Kuram ve Uygulamada Eğitim Yönetimi
Educational Administration: Theory and Practice
2022, Cilt 28, Sayı 1, ss: 64-74
2022, Volume 28, Issue 1, pp:64-74
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Factor Analysis Affecting the Implementation of the Generative Learning Model with a Cognitive Conflict Strategy in the Computational Physics Course during the COVID-19 Pandemic Era

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Article History

Article Submission
24 November 2021
Revised Submission
22 February 2022
Article Accepted
30 March 2022

Abstract

This study aimed to analyze the factor model affecting the implementation of the Generative Learning Model with a Cognitive Conflict Strategy in the Computational Physics Course during the COVID-19 pandemic era. This study used quantitative descriptive data. The research respondents were 105 Physics study program students who took the Computational Physics course for the 2020/2021 academic year. A questionnaire with the Likert Scale used for the survey has been tested for validity by experts and limited tryout. The questionnaire used has high validity and reliability. Data were used for modeling structural equations through Exploration Factor Analysis (EFA). EFA results were used to determine the level of Confirmatory Factor Analysis (CFA) to obtain a complete Structural Equation Modeling. The results show that dynamic interactions and interdependent correlations are formed between variables that affect the implementation of Computational Physics learning. After analyzing the 20 (twenty) variables, it was formed 5 (five) factors affecting the implementation of the Generative Learning Model with a Cognitive Conflict Strategy in the Computational Physics Course. The five influencing factors are 1) the learning syntax and teaching materials used (x1); 2) the activity of expressing ideas (disclosure) and model practice (x2); 3) learning styles and creative thinking (x3); 4) Attitudes and final target score of learning (x4); 5) attitude towards learning materials and learning methods (x5). The five factors produce a model $F = 0.366\,x1 + 0.161\,x2 + 0.959\,x3 + 0.682\,x4 + 0.549\,x5$.

Keywords: Factor analysis, Generative learning, Cognitive conflict.

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1. Introduction

Computational Physics acts as a bridge between Theoretical Physics and Experimental Physics. Students have difficulty when faced with questions related to making problem-solving algorithms. On the other hand, Computational Physics is built on the basis of numerical analysis and the creation of problem-solving algorithms (AAPT and PPE, 2016, Prosperetti & Tryggvason, 2003). Scientific problem-solving skills, information gathering, and computational skills are important educational aspects for obtaining employment for graduates in engineering and physics (Landau et al., 2012). The discovery learning model through the lecture method which is interspersed with the question-and-answer method and the multiplier question technique supported by textbooks initially can help students understanding teaching materials, but in the last 6 years, this method is no longer effective to be used to build students competence in Computational Physics (Akmam 2018). Routine evaluation and needs analysis related to learning are important in the academic field (Fathema & Akanda, 2020). Needs analysis plays an important role in shaping assumptions and practices of continuous learning and training (Alhawsawi & Jawhar, 2021). A survey has been conducted on 132 students to find out the needs of students in the Computational Physics course.

The results of the needs analysis show that students need 1) facilities to build their own knowledge so that lectures are more meaningful (50.76, 21.97), 2) directions on how to make algorithms for solving Physics phenomena with computations (54.55, 33.33), 3) structured tasks to help understand concepts (47.73, 41.67), 4) challenge questions on each new topic to arouse curiosity (52.27, 25.00), and 5) changes in strategies and methods as well as learning steps by lecturers (33.33,29.55), as well as textbooks that can provoke curiosity in learning Computational Physics (49.24, 9.09). Students consider that 1) the practicum module has facilitated students to build their own knowledge (50.00, 12.88), 2) the importance of critical thinking in building knowledge (50.76, 37.12), 3) the importance of creative thinking in building problem-solving knowledge (52.27, 39.39) and discuss with friends (55.64, 28.57), as well as 4) self-evaluation on what has been done (52.27, 29.39). Numbers in brackets indicate (the percentage on agree and strongly agree).

Starting from the results of the needs analysis above, a generative learning model with cognitive conflict-oriented strategy has been developed to meet the needs above. This learning model is based on the theory of constructivism and cognitivism. Students build their own new concepts based on old concepts that they already have not in a vacuum, but in a social environment where they interact and restructure ideas based on the phenomena they face (Waldeyer et al., 2020). The generative learning model developed is based on (Osborne & Wittrock, 1983) explained by (Anderson, 2010). This model is implemented in Physics course (Maknun, 2015; Rosdianto, 2017; Akmam et al., 2019; Silitonga et al., 2020) and generative learning strategy (Pilegard & Fiorella, 2016) as the base model. This generative model is combined with the design of learning process with cognitive conflict strategy that has been implemented on various Physics topics (Sutopo, 2014; Astra et al., 2019; Asikin et al., 2017); to encourage students to test the truth of their initial conception whether or not it is in accordance with the scientists' conception—with the deep-thinking process.

This learning model encourages, treats, facilitates student as an independent learning subject who is responsible, creative, innovative, sportive and critical, and optimally actualize oneself in the aspect of intellectual and spiritual intelligence. This is a learning model that can form professional attitudes, skills and people with character (Jalinus & Abrian, 2015).(Verawadina, wt, al, 2020); (Krismadinata, et, al, 2020); (Hendriyani, et, al, 2020). The generative learning process affect the development of the ability to transmit knowledge and improve the ability to calibrate the learning process as well as better metacognitive awareness.

Cognitive conflict strategy has three main keys in the learning process, namely collaboration, reformulation and awareness (Rahim, Noor, & Zaid, 2015). The advantages of cognitive conflict strategy are that it is paying attention to students' conceptions, paying attention to the correlation between concepts, actively involving students and helping them understand concepts, and instilling new concepts correctly and long-lastingly. Students through cognitive conflict learning strategy can reduce their misunderstanding of the Computational Physics materials (Akmam et al., 2018), be more productive in realizing the results of ambidexterity innovation (Bedford, et. al., 2019) and reconstruct their knowledge (Štuikys, et.al., 2016). Students' scientific thinking and behavioral responses are concentrated on achieving meaning from the stimuli received (Bruner et al., 2017). Thus, learning that starts with cognitive conflict will be far from affective conflict (Schmid, et.al., 2015; Schmid et al., 2015; Kuhn, 2015), has a significant positive effect on social reputation and achievement (Chang, & Lo, 2015). The implementation of cognitive conflict strategy can support analytical thinking (Bronstein et al., 2020). So, cognitive conflict strategy can be used to trigger students to feel challenged to learn a new topic—the assimilation process to build knowledge about Computational Physics which is packaged in a learning model.

The generative learning model with cognitive conflict strategy is oriented to creative thinking to bring about conceptual change through the discovery process that students must use in the model, so that students are active and creative in assimilating existing knowledge to form new knowledge. Several experts have conducted studies on the advantages of generative learning to encourage active and creative students to form knowledge, among others (H. Lee et al., 2008; Made, 2014; Tang et al., 2014; Olusegun, 2015; Pilegard & Fiorella, 2016). All previous researches revealed strengths and weaknesses and came up with recommendations for generative learning to encourage creative thinking centered on the construction of knowledge through object design, metacognitive assessment, reflection and understanding, and higher-order thinking skills.

Based on the description above, a generative learning model with a cognitive conflict strategy which is oriented to creative thinking has been developed with 6 (six) stages, namely: orientation, cognitive conflict, disclosure, construct, and application as well as reflection. The orientation stage aims to attract attention and motivate students to the topics that will be discussed explicitly (Adeyemi & Awolere, 2016, Maknun, 2015) and functions as prior knowledge activation in an effort to achieve meaningful learning through cognitive processes in associative memory (Liu et al., 2017). The cognitive conflict stage contains elements of information that is meaningful; challenging student concepts; attracting attention; and motivating (Rahim et al., 2015). It aims to help students to recognize misconceptions and serves to encourage students to realize ambidexterity (Bedford et al., 2019) and enhance the processing of irrelevant stimuli (Ligeza & Wyczesany, 2017; Cook & Artino, 2016). The disclosure stage aims to trigger students to think about problem-solving ideas in the form of cognitive conflicts and think ahead through cognitive process control (Baroutsis et al., 2019). This stage serves to give opportunity for students to expand meaning through metacognition to find out which information to choose, what type of knowledge structure to build, and which prior knowledge to activate during learning (Aderibigbe et al., 2016). The construct stage aims for students to achieve conceptual understanding by reformulating the situation, solving ambiguous problems. This stage serves to facilitate students to exploit models and imaginative interventions of causal structures and counterfactual reasoning (Baroutsis et al., 2019).

The application stages aim for students to verify and perfect the designs that have been designed (Ulusoy & Onen, 2014) and think in various dimensions critically and creatively to solve problems (Wechsler et al., 2018). The application stage functions to challenge students to apply what they have learned to build an understanding of the concepts learned and expand their knowledge and skills. The reflection stage aims to give feedback on the construction process and results that have been carried out. Reflection is in the form of responses to activity events, newly received knowledge and evaluation of the process and correcting weaknesses in the knowledge development process. This stage serves to provide corrections and reinforcement of the process and results and mastery of learning materials.

The COVID-19 pandemic has disrupted all aspects of human life, including education. Face-to-face (offline) learning has turned into an online learning system. Online learning during the COVID-19 pandemic has consequences for learning outcomes, where students lose 20% of learning when compared to face-to-face learning (Engzell et al., 2021). Students also face various problems related to depression anxiety, poor internet connectivity, and an unfavorable study environment at home. Students from remote and blank hotspot areas face big challenges during the pandemic (Kapasia et al., 2020). Students are faced with problems of device access and internet quota (Subarkah & Salim, 2021) as well as difficulties in practical activities (Day et al., 2021, Camacho-Zuñiga et al., 2021), increased anxiety, lack of motivation, inability to anticipate problems occurring and inequality of getting information (Gillis & Krull, 2020). The problem of online learning during the COVID-19 pandemic crisis is that student learning styles are not in accordance with the online environment, lack of interaction due to poor communication (Nabukeera et al., 2020).

The implementation of the generative learning model with a cognitive conflict strategy has been carried out according to the syntax designed in the Computational Physics course. This model has a validity of 0.83 and a practicality of 0.85. However, student learning outcomes in Computational Physics are still not optimal during the COVID-19 pandemic. Based on the description above, a study was carried out to determine the model of factors affecting the implementation of generative learning models with cognitive conflict strategy in Computational

Physics course during the Covid-19 pandemic era.

The components of the factors analyzed are factors that affect the implementation of the learning model, including: 1) Students' attitudes towards learning materials and learning (Erdogdu, 2020)—since attitudes towards the learning process is very dependent on the context of education and learning (Pérez-Pérez et al., 2020); 2) Learning methods and attitudes and satisfaction with learning materials (Yuan, 2021); 3) Learning style as research (Alzain et al., 2018) in regards to absorbing, organizing and processing information and development stages of the mind (Gurlitt, 2012) and learning hierarchy (Zanfir & Sminchisescu, 2018); 4) Belief in creative thinking and students' creativity (Benedek, et.al., 2014) and the contribution of creative thinking to individual development (Hürsen & zdal, 2014); 5) Study preparation and time management (Blegur et al., 2019), also time management and discipline (Apriyanti & Shahid, 2021). The final target obtained and the time allocated depend on how the students' attitudes towards learning activities is (Sari et al., 2021); 6) Orientation that ensures meaningful learning (Pietikäinen & Mauno, 2012) and the process of learning and building concepts (Abayomi, et. al, 2020; Prawita, 2019); 7) Teaching materials and student worksheets (Baroutsis et al., 2019), the process of adapting conflicting schemes (Fatimah et al., 2017, Rabin et al., 2020). The introduction of the inhibiting factors for students in learning can help lecturers develop learning design mechanisms that can help students avoid and overcome these obstacles more effectively for better learning outcomes.

2. Methods

This study is quantitative descriptive research using Confirmatory Factor Analysis. The research data were about 1) Attitudes towards learning (SPFK), 2) Attitudes towards learning materials (SMFK), 3) Learning methods (CBFK), 4) Learning styles (GBFK), 5) Creative thinking beliefs (KBKRE), 6) Preparation for attending lectures (PBFK), 7) Teaching materials (BAJAR), 8) Learning model practicability (KMP), 9) Study duration/week (DBM), 10) Final target score (TNA), 11) Competencies submission (PTK) , 12) Orientation (ORI), 13) Cognitive conflict statement (CCG), 14) Disclosure (DSC), 15) Construct (CNST), 16) Concept application (APP), 17) Reflection and evaluation (REV), 18) Language (BHS), 9) Graphics (GRF), 20) Availability of study time (KWB). These data were collected using a questionnaire sheet. A series of questionnaires developed was based on a comprehensive literature review to establish measurement standards for constructing an appropriate structural model. The research respondents were 105 Physics study program students who took the Computational Physics course for the 2020/2021 academic year. The instrument used has been through a validity test by experts. The validity results show that the instrument developed has high validity. The test results show that the instrument developed also has high reliability. This EFA analysis was aimed to 1) determine the validity of a good construction at the initial level and 2) ensure that the variables as strong components forming the factors were maintained to examine the factors affecting the implementation (MPGBKK) in the Computational Physics course. MSA in SPSS software was measured by Kaiser-Meyer-Olkin (KMO) value and factorability correlation matrix. Assuming, if the Bartlett's test of sphericity is statistically significant (that is, $p < 0.05$), then the MSA value is greater than 0.50 (Hair et al., 2019).

3. Results and Discussion

3.1 Results

The factors analyzed in this study were the factors affecting the implementation of the cognitive conflict-based generative learning model (MPGBKK) in the Computational Physics course. The adequacy of the sampling size of 20 (twenty) was tested by the Kaiser-Meyer-Olkin (KMO) method and the Bartlett's test of sphericity. The results of the KMO and Bartlett's tests are as explained in Table 1.

Table 1. The KMO and Bartlett's test factors affecting the implementation of the syntax (MPGBKK) in the Computational Physics course

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.821
Bartlett's Test of Sphericity	Approx. Chi-Square	672.315
	df	153
	Sig.	2.2853E-64

The measurement result of KMO of sampling adequacy (MSA) is 0.821. MSA value > 0.5 indicates that there is a good partial correlation for each variable affecting the implementation (MPGBKK) in the Computational Physics course. Each variable can be predicted and analyzed further. The results of the Bartlett's of Sphericity test obtained a significant level of (p = 2.2853E-64). The value ($p < 0.0001$) indicates that there is sufficient correlation between each factor variable affecting the implementation (MPGBKK) in the Computational Physics course.

The next process was to extract a collection of factor components (variables) into several factors with communalities analysis. The results of communalities analysis obtained the coefficient of determination of each component of the formed factors with a range of values from 0.601 to 0.840. This figure shows that the variables can be explained and grouped into several factors. However, there were variables that were difficult to group because they had a coefficient of determination that was not much different from the two groups of factors. The variables of creative thinking belief, preparation for learning and the final target score planned by students have a coefficient of determination of 0.617, 0.654 and 0.662, respectively, with factor_2 and 0.581, 0.520 and 0.502 with factor_3. In order to be more convincing in grouping the variables, variables extraction was carried out using a multivariate method that transforms the original correlated factor (variable) components into new uncorrelated factors. Extraction results were as explained in Table 2.

Table 2. Total variance to explain the factor variables affecting the implementation (MPGBKK) in the Computational Physics course during the COVID-19 pandemic

	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	7.329	36,647	36,647	7.329	36,647	36,647	5.403	27.017	27.017
2	3.229	16,144	52,791	3.229	16,144	52,791	3.159	15,797	42.813
3	1,918	9.590	62,381	1,918	9.590	62,381	2.433	12.165	54,978
4	1.363	6,816	69,197	1.363	6,816	69,197	2,195	10,977	65,955
5	1.098	5.488	74.685	1.098	5.488	74.685	1,746	8,729	74.685
6	.824	4.121	78,805						
7	.704	3,520	82.325						
8	.592	2,961	85.286						
9	.490	2.449	87,735						
10	.442	2.211	89,946						
11	.365	1,823	91.769						
12	.300	1.498	93.267						
13	.249	1,247	94.514						
14	.236	1.179	95,693						
15	.208	1.042	96,735						
16	.187	.934	97,670						
17	.163	.815	98.484						
18	.114	.571	99,055						
19	.098	.492	99,547						
20	.091	.453	100.00						

Extraction Method: Principal Component Analysis.

The values in Table 2 show that the contribution of the Attitudes towards Computational Physics learning, orientation, reflection and evaluation as well as final target score variables greatly affect the success of implementation (MPGBKK) in the Computational Physics course during the COVID-19 pandemic era. The results of the analysis of the total variance of each variable obtained those 20 (twenty) variables can form 5 (five) factors. 5 (five) factors formed, each has eigenvalues of 7329, 3.229, 1.918 and 1.363, and 1.098 with each has 8 variables, 4 variables, and the next 3 factors have 2 variables.

In the final stage of analysis, a Rotate Component Matrix with the varimax method—which is the extraction that maximizes the loading factor through the Kaiser normalization method was performed. The loading factor value is the magnitude of the correlation between the formed factor and formation variable. The rotation results of the matrix components were presented then grouping analysis was performed. The grouping of variables into each factor was formed based on the loading factor value (correlation value) of each variable to the formed factor. The loading factor value used was ($0.7 \le r < 0.9$) (which means there is a strong correlation between the variables and the formed factor. The formation of the names of the seven elements formed is presented in Table 3 below:

Table 3. Rotated Component Matrix Loading Factor for Each Component

Name of factors	Component Factor	Loading
Syntax_ Teaching materials	Concept application activity (APP) (x1)	0.830
	Competencies submission (PTK) (x2)	0.817
	Reflection and Evaluation (REV), (x3)	0.816
	Cognitive conflict statement (CCG), (x4)	0.780
	Graphics (GRF) (x5)	0.777
	Orientation (ORI), (x6)	0.769
	Construct Activity (CNST) (x7)	0.745
	Teaching materials (BAJAR), (x8).	0.661
Disclosure_ Practicality	Language (BHS), (y1)	0.831
	Disclosure (DSC), (y2)	0.782
	Learning model practicability (KMP), (y3)	0.686
	Availability of study time (KWB),(y4)	0.623
Learning style_ creative thinking	Preparation for attending lectures (PBFK), (z1)	0.859
	Creative thinking beliefs (KBKRE),(z2)	0.837
	Learning style (GBFK), (z3)	0.791
Target_ learning attitude	Study duration /week (DBFKM), (v1)	0.873
	Final target score (TNA), (v2)	0.856
	Attitude towards learning (SPFK), (v3)	0.646
Attitude_ material_ learning methods	Attitude towards learning material (SMFK),(w1)	0.813
	Computational physics learning methods (CBFK), (w2)	0.588

Table 3 shows that there are several loading factor variables ($r < 0.7$), namely BAJAR, KMP, KWB, and SPFK and CBFK. Variable with $r < 0.7$ are grouped into the largest loading factor with the condition $r > 0.5$. If $r < 0.5$ then the variable is excluded

3.2 Discussion

After presenting the analysis, three important results have been shown. First, the KMO measure of the adequacy of sampling to analyze the factors affecting the implementation (MPGBKK) in the Computational Physics course (KMO = 0.821). KMO value greater than 0.70 indicates a strong partial correlation; and is suitable for factor analysis (Hair et al., 2019; Watkins, 2021). This KMO value indicates that all factors can be grouped for further analysis. Second, all of Bartlett's tests of Sphericity have shown good results. All small values less than 0.05 indicate that there is a significant correlation between variables (Hair et al., 2019; Tabachnick & Fidell, 2018). Finally, The EFA for factors affecting the implementation (MPGBKK) in the Computational Physics course achieves good loading to become a retention factor. The loading value of all indicators is above 0.50 (good level).

The Eigenvalue results in Table 2 explain the relative correlation of each factor in calculating the variance of the 20 analyzed variables that can be extracted into five (five) factor components as shown in Table 3. The total variance of the five factor components is:

$$TotVar = 36.647\% + 16.144\% + 9.590\% + 6.816\% + 5.488\% = 74.685\%$$

Factor analysis affecting the implementation of a cognitive conflict-based generative learning model in Computational Physics based on the loading factor value of each variable found that there are weak variables to be grouped because ($r < 0.7$), but they are still feasible to be analyzed (Hair, 2010, Watkins, 2021). The data in Table 3 shows that there are 5 (five) variables that have a loading factor of ($r < 0.7$), namely BAJAR, KWB, and SPFK and CBFK. The BAJAR (teaching materials used in the lesson) variable with $r = 0.661$ means that it has a strong enough determination to form Factor_1. The BAJAR variable with ($r = 0.532$) means that this variable has a strong enough determination to form Factor_2. The SPFK variable (attitude towards learning) has r = 0.646 with factor-4 and r = 0.551 with factor-5, which means that the SPFK variable affects the formation of factor-3 and factor-4. While the KWB variable (Time allocated for study) even though r < 0.7, the value of r = 0.623 with factor-2. Similarly, the CBFK variable (Computational physics learning methods) also has a strong enough correlation to the implementation (MPGBKK). Teaching materials play an important role in determining the success of students in participating in the implementation of learning (Ariani & Yolanda, 2019). Teaching materials help students to gain instructional experience and online learning effectiveness (Shi et al., 2020). The CBFK and KWB variables are less affecting the implementation of a cognitive conflict-based generative learning model in Computational Physics course during the COVID-19 pandemic. This is due to the fact that during the COVID-19 pandemic, Computational Physics learning took place online through visual conferencing. Visual conference learning activities are very dependent on the smoothness of internet signals and the student learning environment. Students cannot use their study time effectively [unless these two factors are fulfilled]. The five newly formed factor models can be explained as follows.

1). Learning stages and teaching materials

Table 3 shows that the first factor formed is named Syntax_ Teaching materials, which is mathematically formulated with

$$F1= 0.830\ x\_1+0.817\ x\_2+0.816\ x\_3+0.780\ x\_4+0.777\ x\_5+0.769\ x\_6+0.745\ x\_7+0.661\ x\_8$$

This equation shows that the activity of applying the knowledge that has been built (x1) is the main variable forming the Syntax_ Teaching materials factor. Concept application facilitates students to creative problem-solving with high expectations (Wechsler et al., 2018). The productive expectation of ideas enables students to make important predictions about further information processing in learning. Competencies submission to be achieved in (x2) really helps students focus on the activities and concepts to be learned (Adeyemi & Awolere, 2016).

Reflection and evaluation (x3) activities obtain a high correlation meaning that the variable will determine the success of the implementation of Computational Physics learning. Immediate reflection is important for students to reduce problems and improve their academic and work performance (Uukkivi A. Labanova O.). This is because reflection and evaluation activities in the classroom have a positive effect on student learning outcomes and improve their academic performance (Couto Zoltowski & Pereira Teixeira, 2020); developing their creativity and critical thinking skills (Thorley, 2018) and improving their self-efficacy and self-regulation (de Bruin, 2018).

Orientation (x6) is an early stage in generative learning and has an important role in stimulating student interest and curiosity in solving a problem. Orientation will ensure learning to be meaningful (Pietikäinen & Mauno, 2012). Students will be passionate and actively involved in the learning process to build concepts and participate in controlling the learning process (Abayomi, et. al, 2020; Prawita, 2019). Student at the construct activity (x7) exploit causal models and possible consequences of imaginative intervention structures of cause-and-effect and facilitate counterfactual reasoning (Baroutsis et al., 2019). The process of adapting the scheme occurs when students face a phenomenon that contradicts (conflicts) with the understanding that they have believed to be true (Fatimah et al., 2017). Cognitive conflict statements (x4) can increase the stimulus for students to process irrelevant information to get new concepts (Ligeza & Wyczesany, 2017). The newly discovered concepts must be tested for their application in other practical conditions (Cook & Artino, 2016). The teaching materials used (x8) are the main support and source of inspiration for students to be able to build knowledge in resolving the cognitive conflicts they face. Teaching materials are supported by attractive language and graphic design. Variables of competencies submission, orientation, cognitive conflict statement, concepts and constructs application as well as reflection and evaluation are the syntax of the generative learning model based on cognitive conflict that was developed. The implementation of learning must be supported by teaching materials with attractive graphic designs.

2) Disclosure and Practicality

The second factor formed is named Disclosure_ Practicality, which is mathematically formulated with

$$F2= 0.831\ y\_1+0.782\ y\_2+0.686\ y\_3+0.623\ y\_4$$

Disclosure in the form of metacognition involves awareness and control of cognitive processes forming the structure of knowledge that is built and prior knowledge (Pilegard & Fiorella, 2016). Students will connect their own learning experiences with the topics will be studied (Rosdianto, 2018). Students enrich their discriminatory ideas with a clear conceptual structure (Krähmer, 2020) with the feedback given to encourage them to think ahead (Baroutsis et al., 2019). The process of disclosure stimulates creative cognition that is important for constructing and exploring ideas to solve problems (Calabretta et al., 2017). The real efficiency implications of disclosure variable that is known are very helpful in making effective real decisions (Goldstein & Yang, 2019). The realization of the activity is closely related to the language used in teaching materials and student worksheets, as well. So, if the disclosure activity (y2) is expressed in short, concise and meaningful language (y1), it will certainly save learning time (y4). Meaningful learning takes place in a short time; thus, it produces practical learning (y3). Therefore, it appears here that the clarity of the language used in teaching materials and student worksheets (y1) as well as student activities when trying to express ideas (Disclosure, y2), are the two main variables forming the Disclosure_ Practicality factor.

3) Learning style and creative thinking

The third factor formed is named Learning style_ creative thinking, which is mathematically formulated with

$$F3= 0.859 z_1+0.837 z_2+0.791 z_3$$

The learning style_ creative thinking factor contains 3 (three) variables, namely preparation for attending lectures (z1), creative thinking beliefs (z2) and learning styles (z3).Creative thinking is the ability to think consistently in an effort to produce innovative and original work. Creative thinking skills can be seen from students' creativity which is closely related to intelligence (Benedek, et.al., 2014). Creative thinking contributes to individual development (Hürsen & zdal, 2014) in processing the information that has been obtained. The combination of how students absorb, organize and process the information that has been obtained is called learning style (Alzain et al., 2018). Preparation is related to students' initial knowledge of the material to be discussed. Based on the development stages of mind, one, in learning, must plan carefully what will be learned (Gurlitt, 2012) and follow the learning hierarchy (Zanfir & Sminchisescu, 2018). The stages referred to here are assimilation, accommodation, and equilibration. Thus, it is clear that preparation for attending lectures (z1) and creative thinking beliefs (z2) have a strong influence on the formation of the learning style_ creative thinking factor

4) Target scores and learning attitudes

The fourth factor formed is named Target_ learning attitude, which is mathematically formulated with

$$F4= 0.873 v_1+0.856 v_2+0.646 v_3$$

This formula shows that 2 (two) variables greatly influencing the formation of this factor are the duration of study in weeks (v1) and the final target score to be achieved by students (v2). This condition shows that the success of students in learning depends on how they manage their time to study. The results are in line with the findings of (Blegur et al., 2019) and (Apriyanti & Shahid, 2021) in relation to time management. The final target score to be obtained and the time allocated (for studying) depend on how students' attitudes towards learning activities (v3), especially during the COVID-19 pandemic (Sari et al., 2021). This is because the learning activities during the COVID-19 pandemic cannot be fully controlled by lecturers. Thus, students' attitude toward learning is positively related to academic achievement (Erdogdu, 2020). So, if students have a positive attitude towards the topic being discussed, of course they will devote time and thought to understand the topic being discussed.

5) Attitude towards the material and learning methods

The fifth factor formed is named Attitude_ material_ learning methods, which is mathematically formulated with

$$F5= 0.813 w_1+0.588 w_2$$

This Attitude_ material_ learning methods factor is formed by 2 (two) variables, namely attitudes towards learning materials (w1) and learning methods (w2). The material discussed in this study is Computational Physics. These results indicate that attitudes towards learning materials will determine a student's learning methods. A positive attitude towards learning materials can increase accessibility and motivation in learning (Valantinaitė & Sederevičiūtė-Pačiauskienė, 2020). Students' attitudes and satisfaction with learning materials affect the way they learn, especially during the COVID-19 pandemic (Yuan, 2021). The communication process in the learning process is very dependent on the context of education and learning (Pérez-Pérez et al., 2020)

4. Conclusion

We analyze several important variables as factors influencing implementation of the Generative Learning Model with a Cognitive Conflict Strategy in the Computational Physics course during the Covid-19 pandemic era based on learning theory. The results of the study indicate that dynamic interactions and interdependent correlations are formed between variables that affect the implementation of Computational Physics learning. After analyzing the 20 (twenty) variables, it was formed 5 (five) factors affecting the implementation of the Generative Learning Model with a Cognitive Conflict Strategy in the Computational Physics Course. The five influencing factors are 1) the learning syntax and teaching materials used; 2) the activity of expressing ideas (disclosure) and model practice; 3) learning styles and creative thinking; 4) Attitudes and final target score of learning; 5) attitude towards learning materials and learning methods. Limitations, First, the research framework was carried out on 5 (five) classes of students at one university in the same field of study. Thus, future studies are encouraged to apply and expand this research framework in different courses and colleges. Second, the research data analyzed is quantitative, so that a qualitative research paradigm can be adopted to explore additional information and findings regarding similar learning designs and topics. Third, the research design was self-reported, although the problem was not a serious one.

5. Acknowledgments

The authors would like to express our gratitude to the Rector of Universitas Negeri Padang and Lembaga Penelitian dan Pengabdian Masyarakat Universitas Negeri Padang for funding this work with a contract number: 858/UN35.13/LT/2021; also, anonymous reviewers and instrument validators who have provided valuable feedback

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