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Integration of cognitive conflict in generative learning model to enhancing students' creative thinking skills

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Abstract

In the complexity of the Fourth Industrial Revolution era, the importance of creative thinking is increasingly emphasized in the context of learning computing and algorithms. These skills are instrumental in inspiring innovative solutions, addressing complex challenges, and fostering the development of advanced technologies that characterize the transformative landscape of Industrial Revolution 4.0. This study aims to determine the effectiveness of the generative learning model based on cognitive conflict in improving the creative thinking skills (CTS) and learning outcomes of students in the computational physics and algorithms & programming courses. This research used mixed methods consisting of pretest-posttest control group design and snowballing technique. The research instruments consist of cognitive tests, psychomotor tests, affective tests, CTS tests, observation questionnaires, and interviews. The research sample consisted of 138 students taking computational physics and algorithms & programming courses. Quantitative data were analyzed using multivariate analysis of variance and qualitative data were analyzed using narrative analysis. The findings indicate that this model effectively improves students' CTS and learning outcomes. Furthermore, the cognitive conflict aspect encourages students to be creative in analyzing and solving problems. This model has the potential to be used to optimize students' potential in facing the demands of the fourth industrial revolution.

Keywords: algorithm & programming, computational, conflict cognitive, creative thinking skills, generative learning

INTRODUCTION

Creative thinking skills (CTS) are globally recognized as essential skills to meet the demands of life in the 21st century. Developing these skills is crucial to prepare students for addressing complex problems in the future and the workforce (Albar & Southcott, 2021; OECD, 2019; Thornhill-Miller et al., 2023). In the context of education, CTS not only assists students solve problems but also enable them to innovate and adapt to rapid changes (Berestova et al., 2021; Yang & Zhao, 2021). Education that encourages creative thinking assists students to understand subject matter more deeply while also developing their creative, analytical, and problem-solving abilities (Calavia et al., 2021). Integrating and promoting creative thinking within educational curriculum not only prepares students for academic challenges but also equips them with the skills needed to succeed in their professional and personal lives (Ball et al., 2016; Thornhill-Miller et al., 2023). Therefore, it is crucial for educational institutions to emphasize the development of these skills through relevant curriculum and innovative teaching models. The curriculum approach should balance fundamental computational understanding with practical experience, and align learning objectives that blend theoretical

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Contribution to the literature

- Activities in the disclosure, construct, and application stages of the generative learning model based on cognitive conflict (GLBCC) model can stimulate students' creative thinking abilities. The disclosure, application, and construct stages are associated with computational thinking skills that can enhance creative thinking in computational physics and algorithms & programming.
- Activities involving idea generation and concept development in the form of algorithms or flowcharts represent cognitive processes (brain skills). Testing algorithms and coding require computational thinking skills, which blend cognitive abilities with technical expertise (hard skills). Logical thinking skills involve analyzing problems using clear reasoning and generating potential solutions, closely related to Computational Thinking skills in the aspect of creativity in problem management and formulation, necessitating the development of thought processes.
- The implementation of the GLBCC model, particularly in the disclosure, construct, and application stages, relates to computational thinking skills that can foster students' creative thinking abilities in computational physics and algorithms & programming, constituting manual skills that must be supported by cognitive abilities.

knowledge, computational comprehension, and practical implementation (Hall et al., 2022).

Lecturers at universities are responsible for developing these skills, including physics lecturers. Moreover, physics lecturers have to respond to these challenges by integrating theoretical and practical materials to foster the competencies required in the workforce and create new job opportunities. Therefore, improving learning models and teaching quality is imperative to realize this goal (Hidayati et al., 2023). In courses such as computational physics and algorithms & programming, students are expected to not only understand theoretical concepts of physics and algorithms, but also be able to apply this knowledge creatively in solving complex problems. Computational physics and algorithms requires students' ability to integrate physics principles with computational algorithms to design innovative solutions. In other words, both of these courses require more than just an understanding of concepts. Therefore, lectures must create a learning environment in courses such as computational physics and algorithms & programming that supports exploration and experimentation. They should also provide facilities and resources that aid in developing students' CTS (Tikva & Tambouris, 2021). However, currently there is no research that specifically discusses the effectiveness of a learning model in the context of computational physics and algorithms & programming courses. The success of implementing a learning model often depends on the context and characteristics of a particular course. The generative learning model is a learning model that suits the special needs of computational physics and algorithms & programming courses is generative learning models (Cikmaz et al., 2021; Kusairi et al., 2020).

The generative learning model is based on constructivism theory, facilitating students in building new concepts based on old concepts that students already have (Buchner, 2022). Generative learning was originally introduced by Wittrock (1992), consisting of motivation, attention, processing information, generative learning, subsumption, restructuring, and problem-solving. This learning continues to experience development based on contemporary views. The generative learning syntax proposed by Flick (1996) consists of engagement, exploration, elaboration, and evaluation. Meanwhile, the generative learning syntax proposed by Kusairi et al. (2020) consists of engagement, exploration, transformation, presentation, and reflection. Futhermore, the generative learning syntax proposed by Ulusoy and Onen (2014) consists of preliminary, focusing, challenge, application, and evaluation. The generative learning that syntax consists of exploration, focusing, challenge, and application (Wena, 2018). Maknun (2015) proposed a generative learning syntax consisting of orientation, disclosure, challenges and reconstruction, implementation, and evaluation. Pilegard and Fiorella (2016) identified a generative learning syntax consisting of utilization, metacognitive, judgment, self-regulation, and learning outcomes. This overall concept shows that generative learning involves a series of steps designed to stimulate student involvement, exploration, elaboration, evaluation, and reflection in building deep understanding.

All the syntaxes proposed by the research have advantages and disadvantages, each providing several recommendations. Generative learning must be supported by creative thinking focused on knowledge construction through object design (Fiorella, 2023). Assessment in generative learning must be metacognitive because students' self-reflection is often inaccurate. On the other hand, the ability to make accurate self-reflective assessments is an important activity in generative learning (Pilegard & Fiorella, 2016). Learning with the generative learning model is prone to misconceptions; evaluation-based reflection requires further investigation. Generative learning

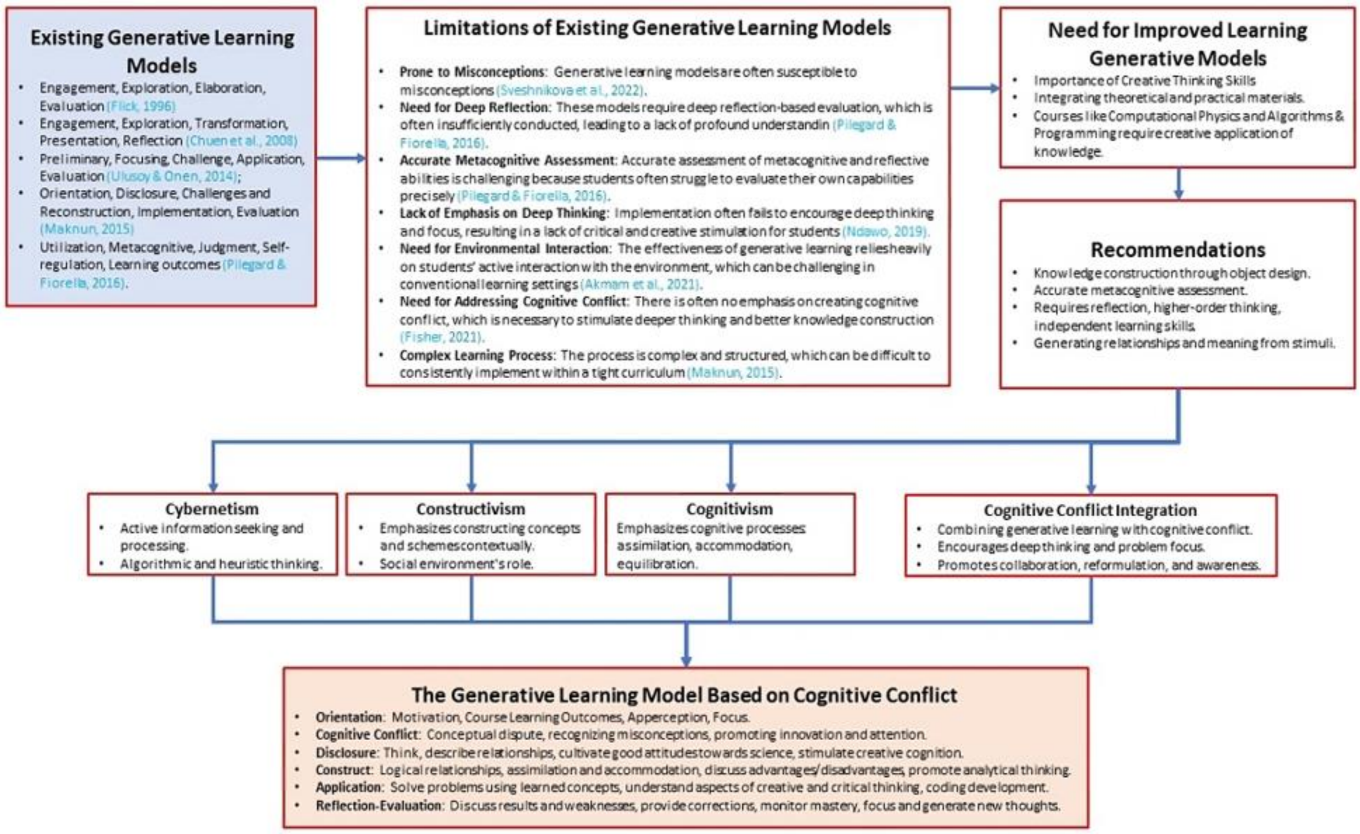

Figure 1. The conceptual framework for developing the GLBCC model (Source: Authors' own elaboration)

requires a process of generating relationships and meaning in building knowledge based on acceptable stimuli that needs to be analyzed further. Understanding higher-order thinking skills and independent learning skills must be a concern in implementing generative learning (Ndawo, 2019). Apart from that, the implementation of the generative learning model does not emphasize the process of focusing and encouraging students to think deeply. Therefore, it is necessary to add a cognitive conflict stage aimed at making students focus on the problem and encouraging students to think deeply. Cognitive conflict strategies have a role in encouraging the process of collaboration, reformulation, and awareness in learning (Fisher, 2022). The hope is that through steps that contain cognitive conflict, students can focus on proposing ideas (disclosure) according to their wishes (Brod, 2021).

Given this identified gap, it is imperative to determine the effectiveness of the combination of generative learning and cognitive conflict in improving CTS and computational skills in the form of generative learning based on cognitive conflict model oriented to CTS. Generative learning based on cognitive conflict model (stated as the GLBCC model) was developed based on the learning theory of cognitivism, constructivism, and cybernetics. The conceptual framework for developing this model is shown in **Figure 1**. Furthermore, this model has a cognitive process that allows students to interact with the environment. The process follows stages of assimilation, accommodation, and equilibration (Akmam et al., 2021). In the constructivism view, a learning model required to emphasize the process of constructing concepts and schemes that are contextual in nature (John, 2018) through the process of assimilation and accommodation with due respect to the social environment (Detel, 2015). Likewise, the GLBCC model also emphasizes that process in constructing knowledge and developing student skills. In the cybernetism, The GLBCC model has a cybernetism view, which emphasizes the need for learners to actively seek and process information. Compared to information technology, computers can only process the data provided. The rate at which students process information depends on the freshness of their thoughts, feelings, physical fitness (Li et al., 2023), and skills (Mao et al., 2022). Based on the cybernetism theory, there are two forms of thinking process, namely algorithmic and heuristic (Ürey, 2021;Shin, 2022), which both focus on the predetermined goal. The GLBCC also accommodates these activities.

The first stage of the GLBCC model (orientation) has several aspects, including motivation, delivering course learning outcomes, apperception of material, providing directions to attract students' attention explicitly, as well as focusing on the activities and concepts to be learned (Adeyemi & Awolere, 2016), as well as carrying out more humanistic learning (Kafai et al., 2019). Students can build an impression about the concept to be studied (Yi et al., 2016) as well as the construct psychology (Zheng et al., 2019), which makes learning more meaningful (Andres, 2019; Maknun, 2015);

The second stage (the creation of cognitive conflict) is often carried out to make students experience conceptual dispute, which helps in the recognition of misconceptions. Cognitive conflict serves as a complement, promotes the realization of superior agility innovations (ambidexterity) (Bedford et al., 2019), as well as increases the processing of irrelevant stimuli (Ligeza & Wyczesany, 2017). A previous study revealed that it contains several elements, namely

(1) meaningful information,

(2) ability to challenge existing student concepts,

(3) ability to attract attention,

(4) motivation, and

(5) convenience (Rahim et al., 2015).

Moreover, cognitive conflict stimulates CTS, which is important for constructing and exploring effective solutions and ideas to help students recognize dissatisfaction (Akmam et al., 2019; Eranova & Prashantham, 2017).

In the third stage (disclosure), students at were given time to think about ideas, which can be used to solve the cognitive conflict problem (Baroutsis et al., 2019). They are led to describe the relationship between the process of sharing and the construction of knowledge as a whole (Aderibigbe et al., 2016). It has always been crucial to cultivate good attitudes towards science and science education in order to study computational physics (Kapanadze et al., 2023). The disclosure process stimulates creative cognition, which is important for constructing and exploring ideas to solve problems (Calabretta et al., 2017) as well as to bring students to a higher understanding using their language. The real efficiency implications of expressing ideas regarding variables already known are very helpful in making real effective decisions (Goldstein & Yang, 2019).

In the fourth stage (construct) students construct logical relationships from several concepts and principles to form models using old and new information through assimilation and accommodation processes. Furthermore, learners with reconstructed concepts can exploit causal models and possible consequences of imaginative interventions of influential structures and counterfactual reasoning (Baroutsis et al., 2019). They also have the ability to discuss the advantages and disadvantages of ideas as well as provide opportunities to develop concepts, which helps to improve their analytical thinking skills (Prawita et al., 2019). These types of discussion activities are important tools for promoting students' engagement. This enables communication and collaboration between students and educators, thereby promoting the development of higher-order thinking skills (James et al., 2022). Model formation, numerical analysis, and algorithms are carried out through discussion groups, while coding development through practicum was performed individually.

In the fifth stage (application), students were given the opportunity to solve problems through the application of concepts that have been obtained by seeking solutions to the Physics model on the activity sheets (Ulusoy & Onen, 2014). They were also asked to understand the various aspects of creative and critical thinking to solve problems and generate valuable predictions to make predictive coding for further information processing (Wechsler et al., 2018). Coding activities are often carried out in the implementation stage to explain or simulate physical phenomena. Moreover, students can test the developed alternative ideas (algorithms) to solve various problems through practical coding simulations.

The sixth stage (reflection) is a form of response to activities, newly received knowledge, evaluation, and weaknesses correction in the knowledge-building process. Activities in this phase include:

(1) discussing the results and the weaknesses found,

(2) discussing the weaknesses and strengths of the work process and results,

(3) providing corrections and strengthening of processes and results, and

(4) monitoring students' mastery of the learning materials.

Educators also assess the level of students' understanding after the development of a concept and its application. The first reflection was carried out through class discussion on the construct and application that have been performed. This reflective process is very important due to the presence of different students' characteristics (ways of thinking and behaving), and it aids the quick achievement of goals (Makhanya et al., 2021). Reflection also provides focus and generates new thoughts for students (Abegglen et al., 2021).

The GLBCC syntax focuses on six indicators of creative thinking ability, namely fluency, flexibility, originality, elaboration, analysis, and evaluation. During the disclosure stage, the creative thinking indicators that can be enhanced are fluency, flexibility, elaboration, and originality. Research by Pi et al. (2019) shows that the disclosure stage is crucial for stimulating these creative thinking indicators. In the construct and application stages, the indicators that can be improved are flexibility, elaboration, and analysis. Sibo et al. (2023) state that activities in the construct and application stages involve applying ideas in more specific contexts and testing the effectiveness of those ideas, thus developing flexibility, elaboration, and analysis. In the evaluation and reflection stage, evaluation skills are enhanced. Hao et al. (2016) emphasize the importance of evaluation in the creative thinking process, where individuals analyze their thought outcomes, verify the accuracy of obtained information, and assess the effectiveness of the generated solutions.

Implementation of the GLBCC model on a limited scale in trials for computational physics learning is supported by book support tools, educators' manuals, lecture program units, semester lecture plans, and students' worksheets. Furthermore, the validity of these tools has been tested, and they are valid in content and construction. The validity coefficient score of the model and supporting tools ranged from 0.76 to 0.95 with an average of 0.822 (good category). According to experts, the GLBCC model and the support system are valid in terms of content and construction. The GLBCC model and tools were also tested on a limited scale to determine their practicality, which was viewed from the aspects of instructions for use, achievement of course learning outcomes, students' responses, educators' difficulties in following each learning syntax, and time availability. The test objects were also declared practical with a 95% confidence level based on the Aiken scale (Azwar, 2019). The practicality coefficient of the GLBCC model and supporting tools by users (educators) was between 0.78 to 0.98, which was placed in the very practical category. This indicates that the respondent attainment level (RAL) of the test objects were in a very high category. The practicality coefficient from the students' view was between 0.68 to 0.82 (30 people). This indicates that RAL GLBCC and its supporting tools are in the high category based on the Aiken scale (Azwar, 2019), but they have not been used on a wide scale. Therefore, this study aims to determine the effectiveness of the generative learning model based on cognitive conflict (GLBCC) in improving the CTS and learning outcomes of students in the computational physics and algorithm & programming courses. The effectiveness of the GLBCC model is obtained by comparing the learning outcomes and CTS of students with two other learning models, namely the guided inquiry learning (GIL) model and expository learning (EL) model.

METHODOLOGY

Research Design

This research uses mixed methods. This method is deemed relevant to the research as it combines the strengths of both quantitative and qualitative data. The quantitative method, through experimental design, provides objective data on student learning outcomes and CTS. In contrast, the qualitative method, such as interviews and observations, explores students' experiences and perceptions in depth (Gibson, 2017). By integrating these two approaches, the research achieves a more comprehensive and nuanced understanding of the effectiveness of the learning model, as well as the factors influencing student learning outcomes and CTS. Quantitative research employed an experimental pre-/post-test control group design to assess the effectiveness of the GLBCC model (Creswell & Guetterman, 2019). The effectiveness of the model is obtained by comparing the learning outcomes and CTS of students after being taught through the GLBCC model as experimental group 1, the GIL model as experimental group 2, and the EL model as the control group in the courses of computational physics and algorithms & programming. GIL is chosen because it aligns with active learning principles, emphasizing active student participation, exploration, and discovery. GIL fosters the development of inquiry skills and problem-solving abilities (Chen et al., 2018; Sotiriou et al., 2020), crucial in subjects like computational physics and algorithms & programming. Empirical evidence supports the effectiveness of GIL in enhancing learning outcomes across cognitive, affective, and psychomotor domains (Berie et al., 2022), making it an ideal model for comparison with the innovative GLBCC model. Furthermore, GIL's suitability for science and technology education, where hands-on learning is critical, reinforces its relevance in this research. Meanwhile, the inclusion of EL is a strategic choice for several compelling reasons. This traditional model emphasizes direct knowledge transmission from instructor to student, primarily through lectures and presentations, in stark contrast to the student-centered and constructivist methods of GLBCC. By employing EL as a control, the study can effectively evaluate the impact of these modern, interactive teaching strategies on learning outcomes and CTS compared to the conventional, structured educational framework. Additionally, EL's inclusion allows assessing whether active engagement, problem-solving, and reflection (key elements of GLBCC) yield superior educational benefits over traditional didactic instruction, particularly in fostering deep understanding and student engagement.

Samples from each course are randomly divided into 3 groups. The first group attends lectures using the GLBCC model; the second group attends lectures using the GIL model; the third group attends lectures using the EL model. The effectiveness of the model is measured through learning outcomes (LO) with four latent variables: LO in the cognitive domain (LOC), LO in the psychomotor domain (LOP), LO in the affective domain (LOA), and CTS. Effectiveness analysis was conducted by comparing students' learning achievements at the beginning, during, and end of the learning process. The GLBCC model was applied to students enrolled in computational physics and algorithms & programming courses, with the experimental class using the GLBCC model and the control class using the GIL and EL models. The syntax of the GLBCC model for this study comprised six stages, as depicted in **Table 1**.

The syntax of the guided inquiry model encompassed six stages outlined in **Table 2**.

Table 1. The syntax of the GLBCC model (Akmam et al., 2022; Maknun, 2015)

Stage	Description
Orientation	Lecturer provides motivation and communicates learning outcomes and expectations. Students form impressions about the concepts to be studied and express initial conceptions based on prior learning, relating them to the learning objectives.
Conflict cognitive	Lecturer creates situations that challenge students' cognitive structures by presenting contradictory phenomena through simulations, animations, or thought-provoking questions, encouraging students to explore alternative answers to observed symptoms.
Disclosure	Lecturer encourages students to contribute ideas based on their learning experiences related to the observed phenomena, connecting them to the topics being studied, and guiding students in constructing concepts.
Construct	Students begin organizing and constructing a cognitive framework by modifying the structure and relationships between existing concepts. They develop problem-solving algorithms based on their analysis, clarify the algorithms, and present their work to the entire class.
Application	Students apply the concepts they have learned to create algorithms. They are given opportunities to develop more complex algorithms and test alternative approaches to solve various problems.
Reflection	Students verify the compatibility of their source code with the algorithm and determine whether the created source code can effectively solve the given problem. They analyze their learning, identify strengths and weaknesses in the learning process, and provide constructive ideas for improving their learning. Additionally, students undertake project assignments aimed at solving computational physics phenomena.

Table 2. The syntax of the guided inquiry model (FitzGerald & Garrison, 2016; Maknun, 2020; Sarwi et al., 2016; Ural, 2016)

Stage	Description
Orientation	Lecturer creates a conducive learning environment & prepares students for learning process.
Observing	Students are given a phenomenon containing a problem to observe and identify. Based on the information obtained, they formulate a solution.
Making a hypothesis or asking a question	Lecturer provides opportunities for students to generate hypotheses and guides them in determining and prioritizing relevant inquiries.
Designing the experiment	Lecturer provides opportunities for students to determine algorithms to test hypotheses. Students are asked to classify variables observed in the phenomena.
Conducting experiments or coding to solve problems computationally or through experiments	Students carry out experiments according to the created algorithm. An important factor in conducting experiments is the compatibility between the algorithm, coding, and the resulting output. Students test the generated hypotheses (compiled algorithms) to determine if they can correctly accomplish the given tasks.
Analyzing data and writing experiment reports	The final stage of guided inquiry learning involves making temporary conclusions based on the obtained data. The lecturer provides an opportunity for each group to present the results obtained through data processing and guides them in creating an experiment report.

The syntax of the expository model outlined in **Table 3**. Meanwhile, qualitative research was employed to investigate students' learning processes.

These three models have different emphases in their implementation. In terms of learning processes, GLBCC places a strong emphasis on cognitive conflict and deep conceptual change, fostering critical thinking through the exploration of contradictions and subsequent reflection. GIL focuses on inquiry and discovery, encouraging students to generate and test hypotheses as they engage actively in the learning process. EL adopts a more teacher-centered approach, prioritizing the direct transmission of knowledge and structured practice. In terms of the role of students, both GLBCC and GIL position students as active participants in their learning journey, facilitating knowledge construction through exploration and inquiry. These models promote active engagement, collaboration among peers, and exploration of new concepts. In contrast, EL tends to involve students passively. receiving information, with less

Test I (pre-test) is conducted after the pre-research to assess the initial capabilities of the research subjects. Test II (post-test) is conducted after the treatment aimed at determining students' learning achievements following the implementation of the GLBCC model, GIL model, and EL model. All models are applied to computational physics and algorithms & programming courses.

Population and Samples

The sampling technique employed is Convenience Sampling, which involves selecting subjects who meet the research criteria (Creswell & Guetterman, 2019). This technique is considered to adequately address the representation of the population selection process and minimize potential bias for several reasons. First, it allows the researcher to obtain a sufficiently large and relevant sample efficiently, given that all participants are students from the department of physics enrolled in the computational physics and algorithms & programming courses at Universitas Negeri Padang.

Table 3. The syntax of the expository model (Heryadi & Sundari, 2020; Murillo Egurrola & Flórez García, 2023; Odunayo Victor & Theodora Olufunke, 2021)

Stage	Description
Introduction	The teacher introduces the topic to the students and explains the learning objectives, relevance, and scientific significance of the topic, and then connects the topic to the students' prior knowledge.
Explanation	The teacher provides systematic and structured explanations of the physics topic by using examples, illustrations, and analogies to facilitate student understanding of physics concepts, and next uses clear and emphasizes on mathematical modeling and problem-solving.
Questioning and discussion	The teacher allocates time for questions and discussion about the physics topic and encourages students to use scientific reasoning and evidence-based arguments in their discussion. Then the teacher provides adequate answers and clarifications to physics questions that may arise.
Practice and application	The teacher gives students physics exercises to apply their understanding of the Physics concepts and assigns relevant and engaging physics experiments or projects. Next, the teacher provides constructive feedback on students' physics work, and guides them towards scientific accuracy and precision
Evaluation	The teacher gives students physics exercises to apply their understanding of the physics concepts and assigns relevant and engaging physics experiments or projects. Next. the teacher provides constructive feedback on students' physics work, and guides them towards scientific accuracy and precision

Table 4. Instrument indicators for creative thinking skills (Cummings & Blatherwick, 2017; Dilekçi & Karatay, 2023; Rosen et al., 2020)

Indicator	Description
Fluency	Can provide many alternative answers based on the problems given correctly
Flexibility	Can give ideas in different ways and have the right value, and related material that has been taught before
Elaboration	Can develop ideas and details of an observed object
Originality	Create his own thoughts through a problem and can give birth to new expressions or terms
Analysis	Can understand the meaning of a graph, diagram, or table and interpret it and group it according to the meaning given
Evaluation	Can state the results of his thoughts as a solution to a problem and prove the truth of the information obtained and can evaluate the truth

Second, the target population comprises students with similar backgrounds and educational levels, which helps reduce significant variability in the data. Third, by evenly dividing the sample into three groups within each course, the study ensures that each learning model is consistently applied across the sample. Additionally, conducting the research over two periods (2022 and 2023) enhances the accuracy and consistency of the results. The research sample consists of 138 participants in the computational physics course and 138 participants in the algorithms & programming course. According to the research design, the samples for each course are divided into three groups, with each group comprising 46 individuals. The research was conducted over two periods, namely in 2022 and 2023, resulting in each class consisting of 23 individuals in each group for each course.

Instruments

Six types of instruments were employed, encompassing cognitive, psychomotor, and affective tests, as well as creative thinking ability tests, observation sheets, and interviews. The test instrument for learning outcomes in the cognitive domain consisted of essay questions for the computational physics and algorithms & programming course. Observation sheets were used to assess learning outcomes in the psychomotor and affective domains. These quantitative instruments are crucial for measuring the impact of the learning model on various aspects of student learning. Cognitive tests assess students' understanding of the concepts taught, which underpin creative thinking. Psychomotor tests measure students' practical skills in applying theory, which is important for testing creative ideas in real-world contexts. Affective tests gauge students' attitudes, which encourage creative thinking. Qualitatively, interview guide sheets and questionnaires were employed. The use of interview guide sheets and questionnaires in this study is essential for obtaining in-depth and comprehensive data on students' learning experiences and their perceptions of the implemented learning model. Interview guide sheets allow the researcher to explore information thoroughly through direct interaction with respondents. This approach helps identify perceptions, opinions, and experiences of students that may not be revealed through written tests.

CTS were measured using observation sheets for project assignments and open-ended questions derived from the Torrence test. All instruments in this study demonstrated good validity and reliability. The instrument indicators for CTS are presented in **Table 4**. By integrating these various types of tests, the research can provide a comprehensive evaluation of the effectiveness of the GLBCC model compared to GIL and EL, as well as its impact on the development of students' CTS.

Table 5. ANOVA learning outcomes and students' creative thinking skills in the implementation of the GLBCC, GIL, and EL in computational physics and algorithms & programming (Levene's test of equality of error variances[a])

	F	df1	df2	Sig.
LO the cognitive domain (LOC)	3.179	5	270	0.083
LO the psychomotor domain (LOP)	4.110	5	270	0.065
LO the affective domain (LOA)	22.811	5	270	0.058
Creative thinking skills (CTS)	15.632	5	270	0.094

Table 6. Multivariate tests

Effect	Value	F	Hypothesis df	Error df	Sig.	Partial eta squared
Wilks' lambda	0.508	26.879[b]	8.0	534.0	0.000	0.287
Hotelling's trace	0.934	31.039	8.0	532.0	0.000	0.318
Roy's largest root	0.896	60.000[c]	4.0	268.0	0.000	0.472

Analyzing of Data

The potential effectiveness of the model was analyzed using MANOVA (multivariate analysis of variance) to compare competencies among groups educated using the GLBCC, GIL, and EL models. MANOVA statistical tests include Wilks' lambda, Pillai's trace, Lawley-Hotelling, and Roy's largest root. Learning outcomes in the psychomotor domain were observed when students made algorithms and coding. The aspects observed in the algorithm include completeness, accuracy in using symbols, structure, and creativity, while those examined during coding are syntax accuracy, traceability, result accuracy, and user-friendliness. The results of learning in the affective domain were obtained from observation sheets starting from behavior involving feelings and typical behavioral pattern, such as attitudes, interests, self-concept, values, and morals. Meanwhile, the affective indicators observed include discipline, courtesy of compensation, independence, responsibility, and honesty. Qualitative data was analyzed using the snowballing technique. The termination relationship for each learning syntax was analyzed by bivariate Pearson correlation.

The normality of the learning outcomes and creative thinking abilities data was analyzed using the one-sample Kolmogorov-Smirnov test. The homogeneity of data was analyzed using Levene's test of equality of error variances. The research questions' answers were analyzed using MANOVA statistics and effect size analysis (the partial eta squared [η^2]).

RESULTS

Implementation of the GLBCC, GIL, and EL models in Computational Physics and Algorithms & Programming

At this stage, the variance of learning outcomes (cognitive, psychomotor, and affective) and students' creative thinking in the computational physics and algorithms & programming courses, after implementing the GLBCC, GI, and EL models, is analyzed. The analysis of variance of the learning outcomes of experimental group 1, experimental group 2, and control group is conducted using MANOVA. The normality of the data is analyzed using the Kolmogorov test at a significance level of 0.05. Then, the homogeneity of variances among the three sample groups is analyzed using Bartlett's Levene's test of equality of error variances, and the results are presented in **Table 5**.

In **Table 5**, the results of the analysis of variance for learning outcomes and students' creative thinking abilities during the computational physics and algorithms & programming lectures are presented. The Levene's test results indicate that for LOC, the F value is 3.179 with a significance of 0.083; for LOP, the F value is 4.11 with a significance of 0.065; for LOA, the F value is 22.811 with a significance of 0.058; and for CTS, the F value is 15.632 with a significance of 0.094. This study adopts a significance level of 0.05. **Table 5** shows that the significance values of F for LOC, LOP, LOA, and CTS are greater than 0.05, indicating that all four variables have homogeneous variances, allowing MANOVA to proceed. Furthermore, based on the results of the homogeneity test of covariance matrices, Box's M value is 34.943 with a significance of 0.205. Since the obtained Box's M value is greater than 0.05, it indicates that the covariance matrices of the dependent variables (LOC, LOP, LOA, and CTS) are equal at a significance level of 0.05. Therefore, MANOVA analysis can be continued. The results of MANOVA are presented in **Table 6**.

Table 6 shows $F(8,534) = 26.879$, sig < 0.0001; Wilk's lambda = 0.508, ηp^2 (effect size) = 0.287. A Wilk's lambda value smaller than 0.05 indicates that there are differences in the learning outcomes of the cognitive (LOC), psychomotor (LOP), affective (LOA), and CTS domains among students who received instruction using the generative learning based on cognitive conflict model (GLBCC) compared to the GIL and EL models. The results of tests of between-subjects effects are shown in **Table 7**.

The analysis results in **Table 7** show the test outcomes of the between-subjects effects, where for each LOC, LOP, LOA, and CTS, the F-values are 59.437, 34.534, 24.177, and 73.851, respectively, all with sig. < 0.001. These univariate results indicate that differences

Table 7. Results of inter-subject effect test of implementation of GLBCC model, GIL model, and EL model in computational physics and algorithms & programming courses

Source		Type III sum of squares	df	Mean square	F	Sig.	Partial eta squared
Model	LOC	31,779.848	2	15,889.924	59.437	.000	.306
	LOP	8,276.203	2	4,138.101	34.534	.000	.204
	LOA	4,859.964	2	2,429.982	24.177	.000	.152
	CTS	18,607.848	2	9,303.924	73.851	.000	.354
Error	LOC	72,181.870	270	267.340			
	LOP	32,353.217	270	119.827			
	LOA	27,136.783	270	100.507			
	CTS	34,015.435	270	125.983			

Table 8. Tukey HSD post-hoc comparison of several types of learning outcomes and learning models used in computational physics and algorithms & programming course

Dependent variable			Mean difference (I-J)	Standard error	Significance	95% confidence interval	
						Lower bound	Upper bound
LOC	GLBCC	GIL	17.9674	2.41076	0.000	12.2859	23.6489
		EL	25.5978	2.41076	0.000	19.9164	31.2793
	GIL	EL	7.6304	2.41076	0.005	1.9490	13.3119
LOP	GLBCC	GIL	6.6304	1.61398	0.000	2.8267	10.4341
		EL	13.4130	1.61398	0.000	9.6094	17.2167
	GIL	EL	6.7826	1.61398	0.000	2.9789	10.5863
LOA	GLBCC	GIL	2.3370	1.47815	0.256	-1.1466	5.8205
		EL	9.8370	1.47815	0.175	6.3534	13.3205
	GIL	EL	7.5000	1.47815	0.217	4.0164	10.9836
CTS	GLBCC	GIL	10.7174	1.65492	0.000	6.8172	14.6176
		EL	20.0978	1.65492	0.000	16.1977	23.9980
	GIL	EL	5.3804	1.65492	0.071	5.4803	13.2806

in the instructional models lead to significant differences in the values of LOC, LOP, LOA, and CTS. The tests of between-subjects effects reveal the relationship between the instructional models and each learning outcome and creative thinking skill. Furthermore, a Tukey HSD Post Hoc multiple comparisons analysis was conducted to determine the comparisons of each type of learning outcome and creative thinking skill resulting from the instructional models used in the computational physics and algorithms & programming learning. The results are presented in **Table 8**.

The results of the Tukey HSD post hoc test in **Table 8** indicate that the dependent variables, such as LOC, LOP, and CTS, after implementing the GLBCC, GIL, and EL models in computational physics and algorithms & programming learning, have significance values less than 0.05, except for CTS with the implementation of the GIL and EL models. These results show that there are significant differences in LOC, LOP, and CTS due to the implementation of the GLBCC, GIL, and EL models. The significance value for LOA with the implementation of the GLBCC, GIL, and EL models is greater than 0.05. This result indicates that the implementation of the GLBCC, GIL, and EL models does not lead to significant differences in LOA. An interesting finding is that the significance value for CTS due to the implementation of the GIL and EL models is 0.071 (greater than 0.05). This means that there is no significant difference in CTS due to the implementation of the GIL and EL models. The average values of LOC, LOP, and CTS with the implementation of the GLBCC model are higher than those with the GIL and EL models. Therefore, it can be said that the implementation of the GLBCC model is effective in teaching physics, especially in the computational physics and algorithms & programming courses.

Analysis of the Influence of The GLBCC Model Stages on Learning Outcomes

The correlation results in **Table 9** show that cognitive conflict statements (x3), disclosure (x4), construct (x5), application (x6), reflection evaluation (x7) have a positive effect on creative thinking abilities, especially in the case of creative thinking in the analyzing and problem-solving section.

These findings indicate a positive correlation between each stage in the GLBCC model and CTS (significant at the 0.01 level). Specifically, the stages of cognitive conflict statements (x3) and disclosure (x4) exhibit strong correlations with students' CTS, with correlation indices of 0.748 and 0.659, respectively. Moreover, the stages of learning outcome statement (x1), construct (x5), application (x6), and reflection (x7) demonstrate strong positive correlations with learning outcomes in the cognitive (y1), psychomotor (y2), and affective (y3) domains, each with correlation indices of 0.793, 0.697, 0.896, and 0.717, respectively. This suggests

Table 9. Bivariate Pearson correlation analysis test results

	Learning phases (X)							Learning outcomes (Y)			
	x1	x2	x3	x4	x5	x6	x7	y1	y2	y3	y4
	Correlation coefficient'										
Learning outcome statement (x1)	1.000	.362**	.357**	.350**	.443**	.547**	.320**	.793**	-.031	-.062	-.193
Orientation (x2)	.362**	1.000	.367**	.246*	.676**	.633**	.188*	.037	.006	.833**	-.180
Cognitive conflict statements (x3)	.357**	.367**	1.000	.258*	.339**	.415**	.349**	.442**	.813**	.857**	.748**
Disclosure (x4)	.350**	.246*	.258*	1.000	.165	.358**	-.039	.561**	.255*	-.014	.659**
Construct (x5)	.443**	.676**	.339**	.165	1.000	.577**	.193	.697**	.770**	.613**	.490**
Application (x6)	.547**	.633**	.415**	.358**	.577**	1.000	.325**	.896**	-.026	.411**	.505**
Reflection (x7)	.320**	.188	.349**	-.039	.193	.325**	1.000	.717**	.045	-.069	.366**

Note. *Correlation is significant at the 0.05 level (2-tailed) & **Correlation is significant at the 0.01 level (2-tailed)

Table 10. Tests of between-syntax of learning GLBCC model effect

Source		df	Mean square	F	Sig.	Partial eta squared
Orientation (x2)	Sb1	10	2,430.293	6.415	0.000	0.243
	Sb2	10	3,152.993	18.457	0.000	0.480
	Sb4	10	8,153.487	11.756	0.000	0.370
Cognitive conflict statements (x3)	Sb1	10	1,268.116	3.347	0.002	0.274
	Sb2	10	235.609	2.379	0.021	0.134
	Sb3	10	971.262	2.990	0.004	0.252
	Sb4	10	2,496.511	3.599	0.001	0.288
Construct (x5)	Sb1	10	1,155.123	3.049	0.003	0.276
	Sb2	10	808.896	4.735	0.000	0.372
	Sb3	10	1,709.121	5.262	0.000	0.397
	Sb4	10	4,379.466	6.314	0.000	0.441

Note. a. Weighted least squares regression–weighted by practicality of GLBCC model; Sb1: Student behavior in computational physics learning; Sb2: Students' attitude towards computational physics material; Sb3: How students learn in computational physics; & Sb4: Student preparation for learning computational physics

that cognitive conflict statements (x3) and disclosure (x4) significantly stimulate creative thinking while learning outcome statements (x1), construct (x5), application (x6), and reflection (x7) substantially contribute to the formation of students' cognitive structures. Furthermore, cognitive conflict statements (x3) and constructs (x5) significantly influence learning outcomes in the psychomotor domain. Meanwhile, the orientation (x2), cognitive conflict statements (x3), and construct (x5) stages play a crucial role in determining student behavior in computational physics lessons.

Moreover, an effect size analysis for identified positive correlations was also conducted to understand the extent to which the independent variables substantially influence the dependent variables (see **Table 10**). In this analysis, the partial eta squared (η^2) value was used as an indicator to assess the strength of the effect.

Table 10 shows the partial eta squared values, indicating the effect size of the dependent and independent variables. Firstly, the partial eta squared (η^2) values for orientation with student behavior in computational physics lessons (e.g., Sb1, Sb2, and SB4) are (0.243, 0.480, and 0.370), respectively. If the η^2 value is greater than 0.14, the independent variable has a strong effect on the dependent variable (Cohen, 1988; Denis, 2018). The η^2 values for orientation are greater than 0.14, indicating that orientation (x2) has a strong effect on student behavior in computational physics lessons. The same applies to cognitive conflict statements (x3) and construct (x5). Orientation has the biggest effect on students' attitude towards computational physics material (η^2 = 0.48), while construct (x5) has the greatest effect on student preparation for learning computational physics (η^2 = 0.441).

DISCUSSION

The findings of this study indicate that the GLBCC model significantly improves learning outcomes (cognitive, psychomotor, and affective) and CTS compared to GIL and EL. These results align with the literature, which suggests that generative learning based on cognitive conflict can encourage students to be more active in the learning process, thereby deepening understanding and enhancing CTS (Lan et al., 2024). Shi et al. (2020) also demonstrate that learning models emphasizing active student engagement, and the resolution of cognitive conflicts have a substantial effect on learning outcomes. This suggests that GLBCC, by incorporating these elements, provides a robust framework for facilitating deep and meaningful learning.

The GLBCC model integrates the principles of generative learning and cognitive conflict. Generative learning emphasizes active student engagement in the learning process through the creation and organization of new knowledge based on existing knowledge (Osborne & Wittrock, 1983; Wittrock, 1992). Generative theory posits that students learn more effectively when they are involved in generating meaning from new information and integrating it with their existing knowledge. This process creates more complex and robust mental structures (Breitwieser & Brod, 2021; Brod, 2021; Wittrock, 1992). Cognitive conflict occurs when students encounter information or situations that challenge their previous understanding, forcing them to revise and deepen their comprehension (Xie et al., 2022). Effective learning often happens when individuals are confronted with cognitive conflicts that prompt them to adapt their existing schemas. This leads to deeper and more durable understanding, as well as the development of CTS (Heitzmann et al., 2023; Schneider et al., 2022). Students engaged in activities that challenge their understanding tend to show improvements in higher-order thinking skills (Li et al., 2023).

In contrast, GIL and EL place less emphasis on creating deep cognitive conflicts. GIL enhances student engagement through questioning and exploration but may not always generate a sufficient level of cognitive conflict to drive deep revisions in conceptual understanding (Jiang et al., 2018; Madu & Orji, 2015). EL, which focuses on learning through direct experience and reflection, is effective in promoting practical skills but may fall short in addressing conceptual misconceptions that require cognitive conflict for resolution (Susilawati et al., 2021; Toheri et al., 2020). Although GIL and EL are effective in specific contexts, their impact is often less significant compared to methods that combine explicit instruction with activities that more directly challenge students' understanding (Shieh & Yu, 2016).

The strength of GLBCC lies in its ability to foster deeper learning and knowledge construction. By focusing on cognitive conflict, students are encouraged to confront and resolve inconsistencies in their understanding, leading to more profound, meaningful learning and more significant conceptual changes. Additionally, GLBCC enhances CTS by encouraging students to think outside the box and find various solutions to complex problems. This model also increases student engagement and motivation as they are challenged to address cognitive conflicts, creating a dynamic and stimulating learning environment.

Qualitative findings, derived from direct student interviews, revealed that students' stages of disclosure, application, and cognitive conflict were linked to computational thinking skills, thereby potentially enhancing creative thinking abilities in computational physics and algorithms & programming courses within the cognitive conflict-based learning model. Vocational skills, particularly hand skills, in computational physics must be complemented by strong cognitive skills. Students can generate meaningful learning products when their vocational skills are complemented by robust cognitive abilities. The implementation of this learning model necessitates students to proactively prepare for their learning journey, possessing adequate scientific literacy skills, and proficiency in computational thinking (Sovey et al., 2022).

Through the question of how you obtain solutions to each problem given in every lecture. Students with high learning outcomes answer by attempting to think of solutions to problems through examining each variable within the problem. Students try to recognize problem patterns, break down problems into smaller, easier-to-solve parts, and create abstractions and problem-solving algorithms. They relate the problems they face with previous learning to newly obtained information. Meanwhile, students with low learning outcomes immediately do so by searching on Google. Students who look for solutions to problems given directly by searching on Google tend to have low creative thinking abilities. Students think that generally the research results they get are correct. The GLBCC model uses the student-centered principle, encouraging students to think creatively and deeply to find solutions to a given phenomenon. Students think deeply and engage in discovery activities, thereby triggering more meaningful and creative thinking. Students, through fact-finding activities, clarifying problems, searching for ideas, creating solutions, and seeking acceptance (Wechsler et al., 2018), become accustomed to thinking creatively and managing connections between variables (Hürsen et al., 2014). Students' CTS can be enhanced by reading and answering questions that follow the GLBCC model's steps (Angraini et al., 2022). Students must try to find alternative solutions to phenomena given algorithmically.

The first stage, orientation, includes motivation, apperception of material, and focusing on the activities and concepts to be learned. This stage is an essential aspect of any educational process. It is the first stage that sets the tone for the entire learning experience. This, in turn, helps to increase student engagement and motivation, setting the foundation for a successful learning experience. The importance of learning orientation cannot be overstated as it lays the groundwork for the rest of the educational process and contributes significantly to the achievement of learning outcomes. The focus on this stage influences positive outcomes when students move to the second stage of facing cognitive conflict (Andres, 2019; Yi et al., 2016; Zheng et al., 2019).

The second stage, cognitive conflict, aims to create cognitive conflict that can help students recognize their misconceptions through experiencing conceptual disputes. The following is an example of cognitive conflict material presented to students: "integral calculation $\int e^{ax}dx = \frac{e^{ax}}{a} + C$ or $\int \sin(ax+b)\,dx = -\frac{1}{a}\cos(a+b) + C$ or calculating the total magnitude of the magnetic field affected by the electric current in the wire, $B = \frac{\mu_o i}{2\pi}\int_0^{50} \frac{R}{(R^2+S^2)^{3/2}}$ or calculating the energy moment $I = \rho \int_{\emptyset=0}^{2\pi}\int_{\theta=0}^{\pi}\int_{r=0}^{a}(r^2 sin^2\theta)\, r^2 sin\theta drd\theta d\emptyset$ can be calculated easily. Then consider $\int_0^2 \frac{2+\cos(1+x^2)}{\sqrt{1+0.5sinx}} e^{0.5x}dx$ or $x = -\int \frac{Mv}{\beta v+k}dv$. can it also be calculated easily?". The questions that are cognitive conflict like this stimulate creative thinking that plays a significant role in developing effective solutions and ideas to assist students acknowledge their dissatisfaction. The habituation of students experiencing this process certainly has an impact on generating creative thoughts from students (Akmam et al., 2019; Eranova & Prashantham, 2017; Rahim et al., 2015).

Then in the third stage (disclosure), fourth (construct), and fifth (application), students to share their learning experiences related to the observed phenomena and connect them with the topic to be studied. The lecturer guides them to construct scientific concepts based on the shared ideas and evaluate and classify them as the starting point of learning. Then, the students organize and build a framework by changing the structure and relationships between concepts. They share their ideas with other students, which improves their computational thinking skills and critical thinking skills. The students apply their concepts to make algorithms, test alternative algorithms to solve various problems, and validate their concepts through experiments. This process helps to evaluate the level of creative thinking and critical thinking skills of the students. This activity assists students make effective and real decisions (Goldstein & Yang, 2019), form a framework of thinking by using old and new information and forming more complex knowledge (Baroutsis et al., 2019), and capable of generating valuable predictions to create predictive codes for further information processing (Wechsler et al., 2018).

In the last stage (reflection) expectations of productive ideas allow them to make important predictions about further information processing. Reflection and evaluation activities also determine the success of the implementation of learning (Davis & McDonald, 2019), including computational physics lectures and improving academic performance (Couto Zoltowski & Pereira Teixeira, 2020). A previous study revealed that they can increase student self-efficacy and self-regulation (Ikävalko et al., 2023). The disclosure is important in stimulating student interest and curiosity in solving a problem. Students are passionate and actively involved in the learning process, building of concepts, and the control of the learning process (Prawita et al., 2019). The application of concepts can increase the stimulation in processing relevant information to obtain new ideas (Ligeza & Wyczesany, 2017). Students have the opportunity to test and compare the concepts they have developed with other conditions through practical application (Kunis et al., 2023). They were also able to connect with their learning experiences and the topics analyzed (Rosdianto, 2017) as well as enrich discriminatory ideas with a clear conceptual structure (Krähmer, 2020). The feedback provided by the educators helped learners to think ahead (Baroutsis et al., 2019). Furthermore, the disclosure process stimulated creative cognition, which is important for constructing and exploring ideas to solve problems (Calabretta et al., 2017). The efficiency implications of the variable disclosure were very helpful in effective decision-making (Goldstein & Yang, 2019). This type of embodiment is believed to be responsible for the effectiveness of GLBCC model in learning computational physics.

To obtain satisfactory learning outcomes in computational physics course and algorithms & programming course require proper cognitive skills for students such as analyzing physically, mathematically, and thinking computationally. Students often do not work on exercises or structured assignments due to the lack of understanding of Arithmetic and Algebra operations in teaching materials. They also do not understand the meaning of the problems, cannot see with the sample questions given, and do not have time perform the task. Furthermore, students do not submit assignments because they have not studied the algorithms in the activity sheets, have not finished the exercise, and do not know what to do. The indicators above are part of computational thinking related to abstraction, decomposition, pattern recognition, algorithms, logical reasoning and evaluation (Yusoff et al., 2021). This indicates that implementing the GLBCC model requires computational thinking skills and a good understanding of algebra and arithmetic operations. This is because the success of designing algorithms requires computational thinking (Voon et al., 2022).

Students at the orientation stage must think specifically in various ways. They are also required to think of more than one idea, which is an important step toward achieving success in learning (Sandoval-Lucero et al., 2017). Students were then given a cognitive conflict, which requires them to imagine the conceptualization of the given problem, and this contributed to the filling of gaps in the initial knowledge (Fleer, 2022). This shows that syntax orientation can improve indicators of fluency and flexibility (Suardana et al., 2019). The learners were also given problems based on the study material.

The problems were administered to the students with a cognitive conflict syntax, which contains important information that helps students to recognize misconceptions by providing a stimulus. Furthermore, stimulus was given in the form of problems that exist in daily life to facilitate quick understanding (Bektiarso et al., 2021). This shows that cognitive conflict syntax can increase flexibility indicators in students (Rokhmat et al., 2022). The same set of educators guided the students, and this led to the acquisition of similar concepts. Knowledge construction was carried out in the construct syntax, where educators are actively involved in the process. Educators act as facilitators who direct students for quick and efficient construction (Hinck & Tighe, 2020), and this aids the understanding of concepts.

An experiment is an activity that assists students in finding concepts and constructing new knowledge of students. Accommodation of the new conception may occur if students are unhappy with prior concepts and the available alternatives are understandable, tenable, and productive (Alabidi et al., 2023). This shows that the fourth stage (construct) can increase student originality indicators (Suardana et al., 2019). Furthermore, the information obtained in the experimental activity is then used in solving the problems given to them. In application stage, students are required to answer with their own abilities, provide several alternative and original answers. This indicates that the application stage can improve indicators of fluency, flexibility, and originality (Fauziah et al., 2019). The feedback of the problems solved are then provided by the educators.

The provision of feedback on the reflection evaluation syntax to students can improve learning achievement (Calvo & Álvarez, 2018; Dominguez et al., 2020). Furthermore, educators must direct learners to analyze the advantages and disadvantages of learning as well as conclude the process. This shows that the reflection evaluation syntax can increase the originality indicator for students, thereby helping them to create something unique and different from others.

Students can improve their CTS through the learning process and atmosphere in class. The classroom atmosphere must stimulate to learn creatively (Montag-Smit & Maertz, 2017). This is because the ability to think creatively arises from stimulation. Students' creative thinking is affected by intelligence, knowledge, mindset, personality, motivation, and environment (Gu et al., 2021), and these factors cause difference among them. The ability to think creatively can be divided into several types, including analysis, open-mindedness, problem-solving, organization, and communication (Gafour & Gafour, 2021). This ability when differentiated based on the way of thinking is divergent, lateral, aesthetic, systems, and inspirational (Jia et al., 2019), which indicates that someone with creative thinking has different abilities.

The result of this study contributes to the development of both CTS and computational skills. By challenging learners' existing beliefs and forcing them to confront contradictions and inconsistencies, these models create a state of cognitive disequilibrium that motivates learners to seek out new information and perspectives. This process can lead to the development of more complex mental models, improved problem-solving abilities, and greater CTS. Additionally, because these models often involve the use of computational tools or algorithms, learners may also develop greater proficiency in computational skills such as programming, data analysis, and modeling. Overall, the combination of cognitive conflict and computational tools can create a powerful learning environment that promotes both creative thinking and computational skills.

Limitations

The findings of this study indicate that the GLBCC model is effective in improving learning outcomes (cognitive, psychomotor, and affective) and CTS. However, there are several limitations that need to be considered to understand the impact on the generalization of these findings. The experimental research design with control and experimental groups may be affected by uncontrolled external variables, such as teaching quality and student motivation, which can impact internal validity. Additionally, the sample used may not be representative of a broader population, especially if it only includes students from a specific university or region. The short duration of the intervention may not reflect long-term effects, while contextual factors such as university culture and technological support can influence the success of GLBCC implementation. The expertise and involvement of instructors in applying the model are also crucial, and a lack of training or commitment from instructors could diminish its effectiveness.

Recommendations

To address these limitations and enhance the generalizability of the findings, several recommendations can be made. First, employing an experimental design with tighter randomization and control can improve both internal and external validity. Second, involving a larger and more diverse sample from various regions and socio-economic backgrounds can enhance the representativeness and generalizability of the findings. Third, conducting longitudinal research to assess the long-term effects of the GLBCC model on learning outcomes and CTS is crucial. Fourth, providing adequate training and support for instructors to ensure effective implementation of the GLBCC model is essential. By addressing these limitations, future research can offer more generalizable findings and provide a more comprehensive understanding of the effectiveness of cognitive conflict-based learning models in improving learning outcomes and CTS, particularly in computational physics and algorithms & programming.

CONCLUSION

In conclusion, the GLBCC model effectively improved CTS and students' learning outcomes in computational physics and algorithms & programming courses. There were also significant differences in the learning outcomes between the samples using the GLBCC model and GI and EL as control classes. These results also indicated that the GLBCC model can be used effectively improved learning outcome (cognitive, affective, and psychomotor domain) and CTS. The stages in the cognitive conflict-based learning model, especially cognitive conflict statements and disclosure, add positively to students' CTS. Consequently, this study provides design pattern on how to implement learning and create an atmosphere that promotes students to be active, more meaningful and contextual. This model can also be an option for lecturers to facilitate cognitive conflict and generative learning experiences to develop CTS and computational skills. Although this study demonstrates promising results, there are several limitations to consider for future research. By addressing these limitations and expanding research into various areas, the GLBCC model has the potential to make a significant contribution to improving learning outcomes and CTS in diverse educational contexts. Future research will strengthen the empirical evidence regarding the effectiveness of this model and provide better guidance for educators in implementing cognitive conflict-based learning models. Despite the challenges, the potential benefits of this model suggest that GLBCC could be a valuable addition to the higher education landscape.

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