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Improving Students' Mathematical Self-Regulated Learning and Mathematical Flexibility with a Deep Learning Approach

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ABSTRACT

The rapid development of science and technology demands a transformation in mathematics education to develop higher-order thinking skills. This study investigates the effectiveness of deep learning approaches in improving mathematical flexibility (MF) and mathematics self-regulated learning (MSRL) among grade 8 junior high school students in Indonesia. Employing a sequential explanatory mixed-methods design, this quasi-experimental study involved 99 students (68 experimental, 31 control) who completed pre-tests and post-tests measuring MF and MSRL. Quantitative data were analyzed using ANCOVA, t-tests, and regression analysis, followed by qualitative interviews and classroom observation to explain the findings. Results revealed that the deep learning approach significantly improved students' mathematical flexibility ($t = 14.92$, $p < 0.05$), with an average gain of 4.27 points, but did not significantly improve MSRL ($p = 0.165$). Regression analysis demonstrated a significant positive relationship between MSRL and MF ($r = 0.524$, $p < 0.001$), with MSRL accounting for 27.2% of the variance in mathematical flexibility. This study contributes to mathematics education research by providing empirical evidence that deep learning approaches effectively develop mathematical flexibility while highlighting the need for multifactorial interventions targeting affective and metacognitive dimensions to improve self-regulated learning.

ARTICLE INFORMATION

Keywords:
deep learning approach; mathematical flexibility; mathematics self-regulated learning

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INTRODUCTION

The rapid development of science and technology in the 21st century demands transformation in mathematics education, which plays a crucial role in developing logical, analytical, critical, and creative thinking skills. However, recent data reveal concerning trends in students' mathematical competencies. According to the Programme for International Student Assessment (PISA) 2022 results, many students still struggle with problem-solving tasks that require adaptive thinking and flexible application of mathematical concepts (OECD, 2023). Mathematical Flexibility (MF) and Self-Regulated Learning (SRL) have emerged as two competencies receiving primary attention in addressing complex problems, as mathematics functions not only as a tool for solving numerical problems but also as a means for training higher-order thinking skills essential for confronting modern life challenges.

A preliminary study conducted in SMPN 1 Cirebon revealed that approximately 65% of students demonstrated limited ability to apply multiple solution strategies when solving non-routine problems, indicating a significant gap in mathematical flexibility. Furthermore, observations showed that students rarely engaged in self-monitoring and evaluation during problem-solving, highlighting the urgent need for interventions that simultaneously develop both mathematical flexibility and self-regulated learning. Mathematical Flexibility (MF) refers to students' ability to employ diverse

problem-solving strategies and to evaluate and select the most efficient strategies for each context. MF enables students to be more adaptable in confronting non-routine problems, more creative in identifying patterns, and more open to alternative solutions (OECD, 2023). This flexibility is closely related to mathematical creativity and academic success, with findings indicating a significant association between mathematical flexibility and students' performance on national examinations (Hästö et al., 2019). Students who have developed cognitive flexibility in mathematics outperform others in understanding mathematical ideas, using their mathematical expertise, and generating creative solutions to problems (Elhilal, 2025). Studies reveal that cognitive flexibility can be a strong predictor of math achievement in children, with a greater capacity to switch, facilitating the use of different mathematical strategies for problem-solving. Mathematical flexibility has been widely acknowledged as an important learning goal in mathematical education and has received increasing research attention to explore its nature, the mechanisms that facilitate it, and the interventions that promote it (Burg et al., 2022). Therefore, Mathematical Flexibility is an essential competency that must be developed from an early age, as adaptive expertise and the ability to be a flexible problem solver have been shown to have direct links to academic achievement more generally (Arslan & Yazgan, 2015)

Mathematics self-regulated learning (MSRL) refers to students' ability to independently plan, monitor, and evaluate their learning processes. Students with high MSRL can manage motivation, set goals, select appropriate learning strategies, and reflect on their achievements. In Indonesia's education system, this ability plays a crucial role in advancing the objectives outlined in the 2020–2035 Education Roadmap. This strategic plan is designed to ensure that every young person completes secondary education, aiming for full participation at the secondary school level, meaning 100% of eligible students will graduate. Additionally, the roadmap seeks to significantly increase access to higher education by targeting a 50% enrollment rate among eligible students. By supporting these goals, the education system aims to improve the overall quality and inclusiveness of education, fostering greater opportunities for personal development and socio-economic advancement for Indonesian students. This capability is therefore integral to building a more educated population that can contribute effectively to the country's growth and development over the coming decades.

Nevertheless, empirical studies that simultaneously examine how pedagogical approaches that promote deep learning can influence SRL and students' mathematical flexibility at the junior high school level remain relatively limited. Most research focuses on one of the two constructs—either SRL or flexibility—or research is conducted at higher education levels (Xu et al., 2024). In Indonesia, the challenge of enhancing both aspects simultaneously has not been extensively studied, particularly through quasi-experimental designs with adequate sample sizes and valid instruments. Additionally, there is a need to compare the effectiveness of modern approaches, such as deep learning, with conventional teaching methods in local contexts, and to explore the causal relationship between SRL's influence on mathematical flexibility, rather than merely correlation.

Theoretically, this study employs a conceptual framework that integrates theories of mathematical flexibility and self-regulated learning models, as well as deep learning theory (learning for understanding). Mathematical flexibility is the strategic use of diverse, adaptive, creative, and effective solution methods across contexts. SRL is a dynamic process in which students regulate their thoughts, behaviors, and motivation to achieve learning objectives. Deep learning is viewed as an approach emphasizing conceptual understanding, reflection, and application in real-world contexts. This framework assumes that deep learning is not merely a pedagogical technique but also a learning environment that supports SRL, thereby enhancing students' mathematical flexibility.

The theories underlying this research include mathematical flexibility, which encompasses students' ability to use various strategies, utilize different representations, and select or adapt

appropriate strategies in changing problem situations. This concept is rooted in the literature on transfer, mathematical creativity, and non-routine problem solving. Cross-national research shows that although standard algorithms are widely used, students with procedural flexibility tend to be more accurate and transfer their knowledge more effectively to new problems. Self-regulated learning is a theoretical framework in which students regulate their own cognition, motivation, affect, and learning strategies in the learning process, and it plays a crucial role in complex mathematics learning (Star et al., 2022). Recent research has used various techniques, including trace data, to investigate how SRL components develop and influence learning outcomes in secondary education settings (Cristea et al., 2025).

Deep learning in mathematics education encompasses meaningful learning, critical thinking, reflection, and real-world application, and is not merely procedural mastery or memorization. It includes mindful learning, which emphasizes full awareness during the learning process, and joyful learning, which aims to create pleasant, motivating learning environments. This approach emphasizes the quality of students' conceptual understanding and deep engagement. Local literature in Indonesia has discussed deep learning in the context of curriculum, real-life content, and realistic mathematics education (RME or PMRI) as practical manifestations of deep learning (Rahayu et al., 2025). Xu and Pan demonstrated that implementing deep learning-based strategies can improve mathematics learning outcomes among secondary school students, particularly in ethnic minority contexts (Xu & Pan, 2024).

Previous studies have shown that self-regulated learning (SRL) interventions grounded in metacognition-oriented theories and those targeting multiple strategies, including cognitive, metacognitive, and motivational components, tend to yield effective increases in both mathematics achievement and self-regulated learning (Wang & Sperling, 2020). This flexibility is essential for open-ended problems where solution strategies must be adapted and multiple solution pathways explored (Cleary & Russo, 2024). These findings collectively suggest that while SRL focuses on students' ability to regulate their learning processes through metacognitive awareness, goal-setting, and strategy deployment, mathematical flexibility emphasizes the cognitive adaptability needed to shift between different problem-solving approaches—indicating that interventions targeting both dimensions may be necessary for comprehensive mathematical competence development. Regarding mathematical flexibility, cross-national studies by Wang and Star (2023) examined procedural flexibility across several countries, finding that although students know alternative strategies, the spontaneous use of strategies beyond standard algorithms remains low.

Several research gaps have emerged from this review. First, most studies in Indonesia examining deep learning focus on students' conceptual understanding, motivation, or engagement, but few quantitatively measure and comprehensively compare the effects on mathematical flexibility (MF) and mathematical self-regulated learning (MSRL). Second, previous research rarely used quasi-experimental designs with controls and sufficiently large samples at the junior high school level to test the effects of deep learning on flexibility and SRL. Third, the causal relationship between the MSRL and MF has not been extensively studied. Fourth, valid and reliable instruments for measuring MF and MSRL in local contexts require further development.

The primary scientific contribution of this research lies in the methodological approach combination that integrates a quasi-experimental design with explanatory mixed methods to quantitatively measure the effects of the deep learning approach on MSRL and mathematical flexibility, as well as qualitatively explain the mechanisms underlying these influences in local contexts (grade 8 junior high school in Indonesia). This study aims to address the identified gaps by using a quasi-experimental design with adequate samples, quantitative measurement of mathematical flexibility (MF) and self-regulation learning (MSRL), and supporting qualitative analysis to deepen

understanding of the mechanisms underlying the relationships among variables, thereby enabling inference regarding the effectiveness of this approach in improving MSRL and MF.

METHOD

This research employs a mixed-methods approach, integrating quantitative and qualitative methods within a single study to achieve a thorough understanding of the research issue (Creswell & Clark, 2018; Ivankova et al., 2006). The researchers adopted a sequential explanatory mixed-methods strategy, beginning with the collection and analysis of quantitative data, followed by qualitative methods to elucidate further and interpret the quantitative results (Fetters et al., 2013). This explanatory sequential design aims to use narrative data to clarify or interpret numerical outcomes, particularly unexpected ones. The data types were analyzed independently, with qualitative results used to enhance and deepen the quantitative findings. In this design, the researcher initially gathers and examines quantitative data, which then guides the collection and analysis of qualitative data (Ivankova et al., 2006), facilitating a more thorough investigation of the research phenomenon. The explanatory sequential design in this research is presented in Figure 1.

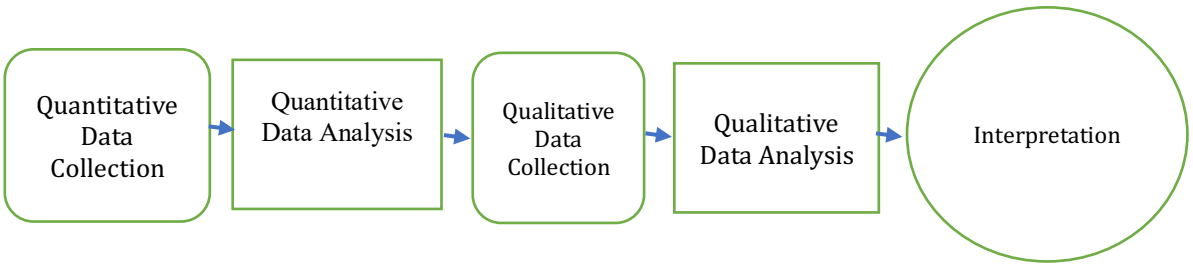

Figure 1. Explanatory sequential mixed method design

Figure 1 explains that this study employs a sequential explanatory mixed-methods design conducted in three systematic phases. The first phase involves a quantitative approach beginning with the administration of pre-tests to measure students' initial levels of mathematical self-regulated learning (MSRL) and mathematical flexibility (MF). Following the pre-test, participants are divided into two groups: one receiving a deep learning-based intervention and the other following conventional teaching methods. Upon completion of the intervention period, post-tests are administered using the same instruments to assess changes in MSRL and MF.

The quantitative data collected from both pre-test and post-test are then analyzed using various statistical techniques, including Analysis of Covariance (ANCOVA) to control for pre-existing differences, independent t-tests to compare group differences, and regression analysis to examine predictive relationships between variables. The second phase shifts to a qualitative approach designed to provide deeper insights into the quantitative findings. This phase encompasses semi-structured interviews with both students and teachers to capture their perspectives and experiences regarding the intervention, systematic classroom observations to document actual teaching and learning practices, and comprehensive documentation of learning materials used during the intervention. All qualitative data are subjected to rigorous thematic analysis to identify recurring patterns, themes, and categories. The final phase focuses on integration, in which the qualitative findings are used to interpret, explain, and provide a contextual understanding of the quantitative results from Phase 1. This integration enables a more comprehensive understanding of how and why the deep learning intervention affects students' self-regulated mathematical learning and mathematical flexibility, thereby strengthening the validity and depth of the overall research findings, as shown in Figure 2.

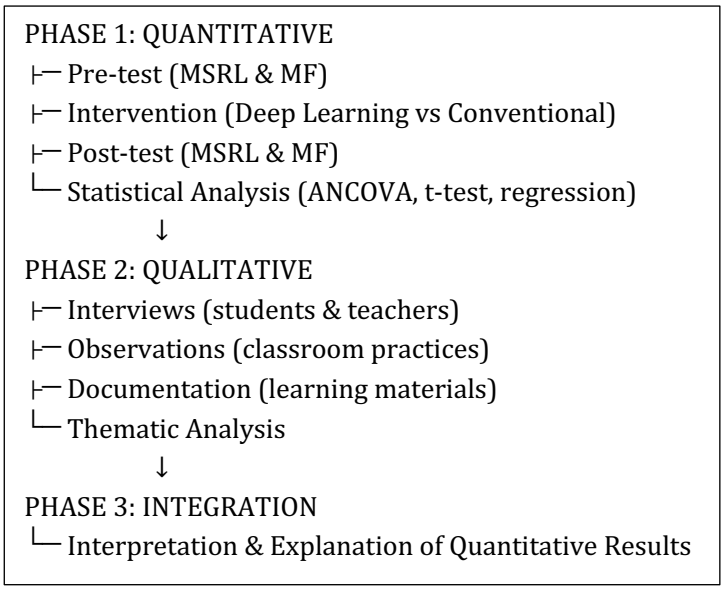

Figure 2. The Phase of the Research Process

The research design employs a quasi-experimental design with both a control and an experimental group, allowing comparison between participants exposed to the intervention and those not exposed. This design enables the assessment of causal effects while accommodating practical constraints that prevent complete randomization. The study integrates a sequential explanatory mixed-methods model, wherein quantitative data collection and analysis occur first through pre-test and post-test measures to evaluate changes attributable to the intervention. This phase provides a structured, numerical assessment of outcomes, establishing whether statistically significant differences exist between groups. The explanatory model enables researchers to explore the effect of the experimental variable (a deep learning pedagogical approach) on the dependent variables (MSRL and mathematical flexibility), and then use qualitative data to explain "how" and "why" these effects occur.

The objectives of this study are as follows: (1) to determine the effect of the deep learning pedagogical approach on improving students' MSRL; (2) to determine whether the deep learning approach can enhance students' MF compared to conventional teaching methods; (3) to determine whether there are differences in MSRL between students who follow deep learning-based instruction and those using conventional approaches; and (4) to determine whether MSRL positively influences mathematical flexibility. The mathematical flexibility instrument consists of a test package designed to measure students' ability to use various strategies, select strategies, and demonstrate representational flexibility in solving mathematical problems, with pre- and post-test administrations. The components, subcomponents, and indicators of mathematical flexibility are presented in Table 1.

Table 1. Mathematical Flexibility Indicators

Flexibility Component	Sub-Component	Flexibility Indicator
Knowledge	Recognizes Multiple Methods	Recognition of multiple methods
	Generates Methods	Ability to generate various solution methods
Preference	Method Selection	Consistency in selecting efficient methods
Use	Occasional Use	Use of efficient methods on some problems
	Consistent Use	Consistent use of efficient methods

From these five indicators, nine mathematical flexibility test items were developed using linear equations in one variable. This test was validated through content and construct validity testing using experts and reliability testing. Testing was conducted by administering the test to 30 students outside the sample class. The mathematical flexibility test item validity results showed that all nine items were valid, with r values > 0.30. Reliability testing using Cronbach's alpha indicated high reliability (α = 0.794). For mathematics self-regulated learning, a closed-ended Likert-scale questionnaire was employed, with responses ranging from 1 to 4. For positive statements, choice 1 indicates conditions that are very unsuitable for the student, and choice 4 indicates conditions that are very suitable for the student. For negative statements, choice 1 indicated conditions that were very suitable for the student, and choice 4 indicated conditions that were very unsuitable. The MSRL indicators are listed in Table 2.

Table 2. Mathematics Self-Regulated Learning Indicators

Variable	Indicators
Mathematics Self-Regulated Learning (MSRL)	Interset
	Task Analysis
	Perception of task difficulty
	Self-efficacy
	Help seeking
	Self-control
	Self-judgement

Based on these indicators, 12 questionnaire items were developed. Similar to the mathematical flexibility test instrument, these questionnaire items were tested for validity and reliability. The test results demonstrated that all items in the assessment were valid, as evidenced by each calculated correlation coefficient (r value) exceeding the threshold of 0.361. This indicates strong item validity, confirming that the individual items effectively measure the intended constructs. Additionally, the test's overall reliability was high, with a reliability coefficient (r) of 0.758. This level of reliability suggests that the instrument produces consistent, stable results across repeated administrations, reinforcing the reliability of the data collected with this measure.

Semi-structured interviews with several students and teachers in the experimental class were conducted to explore the perceptions, experiences, and thinking processes underlying changes in MSRL and mathematical flexibility. The documentation technique involved analyzing teacher notes, learning materials, and student assignments. The inclusion criteria were as follows**:** grade 8 junior high school students participating in a deep learning intervention as the experimental group and students using conventional learning as the control; students who completed pre- and post-tests; and participants willing to be interviewed (for qualitative data). The exclusion criteria were as follows**:** students with excessive absences that prevented full participation in the intervention; incomplete pre-test or post-test data; interview respondents who did not consent to data use; and observations that did not meet observational protocol standards (e.g., not recording important deep learning aspects).

The research sample consisted of 135 grade 8 junior high school students, comprising 90 experimental class students and 45 control class students. After data verification based on the inclusion and exclusion criteria, the qualifying sample consisted of 68 experimental class students and 31 control class students. Quantitative data analysis techniques involved calculating pre-test and post-test scores for MSRL and mathematical flexibility; prerequisite tests (normality, variance homogeneity) of data; followed by comparative analysis between experimental and control groups using *Analysis of Covariance (ANCOVA)* or *Mixed ANOVA* to examine the effect of the deep learning

approach while controlling for pre-test scores; linear regression and simple correlation tests to examine whether MSRL positively influences mathematical flexibility. Qualitative analysis of interview and observation data was conducted thematically to identify main themes explaining how the deep learning approach affects MSRL and mathematical flexibility, using inductive-deductive coding and triangulation across observation, interview, and documentation data to enhance data validity. Quantitative results are first interpreted to determine whether there are significant effects, and then qualitative data are used to explain patterns in the quantitative results (e.g., why some students showed no improvement, obstacles to implementing deep learning, and contextual factors). SPSS software was used for statistical tests (ANCOVA, ANOVA, regression, and correlation). For qualitative data, NVivo coding software or alternative manual coding tools through spreadsheets are used to analyze the data.

The credibility of the quantitative data was rigorously established through the systematic application of several key statistical tests, including assessments of validity, reliability, normality, and homogeneity. Validity testing ensured that the measurement instruments accurately captured the constructs they were intended to measure, confirming the appropriateness of the data for addressing the research questions. Reliability analysis further supported the data's consistency and stability, indicating that the results were dependable across repeated measurements and different sample subsets. In addition to these foundational psychometric evaluations, tests for normality were conducted to verify that the data followed a distribution pattern suitable for parametric statistical analyses, which is critical for the validity of subsequent inferential procedures. Homogeneity tests were also performed to confirm that variances across groups were sufficiently similar, thereby meeting the assumptions required for effective comparison between the control and experimental groups. Together, these comprehensive statistical checks reinforced the robustness and trustworthiness of the quantitative dataset, providing a solid empirical basis for meaningful interpretation and ensuring that the findings derived from this data would be both valid and generalizable within the study's context. Qualitative data credibility testing was conducted through triangulation, discussions with the research team, and case analysis (Sugiyono, 2013). Based on the data sources in this study, credibility testing was conducted through source triangulation, i.e., by comparing data from multiple sources.

RESULTS AND DISCUSSION

To assess how the deep learning method influences students' self-regulated learning in mathematics, a hypothesis test was conducted to evaluate mean differences between pre-test and post-test scores within the experimental group. Table 3 displays the results of the prerequisite tests for the data, specifically the normality test (Shapiro-Wilk) and the homogeneity test (Levene's test).

Table 3. Results of Prerequisite Tests for MSRL Pretest-Posttest

Test	Data	Statistical Test (α = 0.05)	Conclusion
Normality	Pretest-Posttest	Shapiro-Wilk	Not Normal
Homogeneity	Pretest-Posttest	Levene's Test	Homogeneous

Given that the data were uniform but not normally distributed, the mean difference was assessed using the nonparametric Wilcoxon Signed-Rank Test. This test was applied with the condition that a significance value of less than 0.05 would indicate a notable difference in MSRL between the pre-test and post-test. Table 4 displays the outcomes of the Wilcoxon Signed-Rank Test.

Table 4. Results of the Mean Difference Test for MSRL Pretest-Posttest

Test Statistics[a]	Data
	Postes – Pre-test
Z	-1.117[b]
Asymp. Sig. (2-tailed)	.264

a. Wilcoxon Signed Ranks Test
b. Based on negative ranks.

From Table 4, the significance value of 0.264 is greater than 0.05, indicating that there is no significant difference between the pre-test and post-test scores in the experimental group. This means that the deep learning approach did not significantly improve students' self-regulated learning in mathematics. The research findings indicate no significant difference between pre- and post-test scores in the experimental group, using either the mean-difference test or ANCOVA, suggesting that the deep learning approach does not significantly affect improvement in mathematics self-regulated learning (SRL). Furthermore, several aspects of SRL, such as task analysis, do not significantly affect mathematics learning outcomes, particularly when viewed from the perspective of students' learning interest levels (Abror et al., 2024). This indicates that students' affective factors significantly influence the effectiveness of learning approaches. In contrast, Ab (2020) found that SRL in mathematics learning is more influenced by students' internal factors, such as intellectual intelligence and mathematical disposition, rather than by the mere implementation of specific learning strategies. Thus, the results of this study can be interpreted as a failure of the deep learning intervention to improve students' SRL, likely due to the suboptimal role of these internal factors.

The findings reinforce that improving students' self-regulated learning (SRL) cannot rely solely on deep learning approaches but requires a multifaceted strategy addressing multiple dimensions of learning. Research demonstrates that students with high intrinsic motivation and autonomy needs are more likely to adopt deep learning approaches, indicating these factors work synergistically (Núñez & León, 2016). Studies show that mathematics self-concept influences performance both directly and indirectly through intrinsic motivation as a mediating variable, demonstrating that cognitive approaches alone are insufficient without addressing motivational factors (Lai & Hwang, 2016). Higher SRL levels correlate with reduced mathematics anxiety while lower levels increase anxiety, confirming that affective and dispositional factors are integral to learning outcomes (Panadero, 2017). Elementary students struggling with mathematics word problems can develop SRL through teaching approaches offering quantitative feedback and learning prompts, highlighting the importance of scaffolded instruction over single pedagogical methods (Cleary & Russo, 2024). Effective SRL development in mathematics thus requires integrated interventions addressing cognitive strategies, motivation, affect, and contextually relevant teaching approaches. To determine whether the deep learning approach can improve students' mathematical flexibility compared with conventional teaching methods, a mean difference test was conducted on the pre- and post-test scores of the experimental group. Before conducting the test, prerequisite tests were performed, namely the normality (Shapiro-Wilk) and homogeneity (F-test) tests, with the results shown in Table 5.

Table 5. Results of Prerequisite Tests for MF Pretest-Posttest

Test	Data	Statistical Test (α = 0.05)	Conclusion
Normality	Pretest-Posttest	Shapiro-Wilk	Normal
Homogeneity	Pretest-Posttest	Levene's Test	Homogeneous

From Table 5, the pre- and post-test data are normally distributed and have homogeneous variances. Therefore, the mean difference test was conducted using a paired t-test, with the criterion that if the calculated t-value exceeds the t-table value, then reject H_0 and conclude that there is a significant difference. The test results are shown in Table 6.

Table 6. Results of the Mean Difference Test for MF Pre-test and Post-test in the Experimental Group

Variable	T calculated	t table	Conclusion
Mathematical Flexibility	14,92	1,997	A significant difference exists

Because the calculated t-value (14.92) > t-table value (1.997) and p-value < α (0.05), there is a highly significant difference between the pre- and post-test scores of mathematical flexibility. This indicates that the deep learning approach significantly improved students' mathematical flexibility. The gain analysis showed an average improvement of 4.27 points in students' MF. Therefore, the deep learning approach is effective in enhancing students' mathematical flexibility. Consistent with these findings, interviews conducted with several students in the experimental class provided further insights into the implementation of the deep learning approach. Students expressed that mathematics learning was more engaging and enjoyable when technology was integrated into formative assessments and as an instructional medium. Moreover, they reported that this approach enabled them to explore multiple strategies for solving a single mathematical problem.

The research findings demonstrate a highly significant difference between students' pre-test and post-test scores on mathematical flexibility. Gain analysis revealed an average improvement of 4.27 points in mathematical flexibility, suggesting that the deep learning approach effectively enhances students' mathematical flexibility. Furthermore, Tachie (2019) found that successful mathematics learning that emphasizes reflection and self-regulation significantly improves mathematical problem-solving abilities, which are intrinsically linked to mathematical flexibility. Reflection and self-regulation, as components of metacognition, play a crucial role in enhancing a student's ability to solve mathematical problems. These metacognitive skills enable students to analyze tasks, plan effectively, monitor progress, and evaluate the solutions. Similar results were also shown by Coscos et al. (2022), who found that SRL strategies in the context of flexible learning positively influence students' mathematics achievement by strengthening metacognitive strategies. The finding that the deep learning approach significantly improved students' mathematical flexibility aligns with contemporary learning theory, which emphasizes that effective learning strategies must match the requirements and phases of learning tasks. A synthesis of 228 meta-analyses involving between 13 and 20 million students demonstrated that learning strategies are differentially effective depending on the phase of learning, with deep learning strategies compelling when students aim to understand context and apply knowledge in new situations (Losenno et al., 2020) The findings indicate that enhancing mathematical flexibility through a deep learning approach is a complex and multifaceted process that requires the integration of deep cognitive strategies, development of self-regulation, intrinsic motivation, and a supportive learning environment. A holistic approach that combines these elements is more likely to produce meaningful and adaptive mathematics learning compared to interventions that focus solely on a single aspect of learning (Abdullah et al., 2021; Hattie & Donoghue, 2016).

To determine the difference in mathematics self-regulated learning (MSRL) improvement between the experimental group using the deep learning approach and the control group using conventional learning, an analysis of covariance (ANCOVA) was conducted. In this model, pre-test scores were used as covariates to control for students' initial abilities on post-test scores.

Table 7. ANCOVA Results for MSRL

Source of Variation	JK	Df	F	Sig.	Partial η^2
Pre-test	894.84	1	87.96	<0.001	0.478
Group (Experimental vs Control)	19.89	1	1.96	0.165	0.020
Error	976.59	96			

Based on Table 7, the pre-test covariate significantly affected the MSRL post-test scores ($F = 87.96$; $p < 0.001$; $\eta^2 = 0.478$). This indicates that students' initial scores strongly determined their final scores. However, the group factor (experimental vs. control) did not significantly affect post-test scores after controlling for the pre-test ($F = 1.96$; $p = 0.165$; $\eta^2 = 0.020$). The partial eta squared value of 0.020 indicates that the difference in learning approaches explains only about 2% of the variance in post-test scores, which is considered a small effect.

The findings reinforce that improving students' self-regulated learning (SRL) cannot rely solely on deep learning approaches but requires a multifaceted strategy addressing multiple dimensions of learning. Research demonstrates that students with high intrinsic motivation and autonomy needs are more likely to adopt deep learning approaches, indicating these factors work synergistically (Núñez & León, 2016). Studies show that mathematics self-concept influences performance both directly and indirectly through intrinsic motivation as a mediating variable, demonstrating that cognitive approaches alone are insufficient without addressing motivational factors (Lai & Hwang, 2016). Higher SRL levels correlate with reduced mathematics anxiety while lower levels increase anxiety, confirming that affective and dispositional factors are integral to learning outcomes (Panadero, 2017). Elementary students struggling with mathematics word problems can develop SRL through teaching approaches offering quantitative feedback and learning prompts, highlighting the importance of scaffolded instruction over single pedagogical methods (Cleary & Russo, 2024). Effective SRL development in mathematics thus requires integrated interventions addressing cognitive strategies, motivation, affect, and contextually relevant teaching approaches.

To examine the relationship between the MSRL and MF, simple regression and correlation analyses were conducted. The data analysis yielded the following regression equation: MF = -4.0097 + 0.2843(MSRL). This indicates that for every 1-unit increase in the MSRL, MF increases by 0.28 points. The correlation analysis yielded a correlation coefficient of $r = 0.524 > 0$ and significant ($p < 0.001$), indicating a significant positive relationship between mathematics self-regulated learning and mathematical flexibility with a t-statistic of 4.3290 and a t-critical of ±1.997. This correlation was significant at $\alpha = 0.05$. The coefficient of determination indicates that the MSRL accounts for 27.2% of the variation in MF, while other factors influence the remaining 72.8%.

The data analysis results showed a significant positive relationship between mathematics self-regulated learning (MSRL) and mathematical flexibility (MF). This indicates that the higher the students' ability to regulate, monitor, and evaluate their mathematics learning processes, the more flexible they become in selecting and applying problem-solving strategies. This finding aligns with that of Nugroho et al. (2021), who showed that SRL stages, from planning, monitoring, and control to reflection, play important roles in improving mathematical problem-solving abilities. Consistently, Coscos et al. (2022) found that SRL strategies, particularly metacognitive strategies, are closely related to mathematics academic achievement in flexible learning contexts, reinforcing SRL's role as a predictor of learning flexibility. Alyani and Ramadhina (2022) further strengthen this finding by showing a strong correlation ($r = 0.634$) between SRL and mathematical problem-solving abilities, especially in online learning conditions during the pandemic, which demanded greater flexibility in learning strategies.

Therefore, it can be concluded that the deep learning approach not only improves students' academic achievement but also effectively develops mathematical flexibility. This is because the approach emphasizes active student engagement, reflection strengthening, and metacognitive skill development, which directly contribute to the ability to select and adapt strategies in mathematical problem-solving. The deep learning-based approach has been shown to enhance mathematical problem-solving abilities by encouraging students to develop deeper, more flexible knowledge representations.

Furthermore, students with high SRL levels have better metacognitive awareness, enabling them to adapt solution strategies, although flexibility is also influenced by students' cognitive readiness (Rahayuningsih et al., 2021). Similarly, SRL is a cyclical process involving forethought, performance, and reflection phases, in which self-efficacy and the learning strategies students use have been shown to influence flexibility in creative problem-solving (Callan et al., 2022). In educational contexts, linear regression models illustrate the impact of one independent variable on a dependent variable, with the regression coefficient indicating the expected change in the dependent variable (MF, in this case) for a one-unit change in the predictor variable (MSRL). Meanwhile, the positive and significant correlation coefficient suggests a reliable relationship between the variables, underscoring the practical relevance of interventions aimed at enhancing students' self-regulated learning skills to improve their mathematical flexibility and overall academic performance.

Therefore, it can be concluded that the improvement of mathematical flexibility is inseparable from the quality of SRL implementation by students. The better students are at regulating their learning processes, the greater their likelihood of developing varied, adaptive, and creative problem-solving strategies. Consequently, pedagogical interventions focused on SRL strengthening are important to integrate into mathematics instruction so that students can tackle problem-solving challenges with greater flexibility.

The findings of this study reveal that implementing a deep learning approach did not significantly improve students' Mathematics Self-Regulated Learning (MSRL). These findings are based on an analysis of various inhibiting factors that emerged during the field implementation. The primary obstacle identified was the class size of 45 students, which far exceeded the ideal number for effective deep learning. This overcrowded classroom condition made it difficult for teachers to provide individual attention and facilitate deep learning among their students (Blatchford et al., 2011). Personal interactions between teachers and students, as well as small-group discussions, which are key to deep learning, could not be optimally implemented. The scaffolding process, the provision of constructive feedback, and the monitoring of individual progress were severely limited, resulting in an approach that should promote deep conceptual understanding being implemented only superficially. MSRL, as a construct in the affective domain, requires a relatively long transformation time because it involves changes in students' metacognition, intrinsic motivation, learning strategies, and self-efficacy. This study found that the implementation duration was insufficient to produce substantive changes in students' MSRL. Students accustomed to conventional mathematics learning patterns and who tended to be passive showed resistance to change. They still relied heavily on teacher explanations and had not yet developed the independence to regulate their learning. Another inhibiting factor was teachers' limited knowledge and competence regarding the deep learning approach. Most teachers had a limited understanding of the pedagogical principles of deep learning and how to integrate them into MSRL development. The lack of adequate training led to inconsistent implementation with the theoretical principles of this approach, and teachers were less skilled at identifying and addressing individual student barriers in developing their MSRLs.

The findings of this quantitative study indicate that implementing the deep learning approach significantly enhanced students' mathematical flexibility. Mathematical flexibility refers to students'

ability to explore various strategies and alternative methods for solving mathematical problems. Based on direct observations and in-depth interviews, it was found that the deep learning approach created a pleasant, conducive learning environment. This positive learning environment provided psychological space for students to develop their thinking more freely without feeling constrained by conventional methods. Students demonstrated high enthusiasm, as reflected in their active participation and courage in proposing various problem-solving methods. The success of deep learning implementation is inseparable from the integration of learning technology. The use of GeoGebra, Quizizz, and Kahoot was crucial. GeoGebra facilitated dynamic visualization of mathematical concepts, while Quizizz and Kahoot added a gamification element, making learning more interactive and competitive. The integration of these three technologies successfully increased student engagement significantly and motivated them to compete healthily, ultimately encouraging a deeper exploration of mathematical concepts. Another important finding was the development of students' ability to discover various ways of solving mathematical problems. In particular, on the topic of linear equations in one variable, students were able to identify and apply different solution strategies. This cognitive flexibility demonstrates that students experience deep conceptual understanding, not merely procedural mastery.

CONCLUSION

This study provides nuanced insight into the effectiveness of a deep learning approach in mathematics education. The findings demonstrate that although deep learning does not yield a significant improvement in self-regulated learning in mathematics, it is highly effective in improving students' mathematical flexibility. Notably, the strong positive association observed between mathematics self-regulated learning and mathematical flexibility underscores the mutually reinforcing nature of these constructs within the learning process. These results suggest that effective instructional design in mathematics should move beyond singular outcome measures and adopt an integrative approach that addresses multiple dimensions of learning to holistically optimize students' achievement. Thus, this study contributes to mathematics education research by providing empirical evidence that deep learning approaches effectively develop mathematical flexibility while highlighting the need for multifaceted interventions targeting metacognitive dimensions to improve self-regulated learning.

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