Journal of Pedagogical Research
Volume 9, Issue 3, 2025
https://doi.org/10.33902/JPR.202534085

Research Article

Factors affecting mathematics achievement: Online learning, self-efficacy, and self-regulated learning

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Online learning is one of the learning designs considered more efficient in terms of time, as it can be done anywhere and anytime. This study investigates two factors that may influence mathematics achievement in the context of online learning: self-regulated learning and self-efficacy. The researcher aimed to explain the relationships between online learning and mathematics achievement, self-regulated learning and mathematics achievement, self-efficacy and mathematics achievement, self-regulated learning and online learning, self-efficacy and online learning, self-efficacy and online learning with mathematics achievement, and self-regulated learning and online learning with mathematics achievement. The validity of the research instrument was first tested through expert judgment. The sample consisted of grade VIII students from schools implementing the new curriculum in Indonesia. The data were analyzed using Structural Equation Modeling (SEM). The results showed that mathematics achievement is directly influenced by online learning, self-regulated learning, and self-efficacy. Furthermore, when online learning acts as a moderating variable, mathematics achievement is also indirectly influenced by self-efficacy and self-regulated learning.

Keywords: Reward; Transformational leadership; Motivation; Job satisfaction; Primary school teachers

Article History: Submitted 12 February 2025; Revised 3 June 2025; Published online 30 June 2025

1. Introduction

The transition to digital learning systems, accelerated by the COVID-19 pandemic, has introduced challenges to the mathematics learning process. Online learning, initially an alternative, has now become part of long-term learning strategies. However, the effectiveness of online learning depends greatly on students' technical, emotional, and cognitive readiness (Dhawan, 2020). Without direct interaction, students are required to be more independent and active in the learning process.

Mathematics achievement is an important indicator of student success in education. As a subject that fosters logical, analytical, and problem-solving skills, mathematics serves as a critical foundation for other disciplines, particularly in science and technology. Mathematics achievement contributes significantly to student success in STEM fields and real-world problem-solving (Sezer & Namukasa, 2021). However, the global shift to online learning has raised concerns about its impact on mathematics learning outcomes. Empirical studies report a significant decline in

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How to cite: Aviory, K., Retnawati, H., & Sudiyatno, S. (2025). Factors affecting mathematics achievement: Online learning, self-efficacy, and self-regulated learning. *Journal of Pedagogical Research, 9*(3), 276-290. https://doi.org/10.33902/JPR.202534085

mathematics performance with online learning, attributed to reduced teacher-student interaction and a lack of hands-on practice (OECD, 2021; Engzell et al., 2021). This trend suggests that the success of mathematics learning depends not only on access to technology but also on psychological factors such as self-regulated learning and self-efficacy (Misirli & Ergulec, 2021).

Self-regulation is essential in learning mathematics, particularly in online environments. Students are required to be independent in their learning and resourceful in finding information to complete assignments or solve problems. Self-regulation helps students increase motivation, improve performance, and enhance engagement and perseverance (Handoko et al., 2019). The researcher aimed to determine whether self-regulated learning has both direct and indirect influences on mathematics achievement.

Self-efficacy is another psychological factor that plays a key role in students' learning processes. In education, self-efficacy refers to students' belief in their ability to complete academic tasks, including understanding concepts and solving problems. This makes self-efficacy an important factor influencing learning success (Wang & Tambi, 2024). Students with high self-efficacy tend to be more confident in tackling difficult problems, more resilient in the face of challenges, and more consistent in their learning efforts (Liu et al., 2024). In online learning, limited direct interaction with teachers and peers may reduce opportunities for feedback. Students confident in their abilities are more likely to set challenging learning goals, use effective learning strategies, and demonstrate higher levels of self-efficacy. Therefore, self-efficacy is considered a key indicator in evaluating students' readiness for learning, especially in mathematics, which demands conceptual understanding and strong logical reasoning.

These three factors—online learning, self-efficacy, and self-regulated learning—are believed to be interrelated and contribute to mathematics achievement. However, further research is needed to determine the extent to which these factors influence mathematics achievement, both directly and indirectly. The findings will provide valuable input for educators and policymakers in designing appropriate interventions (e.g., self-regulated learning training, self-efficacy-building activities) to optimize mathematics achievement in digital environments. In addition, they will offer strategic recommendations for developing effective and adaptive learning systems that meet the needs of students in the digital age.

1.1. Online Learning

Online learning can be conducted anywhere and anytime. It involves the use of digital communication, virtual collaboration, and asynchronous content delivery (Cheng et al., 2025). When this mode of learning is chosen as an alternative, educators must design effective and efficient strategies to ensure that the expected learning outcomes are achieved. The goal is to prevent any knowledge gaps between students engaged in online learning and those in offline settings.

Many factors need to be considered in the implementation of online learning, including the choice of learning strategies. One common strategy is the use of digital platforms. These platforms are employed to deliver online instruction, facilitate training, and conduct virtual classes. By using such platforms, educators are supported in planning and delivering instruction, as well as in conducting real-time assessments. Digital platforms may include Zoom, Google Meet, Google Classroom, e-learning systems, and others. The use of these tools can significantly assist students in their learning activities. For example, studies have shown that 53% of students use digital platforms to access learning resources, submit assignments, interact with peers, and take online exams (Maqableh & Alia, 2021).

Online learning, as one of the alternative learning approaches, has been implemented in Indonesia over the past four years. In higher education, this design is often combined with offline learning in hopes of encouraging students to learn independently and creatively. However, in primary and secondary education, offline learning is still prioritized, and online learning has not become a standard option. The implementation of online learning requires careful attention to various factors, such as learning strategies, learning media, the learning environment, internet connectivity, and more. This raises the important question: what dimensions influence the impact of online learning on mathematics achievement if it is implemented in the post-pandemic era?

1.2. Self-efficacy

Self-efficacy is defined as students' belief in their ability to solve mathematical problems (Bandura, 2006). Self-efficacy can directly promote students' engagement and perseverance in learning mathematics, contributing to a more effective learning environment (Tan et al., 2025). In the context of online learning, self-efficacy is particularly essential. Several factors influence self-efficacy, including knowledge and experience with online learning, feedback and rewards, online interaction and communication, social influence, and student motivation and attitudes (Peechapol et al., 2018). Students with high levels of self-efficacy are more likely to achieve satisfactory results in online learning (Zimmerman & Kulikowich, 2016). When teacher support is limited, as is often the case in online environments, self-efficacy becomes even more critical. For example, research by Pajares and Graham (1999) found that self-efficacy accounted for 25% of the variance in mathematics achievement among secondary school students.

1.3. Self-regulated Learning

One of the key determinants of success in online learning is self-regulated learning. In online learning, students have greater freedom but also experience less monitoring compared to face-to-face learning. Research shows that students with high levels of self-regulated learning are better able to manage their study time effectively (Broadbent & Poon, 2015), maintain consistent motivation even when studying independently, demonstrate greater resilience to external distractions, and adjust their learning strategies according to the material and their needs. In other words, without strong self-regulated learning skills, students are more likely to face difficulties in completing online learning tasks, such as reading materials independently, taking online quizzes, or actively participating in online discussions.

Self-regulated learning is not an academic skill in itself, but rather a process of self-direction that transforms into academic skills. It is a shared conceptualization involving attitudes, cognition, motivation, and emotions (Ben-Eliyahu & Bernacki, 2015; Panadero, 2017). Self-regulation can be seen as a learning session that is fully organized, planned, implemented, and monitored by the student. In this process, students are responsible for learning as much as possible during their study sessions and for designing their own personal study plans (Broeren et al., 2021).

Research findings indicate that by organizing themselves, students gain clarity about the goals they want to achieve, the knowledge they are expected to acquire, and the higher-quality work they can produce (Ben-Eliyahu & Bernacki, 2015). Students develop plans to improve their performance on assignments (Winne, 2018) and place trust in personal progress and deep understanding rather than trying to impress others. They select effective strategies to apply appropriately to different situations (Winne & Perry, 2000).

Based on the research gap identified, the following hypotheses will be examined:

H1: Online learning has a direct effect on mathematics achievement.

H2: Self-regulated learning has a direct effect on mathematics achievement.

H3: Self-efficacy has a direct effect on mathematics achievement.

H4: Online learning is directly influenced by self-regulated learning.

H5: Online learning is directly influenced by self-efficacy.

H6: Self-efficacy and self-regulated learning have indirect effects on mathematics achievement, with online learning acting as a moderating variable.

2. Method

2.1. Research Design

This study employed a quantitative research design using Structural Equation Modeling (SEM) to examine the relationships among multiple latent variables. The primary aim was to investigate the influence of online learning, self-efficacy, and self-regulated learning on mathematics achievement. SEM was chosen as the analytical method because of its ability to simultaneously evaluate both measurement models (the relationships between latent variables and their observed indicators) and structural models (the relationships among latent variables). This approach enabled a comprehensive analysis of the direct and indirect effects within the hypothesized model, offering a robust understanding of the complex interactions among the constructs under study.

2.2. Participants

This research was conducted in two state junior high schools in Bantul, in the Special Region of Yogyakarta. The schools were selected using random sampling, and the target population consisted of grade VIII students. The selection of grade VIII was based on the ongoing curriculum transition in Indonesia, where the new curriculum is being implemented in grades IV, VIII, and X. At the grade VIII level, students are still studying Compulsory Mathematics, whereas in grade X, mathematics is divided into Compulsory Mathematics and Specialization Mathematics. Additionally, students in grade VIII are typically in the 13–14 age range, a developmental stage characterized by the transition in self-regulation as they begin to integrate ability, goals, and motivation (Wesarg-Menzel et al., 2023).

The study collected data from 149 respondents, who were randomly selected from the two sampled schools.

2.3. Data Collection

This study measured three variables: online learning, self-efficacy, and self-regulated learning. The instruments used were a psychological scale and a questionnaire. The psychological scale was designed to describe aspects of individual personality, while the questionnaire was used to collect factual data. Two psychological scales were employed to measure self-regulated learning and self-efficacy, whereas online learning was measured using a questionnaire. The online learning instrument consisted of 20 items, self-regulated learning consisted of 22 items, and self-efficacy consisted of 13 items.

There were three latent variables in this study: self-regulated learning (Y), self-efficacy (Z), and online learning (X). Self-regulated learning (Y) included five indicators: believing in self-abilities (Y_1), behaving in a disciplined manner (Y_2), having responsibility (Y_3), behaving based on self-initiative (Y_4), and self-control (Y_5). Self-efficacy (Z) included four indicators: belief in the ability to complete mathematical material (Z_1), belief in the ability to complete math-related tasks (Z_2), belief in achieving goals in learning mathematics (Z_3), and belief in resilience and perseverance in learning mathematics (Z_4). Online learning (X) included four indicators: internet network (X_1), learning media (X_2), learning strategies (X_3), and family environment (X_4). Each indicator was measured by five items, with all items rated on a 4-point Likert scale. For self-efficacy and self-regulated learning, the scale was: 1 = never, 2 = sometimes, 3 = often, 4 = always.

2.4. Data Analysis

The first step was to test the content validity of the instruments. Two experts were involved in evaluating the instruments by assessing the suitability between the item grid and the actual items. Content validity was analyzed using Aiken's V, with the formula as follows:

$$v = \frac{\sum_{i=1}^{n}(r - l_0)_i}{n(c-1)}$$

where: r = score given by the expert, l_o = lowest validity score, n = number of experts, and c = highest validity score.

Once the instruments were confirmed to have content validity, they were distributed to the respondents.

The data were analyzed using the Structural Equation Model (SEM) with SMARTPLS 4.0. The bootstrap resampling method (with 5000 resamples) was applied to estimate the significance of the path coefficients. The SEM analysis was carried out in two stages: the measurement model and the structural model.

The measurement model was used to assess item fit within the model, employing second-order Confirmatory Factor Analysis (CFA). The first-order model examined the relationships between indicators (dimensions) and latent variables, while the second-order model assessed the relationships between items and their respective dimensions. Variance Inflation Factor (VIF) estimates were calculated to detect any potential multicollinearity.

The structural model was used to examine the relationships among latent variables. Both Composite Reliability (CR) and Average Variance Extracted (AVE) were estimated for the measurement and structural models. CR represents the internal consistency of indicators in measuring their constructs, while AVE reflects the proportion of variance explained by the construct relative to measurement error.

3. Results

In the first step, the instruments were checked for content validity. Based on calculations using Aiken's V, the online learning instrument obtained values ranging from 0.625 to 0.875, the self-efficacy instrument ranged from 0.75 to 0.875, the self-regulated learning instrument ranged from 0.625 to 0.875, and the mathematics achievement instrument ranged from 0.75 to 0.875. These results indicated that all four instruments demonstrated high content validity and were suitable for use in the research.

The data were analyzed using Structural Equation Modeling (SEM), which was carried out in two stages. The first stage focused on determining the outer model or measurement model. This stage used confirmatory factor analysis to test convergent and discriminant validity. The second stage focused on determining the inner model or structural model. The purpose of this stage was to examine the relationships between latent variables, the effects of indicators on latent variables, the effects of items on indicators, and the direct effects of items on latent variables.

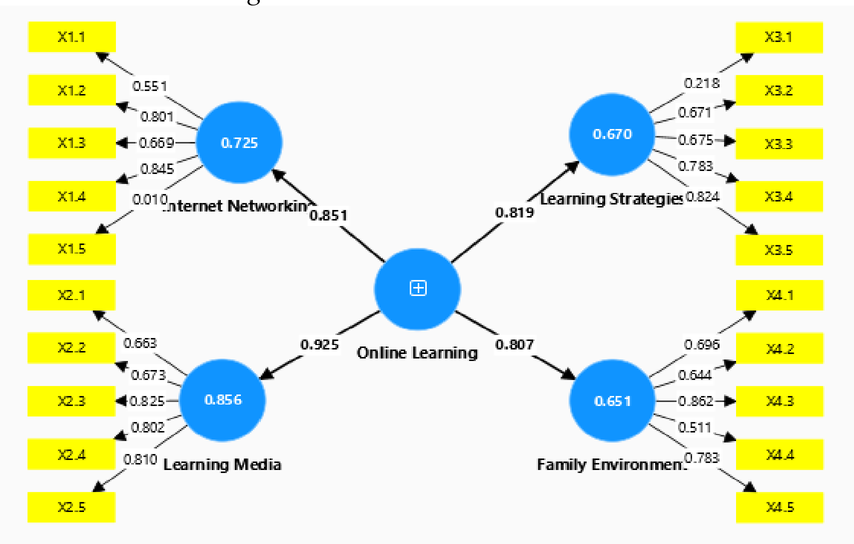
3.1. Measurement Model

The first step in the analysis involved working with the conceptual model. This process was conducted by developing and measuring the constructs. The conceptual constructs were defined by determining the domain of each construct through a review of relevant literature. In this study, the constructs were modeled with reflective indicators, assuming that the covariance among the measurements is explained by variance that reflects the domain of the construct. The conceptual model was designed using a second-order structure for each latent variable. The three latent variables analyzed in this study were online learning, self-efficacy, and self-regulated learning. For the convergence test, a loading factor threshold of 0.5 was applied.

3.1.1. Online learning

The success of online learning can be evaluated through four dimensions: the internet network (X_1), learning media (X_2), learning strategies (X_3), and the family environment (X_4). Each indicator was measured using five question items. The results of the validity test are presented in Figure 1. Two items showed a loading factor of less than 0.5: one item from the internet network indicator ($X_{1.5}$) and one item from the learning strategies indicator ($X_{3.1}$). Therefore, a total of 18 items were found to fit the model.

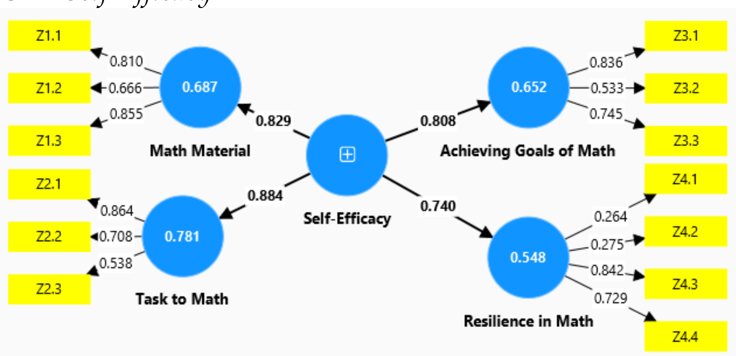
Figure 1
CFA Online Learning



3.1.2. *Self-efficacy*

Self-efficacy consists of four dimensions, such as belief in the ability to complete mathematical material (Z_1), belief in the ability to complete tasks related to mathematics (Z_2), belief in achieving goals in learning mathematics (Z_3), and belief in resilience and tenacity in learning mathematics (Z_4). Each indicator is composed of 3 question items, except for the perseverance in learning mathematics. Based on the results of the CFA test in Figure 2, it can be seen that two items have a loading factor of less than 0.5. The two items measure indicators of belief in resilience and tenacity in learning mathematics, namely $Z_{4.1}$ and $Z_{4.2}$. So, 11 items fit with the model.

Figure 2
CFA Self-Efficacy

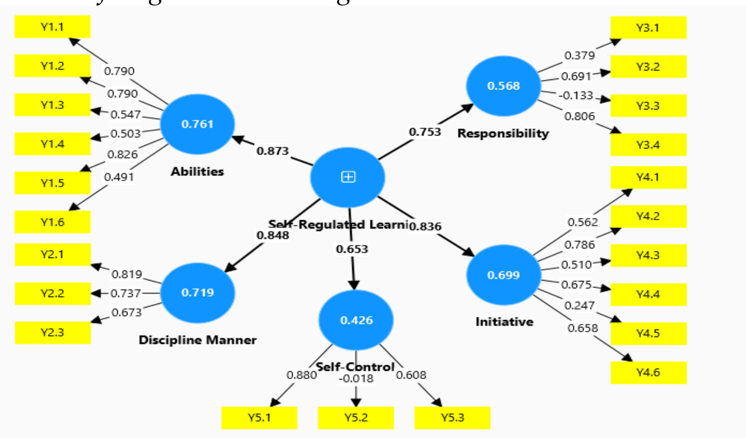


3.1.3. *Self-regulated learning*

Self-regulation learning consists of five dimensions, such as believing in one's abilities, behaving in a disciplined manner, having responsibility, behaving based on one's initiative, and having self-control. The CFA analysis can be seen in Figure 3. The calculation results show that five items have a loading factor below 0.5, one item on the indicator of behaving based on self-initiative ($Y_{4.5}$), one item on the self-control indicator ($Y_{5.2}$), two items on the indicator of having responsibility ($Y_{3.1}$ and $Y_{3.3}$), and one item on the indicator of confidence in one's abilities ($Y_{1.6}$). So, 17 items fit with the model.

Figure 3

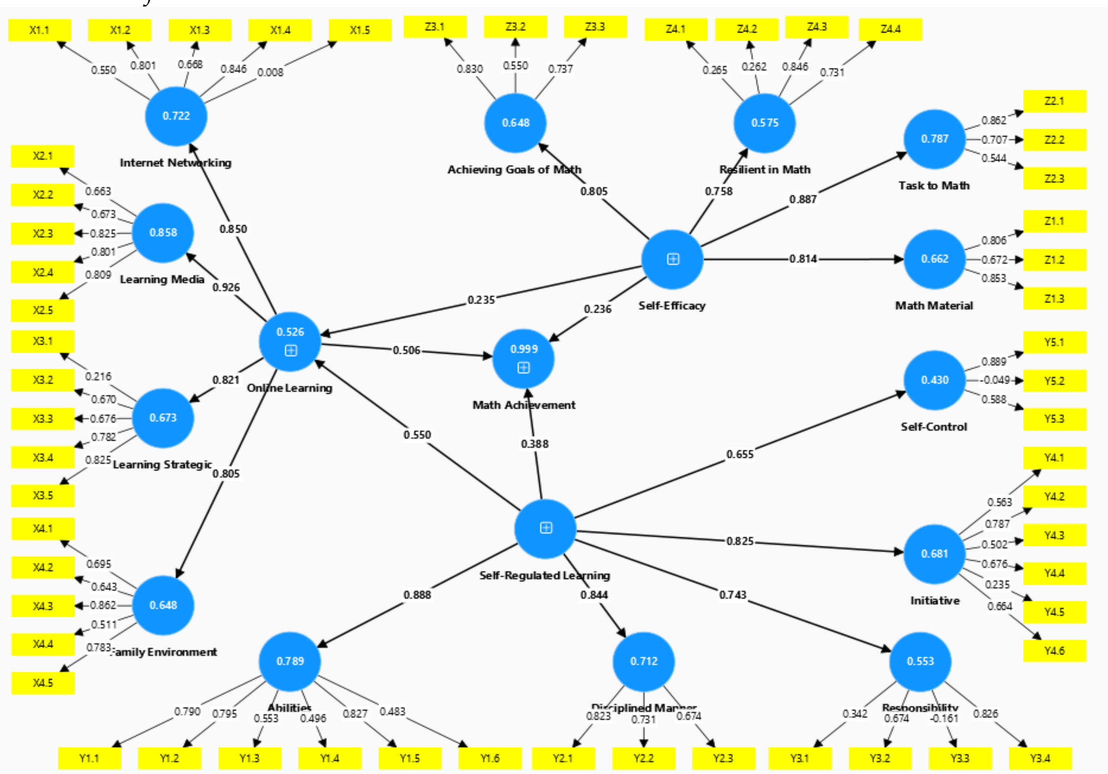
CFA Self-Regulated Learning



After partial testing, it will be tested simultaneously (second-order). This test is done by looking at the loading value that measures each variable. The test uses a second order where the test is carried out through two levels. First, the analysis was carried out from items to latent variables. Second, the analysis is carried out from indicators to variables.

Figure 4

First Model from SEM-PLS



Based on the analysis presented in Figure 4, several items were identified with loading factors below 0.5. These items were excluded from the model to improve its fit. In total, nine items were removed. Specifically, two items were excluded from the online learning variable, five items from the self-regulated learning variable, and two items from the self-efficacy variable. The remaining indicators for each variable had loading factors greater than 0.5, indicating that they were significant and suitable for inclusion in the model. The model was then re-estimated after removing the low-loading items. The revised models are shown in Figure 5. Figure 5a presents the model after excluding nine items, while Figure 5b presents the model after excluding eleven items.

Figure 5a

Structural model after excluding nine low-loading items

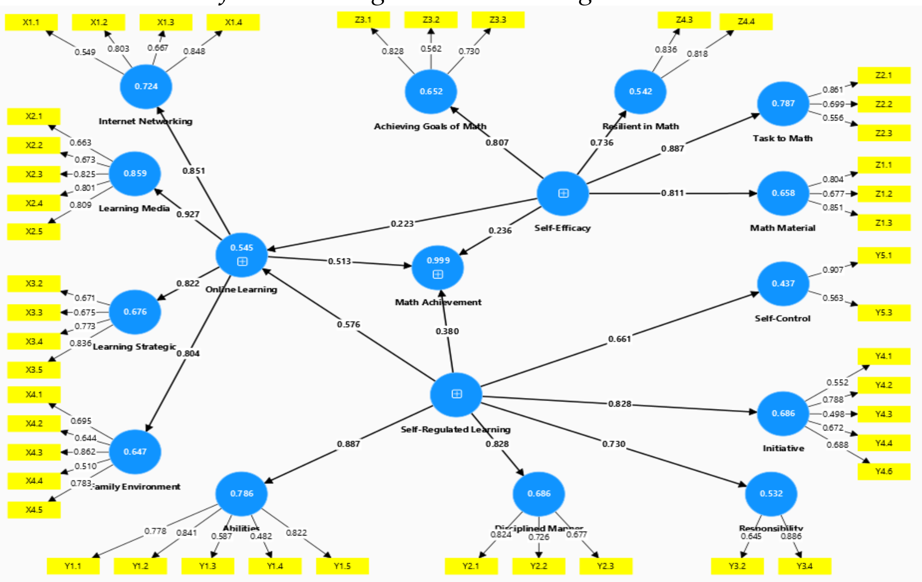
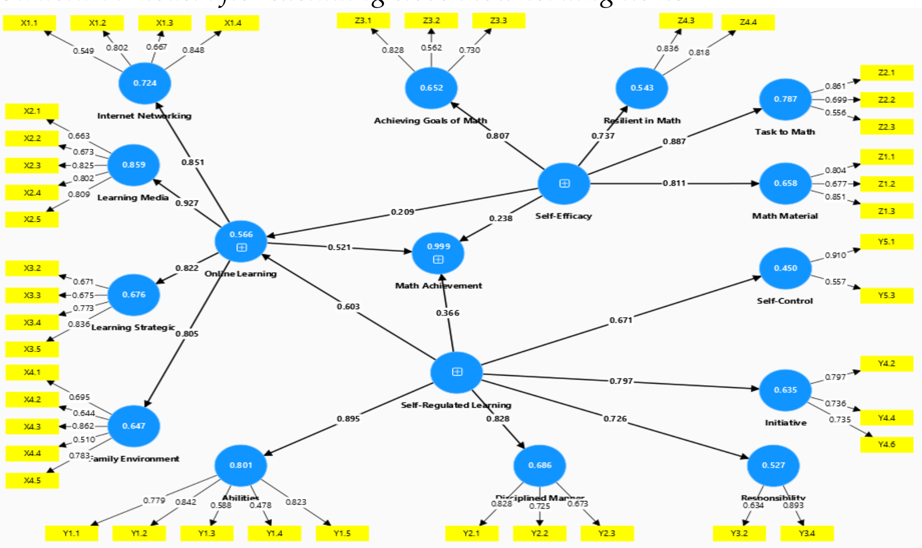


Figure 5b

Structural model after excluding eleven low-loading items



The next step was to conduct a reliability test. Reliability was assessed using the values of CR and AVE. CR represents the consistency of each indicator in measuring its respective construct, with a value greater than 0.7 indicating acceptable reliability. AVE is used to assess the proportion of variance that can be explained by the construct relative to measurement error. The reliability calculations were based on the final model constructs (the second model). The results of the CR estimation showed that all constructs had CR values greater than 0.7, indicating high internal consistency. The results of the reliability estimation for model (a) and model (b) are presented in Table 1.

Table 1 shows that the AVE value for model (b) is above 0.5, indicating good convergent validity. In this model, two items—$Y_{4.1}$ and $Y_{4.3}$—were removed because their loading factors were below 0.70. It is important to note that SmartPLS 4.0 does not automatically detect whether the model is built as a first-order or second-order model. The output generated by SmartPLS 4.0 displays CR and AVE values based on item repetition, rather than values derived solely from the dimensions that measure latent variables. In fact, CR and AVE values for latent variables should be assessed based on the dimensions associated with each latent variable (MacKenzie et al., 2011). Therefore, it is essential to interpret the SmartPLS 4.0 output with caution to ensure accurate conclusions.

Table 1
Contracts Reliability and Convergent Validity Results

	Model (a)		*Model (b)*	
	CR (rho_c)	AVE	CR (rho_c)	AVE
Self-Regulated Learning				
Abilities	0.835	0.513	0.835	0.513
Disciplined Manner	0.788	0.555	0.788	0.555
Responsibility	0.748	0.602	0.747	0.602
Initiative	0.779	0.420	0.800	0.572
Self-Control	0.718	0.571	0.718	0.571
Online Learning				
Internet Networking	0.813	0.527	0.813	0.527
Learning Media	0.870	0.574	0.870	0.574
Learning Strategic	0.829	0.551	0.829	0.551
Family Environment	0.831	0.503	0.831	0.503
Self-Efficacy				
Math Material	0.823	0.610	0.823	0.610
Resilient in Math	0.812	0.684	0.812	0.684
Task to Math	0.754	0.513	0.754	0.513
Achieving Goals of Math	0.754	0.512	0.754	0.512

VIF was also estimated in this model. VIF is used to detect signs of multicollinearity among indicators. According to Hair et al. (2015), indicators are considered free from multicollinearity if the VIF value is less than 5. The results of the VIF estimation are presented in Table 2 and show that all items had VIF values below 5, indicating that multicollinearity was not a concern in this model.

Table 2
Collinearity between Indicators

	VIF
Self-Regulated Learning	
Abilities	2.161
Disciplined Manner	2.103
Responsibility	1.691
Initiative	1.922
Self-Control	1.527
Online Learning	
Internet Networking	2.380
Learning Media	3.213
Learning Strategic	2.058
Family Environment	1.821
Self-Efficacy	
Math Material	1.820
Resilient in Math	1.544
Task to Math	2.422
Achieving Goals of Math	1.770

3.2. Structural Model

The structural model was used to examine the relationships between constructs. Four types of relationships were analyzed: the relationships between latent variables, the relationships between indicators and the latent variables they measure, and the relationships between items and their respective indicators. Figure 6 shows that the loading factors for the dimensions measuring the latent variables are all above 0.7. In addition, the CR values are above 0.7, and the AVE values are above 0.5. These results are presented in Table 3. According to Hair et al. (2015), good reliability is indicated by a CR value greater than 0.7. Therefore, the construct reliability in this study has been confirmed.

Figure 6
Third Model from SEM-PLS

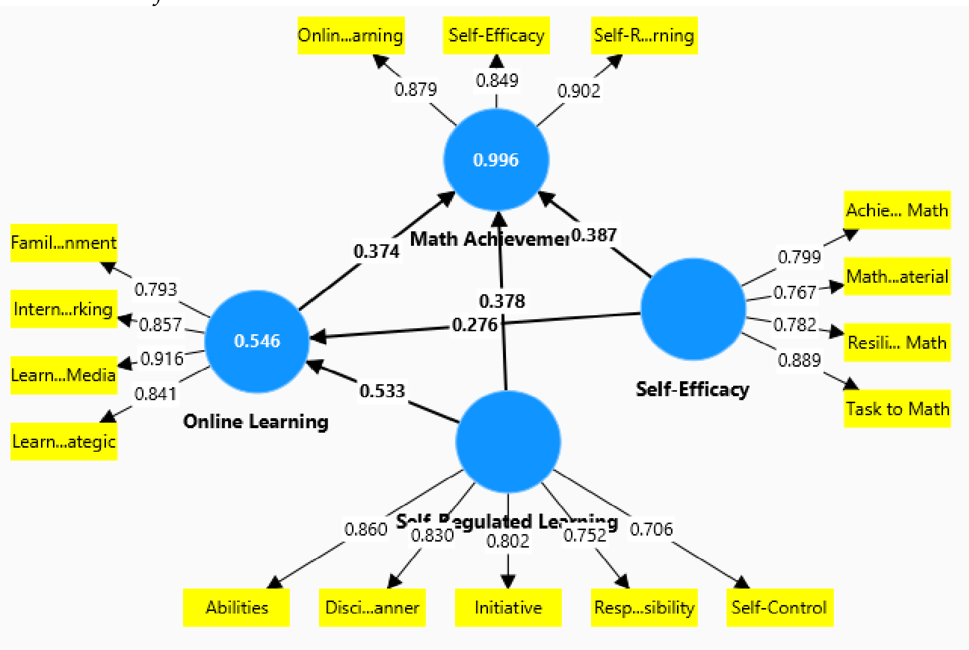


Table 3
Contracts Reliability and Convergent Validity Results

	CR (rho_c)	*AVE*
Math Achievement	0.909	0.768
Online Learning	0.914	0.727
Self-Efficacy	0.884	0.657
Self-Regulated Learning	0.893	0.627

The Heterotrait-Monotrait Ratio (HTMT) was used to assess discriminant validity. The results of this analysis are presented in Table 4. The estimated HTMT values ranged from 0.69 to 0.89, which remain below the threshold of 0.90 recommended for establishing discriminant validity (Roemer et al., 2021). Additionally, the HTMT value for each indicator was greater than the correlations with other indicators, further confirming that discriminant validity was achieved in this model.

Table 4
Heterotrait-Monotrait Ratio (HTMT)

	Math Achievement	*Online Learning*	*Self-Efficacy*	*Self-Regulated Learning*
Math Achievement				
Online Learning	0.898			
Self-Efficacy	0.879	0.697		
Self-Regulated Learning	0.873	0.793	0.719	

The next step was to identify the relationships between the construct variables. The structural model estimation was analyzed using the bootstrapping technique with 5000 resamples, which provided estimates of standard errors. The results of the direct relationships between variables, evaluated at a 5% significance level, are presented in Table 5. The indirect relationships are shown in Table 6. The analysis revealed that all construct variables were significantly related, both through direct and indirect pathways.

Table 5
Direct Effect

Relationship	*Original sample*	*T-statistics*	*p-values*
Online Learning → Math Achievement	0.374	23.441	<.001
Self-Efficacy → Math Achievement	0.387	32.467	<.001
Self-Efficacy → Online Learning	0.276	3.031	0.002
Self-Regulated Learning → Math Achievement	0.378	26.634	<.001
Self-Regulated Learning → Online Learning	0.533	6.277	<.001

Table 5 shows that mathematics achievement is directly influenced by self-efficacy, self-regulated learning, and online learning. In addition, mathematics achievement is indirectly influenced by self-efficacy through the moderating effect of online learning. Similarly, self-regulated learning also indirectly influences mathematics achievement through online learning. These indirect effects are presented in Table 6. The adjusted R-square values for online learning and mathematics achievement are 0.996 and 0.536, respectively, indicating the proportion of variance explained by the model for these two endogenous variables.

Table 6
Indirect Effect

	Original sample	*T-statistics*	*p-values*
Self-Efficacy → Online Learning → Math Achievement	0.103	3.025	.002
Self-Regulated Learning → Online Learning → Math Achievement	0.200	5.941	<.001

4. Discussion

Based on the results of this research, mathematics achievement is directly influenced by online learning, self-regulated learning, and self-efficacy. When online learning acts as a moderating variable, mathematics achievement is also indirectly influenced by self-efficacy and self-regulated learning. Online learning itself has a significant direct influence on mathematics achievement, contributing 37.4% to the variance, while the remaining 62.3% is explained by other unobserved variables. The success of online learning is shaped by four key dimensions: the use of internet networking, learning media, learning strategies, and support from the family environment. These dimensions contribute 85.7%, 91.6%, 85.7%, and 79.3% respectively to online learning. The greatest influence is shown by the use of learning media and learning strategies. This finding aligns with previous research indicating that learning media significantly impacts online learning (Noori, 2021) and that teaching strategies involving prediction, observation, and explanation are essential for the effective implementation of online learning (Jiang & Li, 2024). Since mathematics is an abstract subject, learning it effectively requires concrete visualization. Students should not be burdened merely with assignments; the development of solid knowledge competencies is essential for applying mathematics in problem-solving (Wang et al., 2023).

Students in this study were aged 13–14 years, a stage classified as adolescence. At this age, students may struggle to maintain focus during lessons, which can be influenced by both interest in the subject matter and cognitive aptitude (Hobbiss & Lavie, 2024). They may also face challenges in interpreting situations (Lan et al., 2023). Online learning will be more meaningful when students not only understand themselves but are also able to actively shape and develop themselves in new ways. This highlights why learning strategies are a critical dimension in the implementation of online learning.

Online learning, also referred to as non-face-to-face learning, is conducted using digital platforms such as WhatsApp, Zoom, Google Meet, Google Classroom, and various e-learning systems. During online learning, students must seek out information and reference materials to complete their assignments. They need to exercise self-regulation to plan and manage their study time effectively, which in turn enhances their competencies (Lai & Hwang, 2016). Appropriate learning strategies play a vital role in supporting the learning process and achieving educational objectives.

The family environment is another dimension that significantly influences online learning. Parents, as part of this environment, play an important role. The study found that parental involvement correlated positively with the success of online learning. During online learning, students independently seek information related to assignments and materials provided by educators, benefiting from the flexibility of accessing knowledge anytime and anywhere.

Self-regulated learning directly influences mathematics achievement by 37.8%. It is measured through five dimensions: belief in self-abilities, disciplined behavior, responsibility, self-initiative, and self-control. All five dimensions were shown to significantly measure self-regulated learning. Self-regulation helps students build knowledge, modify their cognition, and enhance motivation to achieve learning goals (Pardo et al., 2017). It supports students in various educational contexts, particularly in developing skills beneficial for science education (Andrew & Erin, 2021). Self-regulated learning also has an indirect effect of 20% on mathematics achievement, a figure slightly lower (by around 18%) compared to its direct effect. Its direct effect on online learning is even greater at 53.3%, underscoring the critical role of self-regulation in online environments. This ability influences knowledge competence, academic performance, creativity, and long-term learning success (Li, 2024). When students act with discipline, initiative, and responsibility, self-regulated learning fosters creativity and independence, aligning with findings that learning initiative correlates with learning independence (Nufus et al., 2024). This is particularly important as self-regulation in children and adolescents tends to be less developed compared to adult learners (Xu et al., 2023).

Self-efficacy was also found to significantly influence both mathematics achievement (38.7%) and online learning (27.6%). Indirectly, self-efficacy affects mathematics achievement by 10.3% through the moderating role of online learning, though this impact is relatively small. The direct effect of self-efficacy on mathematics achievement is stronger than its indirect effect. This supports previous findings showing that self-efficacy contributes positively to online learning (Mais et al., 2021; Prior et al., 2016). Self-efficacy helps streamline learning and enhance student productivity, as it reflects students' beliefs in their abilities to take action toward achieving specific goals (Capron Puozzo & Audrin, 2021). Other studies have shown that social support significantly affects both online learning and self-efficacy (Zheng et al., 2020). A supportive family environment has been shown to promote high self-efficacy (Hu et al., 2020), while effective learning strategies contribute to building self-efficacy in students (Roick & Ringeisen, 2018).

5. Conclusion

The results of this study show that mathematics achievement is directly influenced by online learning, self-regulated learning, and self-efficacy. When online learning functions as a moderating variable, mathematics achievement is also indirectly influenced by self-efficacy and self-regulated learning. However, mathematics achievement during the implementation of online learning was not directly influenced by self-regulated learning or self-efficacy. This suggests the need for further investigation into other factors that might affect mathematics achievement if online learning is applied continuously over a full semester. In this context, the characteristics of the research subjects may also influence the findings. Students aged 13–14 years are in a transitional stage of self-regulation and often struggle to maintain focus during lessons. As a result, their awareness of the importance of scientific knowledge may still be limited. Therefore, noncognitive competencies appear to be a key factor driving the success of online learning at this age.

Online learning can serve as a viable learning approach, especially as it aligns with ongoing technological advancements and offers solutions to some of the challenges of conventional learning. However, its application must account for various influencing factors to make a meaningful contribution to mathematics achievement. Blended learning could be considered as an alternative strategy, particularly when online learning must be implemented over extended periods.

This study provides insights into the factors that affect the implementation of online learning in grade VIII. The findings could inform the design of blended learning strategies if online learning continues to be necessary. It is important to note that this research was limited to academic performance as it relates to knowledge and skill competencies. Future studies might consider additional measures of academic performance, such as creative thinking ability, logical reasoning, critical thinking, and other cognitive skills. Expanding the range of measurements could offer a more comprehensive assessment of mathematics achievement.

Author contributions: Each author made an equal contribution to the current study and has read and given their approval to the article's final published version.

Declaration of interest: The authors declared that there were no potential conflicts of interest.

Data availability: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethical statement: All participants who took part in the study provided their consent for participation, data collection, and analysis of the collected data. All personal information that could lead to the identification of participants has been removed. No additional ethical approval was required.

Funding: No funding source is reported for this study.

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