594	.101	Zscore(R2)	.632	.132	.004
Zscore(M4)	.289	.458	-.095	Zscore(R3)	.625	.310	-.014
Zscore(M5)	.003	.712	-.007	Zscore(R4)	.714	.147	.189
Zscore(M6)	.049	-.101	.699	Zscore(R5)	.225	.040	.640

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

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Determination of which variable is loaded to which factor is by looking at the most significant correlation value. The table above has been sorted from the largest value to the smallest per factor. From this table, it can be seen that the largest correlation of P1 with factor 2 is .539, of P2: .652, and of P3: .688 and so forth. Of all items, for M2, M4, R1 is no more than .5 in all factors. Therefore, in the next analysis, these two items were discarded.

Cluster Analysis

The optimum number of clusters is determined by calculating the Hubert index and D index. The Hubert index is a graphical method of determining the number of clusters. In the plot of Hubert index, the researchers seek a significant knee that corresponds to a significant increase in the value of the measure, i.e., the significant peak in Hubert index second differences plot. The D index is a graphical method of determining the number of clusters. In the plot of the D index, the researchers seek a significant knee (the significant peak in D index second differences plot that corresponds to a significant increase in the value of the measure. Based on both methods, according to the majority rule, the best number of clusters is 3. Therefore, in the K-mean cluster method, 3 clusters were chosen.

Before the cluster analysis was performed, all SRL indicator data were transformed first to the Z-Score. Cluster analysis was conducted on Z-Score by determining 3 clusters to facilitate analysis. The analysis was performed by the K-Means method. In this analysis, items M2, M4, and R1 have been discarded based on the results of the factor analysis that has been done previously. The results of this analysis are shown in Table 11 for Cluster Centers.

Table 11. Final Cluster Centers

Items (Z-score)	Cluster			Items (Z-score)	Cluster		
	1	2	3		1	2	3
Zscore(P1)	-.97204	.66365	-.12001	Zscore(C1)	-1.02269	.76228	-.17777
Zscore(P2)	-.87171	.69194	-.18507	Zscore(C2)	-.89443	.60868	-.10894
Zscore(P3)	-.98617	.58225	-.04858	Zscore(C3)	-1.22404	.69572	-.03856
Zscore(P4)	-.84611	.68496	-.19083	Zscore(C4)	-1.28677	.63609	.03608
Zscore(P5)	-.14318	.24408	-.13578	Zscore(C5)	.05096	.19702	-.18071
Zscore(M1)	-.93448	.75101	-.20629	Zscore(C6)	-.45446	.41355	-.13929
Zscore(M2)	-.99187	.71861	-.15584	Zscore(R1)	-.91042	.47732	.00355
Zscore(M3)	-.52184	.55834	-.22725	Zscore(R2)	-.97632	.63939	-.09880
Zscore(M4)	-.11898	.18305	-.09698	Zscore(R3)	-1.18000	.57686	.03825
Zscore(M5)	-.97204	.66365	-.12001	Zscore(R4)	-.49192	.37654	-.09357
Zscore(M6)	-.87171	.69194	-.18507	Zscore(R5)	-1.02269	.76228	-.17777

Figure 2 shows for Distances between Final Cluster Centers. The number of members of each cluster from the analysis results was 1121 studentsor 19.09% (cluster 1), 2117 studentsor 36.05% (Cluster 2), and 2625or 44.87 % (cluster 3).This number can be the basis for predicting the number of things to consider in achieving learning performance.

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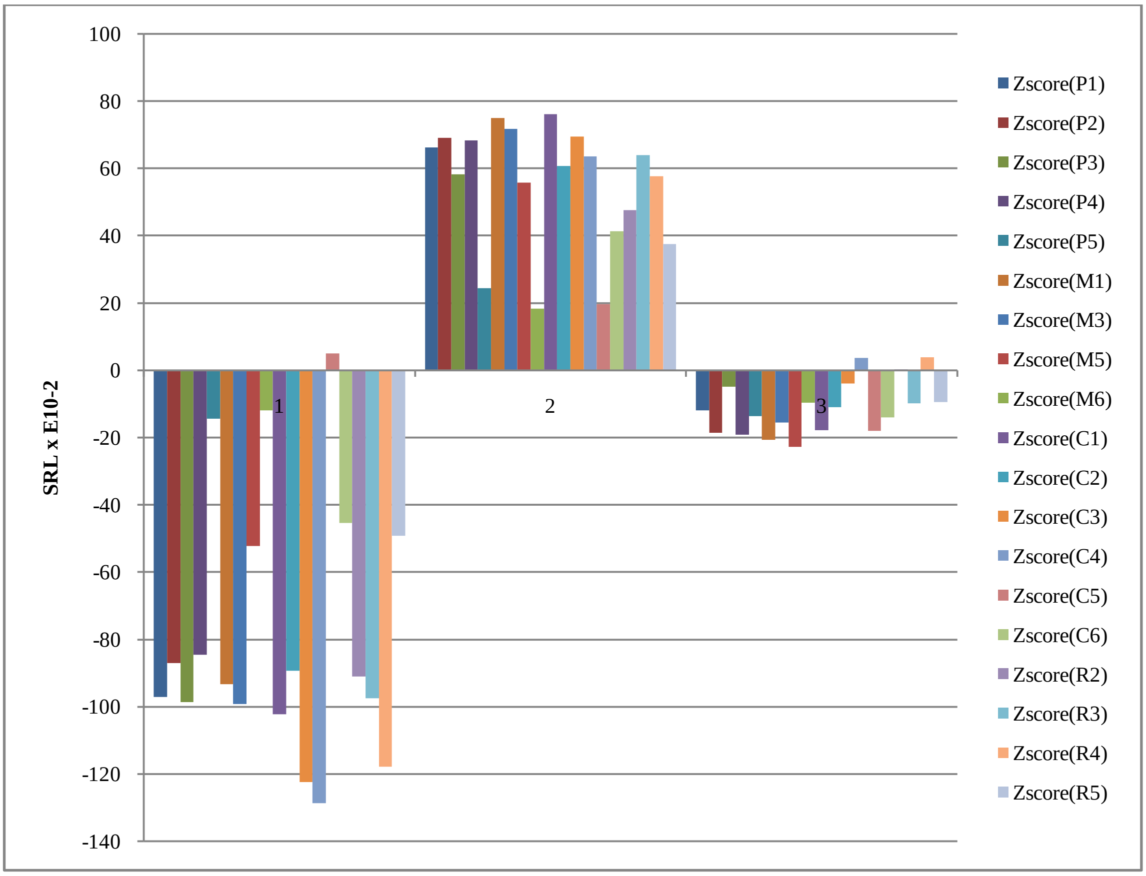

Figure 2. Final Cluster Center

Figure 2 is evidence of the pattern of cluster formation. The analysis can be based on Table 11 or Figure 2. The value in this analysis will be used as the foundation to decide the SRL as the basis to predict the learning performance.

ANALYSIS

The ANOVA results show that there is a significant difference in the Grade effect on SRL. There is a tendency for lower Grades to have a higher SRL than that of High Grades, but the diverse changes occur when students are in Grades 10 to 12. Research that includes an analysis of SRL is associated with age, or in this case, Grades show that younger people have higher SRL than that of in the elderly (Miles & Stine-Morrow, 2004; Price et al., 2010). The factor analysis on the items shows that some items do not provide a loading factor of more than 0.5 (i.e., M2, M4, and R1) so that the item is discarded. The grouping of items with cluster analysis is based on an Eigenvalue of more than 1. It shows that the most optimum number of factors is three, which can be used as an explanation. In the method section of this article, it is stated that these items are derived from the Pintrich model, but data analysis shows that the three factors are the most optimum. These findings explain that the model developed by Zimmerman is the most appropriate one. It includes three factors, i.e., forethought, performance, and self-reflection (See Table 12).

Table 12. SRL Phases

Cyclical self-regulatory phases		
Forethought	Performance control	Self-reflection
• Task analysis	• Self-control	• Self-judgment
• Self-motivation beliefs	• Self-observation	• Self-reaction

There is research that shows the relationship between SRL and the level of online learning technology readiness. If learning success is

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measured at the level of cognitive acquisition, SRL effects the level of acceptance of cognitive presence in online learning (Geng et al., 2019). Research related to SRL in general (not only on online learning) shows a positive relationship between SRL and learning performance or achievement (Dignath et al., 2008; Sadati & Simin, 2017; Banu, 2013). Independent learning in online learning has a significant and direct impact on the students' cognitive presence in online learning settings. The self-study setting is very important in online learning during this COVID-19 mitigation period. With this self-regulation, students have independence in learning to use information from the internet (Hee et al., 2019; Kuo et al., 2014; Aesaert et al., 2017). As other research results show that by having a good SRL, someone who can maintain or change his personality to get moral values in society (de Fátima Goulão & Menedez, 2015) uses their competence (Zhu et al., 2016) in cyberspace. In this setting, students are expected to direct themselves in learning on the online platform during COVID-19 mitigation. This online learning setting allows students to construct and confirm meanings through their own reflection. Therefore, by looking at the SRL profile, the acceptance level of cognitive aspects can be predicted.

In terms of SRL profile, it can be identified from cluster analysis, and there are three: low-level groups (cluster 1), medium (cluster 3), and high (cluster 2) in the SRL indicator (see figure 1). Figure 1 shows that the low SRL group is 19.09%, the medium is 44.87%, and the high is 36.05%. The percentagein the result leads to optimism in online learning that is done suddenly. The change from face-to-face in normal situations to fully online learning is not likely to significantly influence the students' learning performance. This is confirmed by the low SRL group that is only 19.09%.

In relation to the Grade variable, the data shows that, in general, women show a more positive and adaptive self-regulating profile than men. This is reflected by the different percentages of men and women in the high SRL group and the low SRL one identified through cluster analysis. The results obtained for differences in academic achievement show that there is a statistically significant positive relationship between SRL and academic achievement. This means that a higher SRL level leads to higher academic achievement, while a lower SRL level is associated with lower achievement. However, such mentioned differences did not reach a statistically significant result when comparing groups of students with low-SRL profiles with those with intermediate-SRL profiles. The previous statement must be adjusted, which shows that it comes from the medium-SRL level when such skills significantly influence the academic achievement obtained in the academic year. As the results of other research that explains this. SRL covers aspects of metacognition, motivation, and affirmative action. Stages of good independent regulation can support the achievement of learning outcomes (Cho & Cho, 2017; Matzat & Vrieling, 2016). SRL can be in the form of cognitive regulation, motivation regulation, motivation regulation, and emotional regulation (Persico & Steffens, 2017; Tsai, 2013).

CONCLUSION

The findings of our study revealed that SRL could be used as a predictor of learning performance in online learning settings during COVID-19 mitigation. This study expands the literature in online learning related to SRL. By comparing SRL profiles, school management can prepare policies to anticipate students' performance and to improve the processes that are running in online learning.

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