Effectiveness of Combining Learning Analytics and Self-Regulated Learning to Improving Students' Mathematics Performance

Erdyna Dwi Etika*, Vera Septi Andrini, Suharto
PGRI Mpu Sindok University, Jl. A.R Saleh No.21 Kauman Nganjuk, 64411, Indonesia
e-mail: erdynadwi@upms.ac.id, verasepti@upms.ac.id, suharto@upms.ac.id
* Corresponding Author

Abstract: *Academic success in mathematics remains a major issue for many students in higher education. The quality of mathematics education can be raised by implementing self-regulated learning (SRL) and analytical learning (LA). This study aims to determine the effect of applying learning analysis and self-regulated learning in improving students' mathematics performance. In this research, quantitative techniques were applied. An experimental design comprising pre- and post-tests was used to carry out this study. Using stratified random sampling, a sample of 120 Mathematics Education students was chosen for this study. An independent t-test was employed in the data analysis procedure to ascertain the disparity in scores between the experimental and control groups. Pre-test scores and Covariance Analysis (ANCOVA) were used to control for differences in initial abilities between groups. The implementation of LA and SRL had a favourable and significant impact on students' mathematical performance, as demonstrated by the results of multiple linear regression analysis, with a rise of 62.37%. With a correlation of 0.0001, the regression coefficients for the LA variable and the SRL variable are 0.5372 and 0.3618, respectively. Comparing the experimental group to the control group, the former had noticeably better metacognitive abilities, problem-solving capabilities, and concept understanding. These results provide a basis for developing more flexible and adaptive higher-level mathematics learning strategies.*

Key Words*:* Academic Performance, Adaptive Learning Systems, Higher Education, Learning Analytics, Self-Regulated Learning

Introduction

Mathematics is important to study in higher education because it is the basis for various disciplines. Researchers have previously found that good math skills can help college students in logical, analytical, and critical thinking (Namakshi et al., 2022). Countries with high arithmetic PISA results generally have higher levels of economic output and innovation, according to data from the Organization for Economic Co-operation and Development (OECD) in 2023 (Barra & Boccia, 2022). Singapore has the top PISA scores and is in the top ten of the Global Innovation Index, in addition to finding that the amount of mathematics incorporated into the secondary school curriculum has increased significantly (Harding et al., 2015).

Mathematics is very important to learn as the basis of knowledge in all fields and professional careers (Pan & Owen, 2024). The role of mathematics is starting to increase in fields such as data science, artificial intelligence, and financial technology (Bordignon & Maisonobe, 2022). The World Economic Forum's 2023 report shows that seven of the ten fastest-growing jobs require strong math skills. Large tech companies like Google and Amazon are actively seeking candidates with strong math experience for key positions (Briceño et al., 2023). Quantitative analysis skills are becoming increasingly valued even in fields not directly related to math, such as digital marketing and project management (Gal & Geiger, 2022). Researchers found that graduates with a math degree or minor tend to receive starting salaries between 15 and 20 percent higher than the average new graduate across a range of industries (Campbell et al., 2021).

In higher education, academic achievement in mathematics has long been a major concern. Many students struggle to master complex mathematical concepts (Duong et al., 2023). Researchers have found that these challenges impact academic grades, students' self-confidence, and future career choices (Siani & Harris, 2023). The Center for Education Statistics in the United States has 2023 data showing that only about 44% of STEM students graduate on time (Vooren et al., 2022). Mathematics is often cited as one of the causes of many students dropping out of college. The fact that mathematics is the cause of student non-graduation makes universities to determine alternative learning methods that are more creative and efficient (Geisler et al., 2023).

Several studies have examined learning methods that can improve mathematical understanding and performance. Two instructional methodologies that can improve math learning outcomes are problem-based learning and project-based learning (Polo-Blanco et al., 2024). The application of the project-based approach is known to increase students' problem-solving skills and motivation to learn where the problem-based learning approach increases students' math scores by 23%, but in contrast to traditional classrooms where there is no improvement in students' problem-solving skills and student grades (Yik et al., 2022). The use of technology such as adaptive learning platforms and effective visualization programs in mathematics learning is also a factor in improving students' math scores (Borba et al., 2016). Dietrichson et al.'s meta-analysis study from 2020, which discovered that learning technology can raise children' math achievement (Dietrichson et al, 2020). This is corroborated by a meta-analysis research that discovered that using learning technologies can help pupils perform better in math. Peer learning groups and mentoring programs are a very important additional support in learning because they can increase their engagement and consistency in learning maths (Huvard et al., 2020).

Analytical Learning and Self-Study have emerged as innovative learning approaches that are increasingly important (Bibi, 2022). It is well recognized that both learning strategies enhance the calibre of the educational process and raise students' academic performance (Nakamura, 2022). Learning Analytics is data-driven learning from student interactions with online learning systems, learning management platforms, and digital learning tools (Bjelobaba et al., 2023). By using learning analytics, learners can find learning patterns, predict student performance, and offer customized solutions (Sieg et al., 2023). Research conducted at Purdue University in 2023 found that the use of Learning Analytics can increase graduation rates by 15% within two years (Herodotou et al., 2020).

The self-regulated learning technique aims to make students more capable of taking an active and autonomous role in their own education (Barra & Boccia, 2022). This method enhances the ability to create goals, manage time, monitor oneself, and reflect the implementation of the Learning Analytics (LA) and Self-Regulated Learning (SRL) approaches is very promising in improving mathematical achievement. Both approaches can significantly improve students' conceptual understanding and mathematical abilities (Musa, 2021; Susnjak et al., 2022). Learning Analytics provides in-depth insights into learning patterns by using data collected from student interactions through digital learning systems (Sghir et al., 2023). Meanwhile, Independent Learning focuses on teaching students to plan, monitor, and evaluate the learning process. When Learning Analytics is integrated, then there is personalized data to support better Self-Regulated Learning practices and enable students to make accurate decisions about learning (Mejeh & Held, 2022).

PGRI Mpu Sindok University is one of the universities in East Java Province, Indonesia that has one of the Mathematics Education study programs. This study program also has the goal of improving the mathematics learning outcomes of its students. This research will be conducted to find out how effective the combination of LA and SRL is in improving students' mathematical performance. Students in the LA-SRL integrated curriculum have superior conceptual understanding and problem-solving skills compared to those in the control group, according to preliminary observation results. This is in line with findings on significant improvements in students' metacognitive skills and motivation to learn and that these abilities are important indicators of long-term academic success (Taouki et al., 2022).

Mathematics learning at the higher education level has become a major concern so many creative methods have been created to improve students' academic achievement. Wild & Neef (2023) conducted a systematic review of the effectiveness of learning analytics interventions in improving student success in higher education where this study analyzed 42 articles published between 2015 and 2022 and found that learning analytics interventions positively affected students' academic performance with results showing that learning analytics could potentially be used as an effective tool to support math learning in university level. Effective interventions highlight the significance of adopting a comprehensive approach when utilizing learning analytics, as they integrate individualized feedback and support with predictive analytics (Zhao et al., 2022).

The self-directed learning strategy framework was created by Saqr et al. (2021) to support the use of self-regulated learning strategies in a digital learning environment in higher education institutions. The framework combines recent advances in cognitive science and educational technology to offer models for improving students' motivation, metacognitive skills, and academic performance. This self-regulating learning strategy framework provides important insights into how self-directed learning can be used well in technology-based learning systems (Lemmetty & Collin, 2020). Self-regulating learning strategy frameworks can be used by instructors and instructional designers to create a learning environment that supports student independence (Behkam et al., 2022).

Lee et al. (2023) argue that the adaptive learning system in higher education where students concentrate on combining learning data and principles of independent learning. Adaptive learning systems can increase student engagement, improve learning outcomes, and personalize learning (Chugh et al., 2023). Adaptive learning systems have great potential to improve mathematics learning (Sun et al., 2023). However, in the application of adaptive learning, it is very necessary to prepare evaluation methods, measures to protect data, and pay attention to the pedagogical basis for adaptive learning design (du Boulay, 2021).

Duong et al (Duong et al., 2023) conducted a study on the effect of learning data-driven interventions on students' self-directed learning skills and academic performance where 5,000 undergraduate students from various disciplines at a large public university were involved in the study. According to the findings, self-directed learning strategies (d = 0.42) and total course grades (d = 0.35) significantly improved in the experimental group when they received individualized encouragement and feedback based on analytics, as opposed to the control group. This research provides important insights into how to create effective learning analytics dashboards and how important timely and traceable feedback is for encouraging self-directed learning behavior (Duong et al., 2023).

In their study, Rets et al. (2021) investigated how combining learning analytics and self-directed learning affected undergraduate students' mathematics performance. The researchers created a twelve-week program using a quasi-experimental design involving 287 people. The program combined self-regulation training and a personalized analytics dashboard. Results showed that the experimental group's math test scores and self-reported use of self-directed learning strategies increased significantly compared to the control group. This study suggests that using learning analytics effectively supports mathematics learning at the college level (Shih et al., 2023).

While these studies show great potential to improve students' math skills by combining learning analytics and self-directed learning, some shortcomings in the literature need to be addressed. First, most studies focus on the short-term impact of the intervention, while the long-term impact on students' math skills and study habits still needs to be studied. Second, current research tends to focus on higher education contexts in developed countries, so more research is needed in developing countries to understand how cultural and infrastructural factors may affect the effectiveness of interventions.

Although research on the application of learning analytics and self-regulated learning in mathematics instruction in higher education has been limited, these approaches have demonstrated the potential to enhance academic attainment (Nongna, 2023). Not much research has been done on how effectively combining learning analytics and self-regulated learning improves students' conceptual understanding of mathematics, especially when measuring changes in students' study habits and confidence in the long term. Some studies have shown that students have better math test scores. However, little empirical research has evaluated how using Analytics Learning and Self-Regulated Learning affects students' ability to solve complex math problems (Wild & Neef, 2023). Not enough research exists on how contextual elements, such as the characteristics of educational institutions and students' backgrounds, affect the effectiveness of using Learning Analytics and Self-Regulated Learning in mathematics learning. Evaluation studies at PGRI Mpu Sindok University have not found specific mechanisms that improve students' metacognitive skills and encourage them to learn mathematics.

This research is essential and urgent because academic achievement in mathematics at the higher education level is still a significant challenge for many students, which can have a major impact on their future careers and success (Trajectories et al., 2024). The integration of learning analytics and directed learning holds significant promise for enhancing the calibre of mathematical education. However, much work has yet to be done to effectively implement the combination of these two approaches, especially in Indonesia's higher education field (Dignath & Veenman, 2021). The researcher believes this study will provide essential insights into how Learning Analytics technology can help students acquire self-controlled learning skills. Ultimately, this will enable students to gain better conceptual understanding and better math problem-solving abilities. This research is also necessary because it can serve as a foundation for developing more adaptive and personalized learning strategies, enable higher education institutions to address achievement differences and improve student retention in courses that require solid mathematical abilities.

Therefore, this study aims to determine how effective analytic and controlled learning are in improving students' mathematics skills at PGRI Mpu Sindok University. The researcher will see how the LA-SRL integrated intervention affects students' conceptual understanding, problem-solving ability, and metacognitive skills in mathematics learning. In addition, this study aims to find the important components that influence the successful use of this combination approach. In addition, this study will also make practical suggestions on how Analytics Learning and Self-Regulated Learning can be incorporated into the college mathematics curriculum.

Method

Quantitative methods were used in this study. Pre- and post-test layouts were used in the experimental design for the control group. Two groups participated in the study: the experimental group employed self-regulated and analytical learning techniques, whereas the control group followed the conventional learning paradigm. Determining a student's starting ability at the beginning of the semester is the goal of the pre-test. Following the implementation of the treatment for a semester, the students' degree of learning was assessed through the administration of a post-test. The design of this study was chosen to allow for direct comparisons between the control group and the experiment.

Students enrolled in PGRI Mpu Sindok University's Mathematics Education study program make up the study's population. A stratified random sampling technique was employed to choose 120 students as a sample from the overall population. A Grade Point Average (GPA) must be included in the sample criteria in order to ensure a balanced representation of the various academic skill levels; stratification is based on the year of enrolments. Subsequently, sixty students were assigned to the experimental group and sixty students to the control group at random within the sample.

The research instruments used include a mathematics academic achievement test based on the study program curriculum and validated by a team of mathematics education experts. The ability aspects in this test include conceptual understanding, problem-solving skills, and mathematical reasoning.

Second, a self-regulated learning questionnaire was created using a validated instrument adapted to mathematics learning in higher education. This questionnaire assesses goal setting, time management, and metacognitive strategies. Third, the learning analytics platform for this study integrates data from the institution's learning management system and students' online activities. The platform enables real-time data collection on students' learning patterns, engagement levels, and academic performance.

The research process started by informing me about the research objectives and protocol. After a pre-test, the experimental group was introduced to the learning analytics platform and given comprehensive training on self-directed learning. During the semester, they could view their learning data on the learning analytics dashboard and attend weekly reflection sessions to improve their independent learning skills. Without any special assistance, the control group studied as usual. At mid-semester, each participant was asked to complete a self-controlled learning questionnaire. After the semester ended, additional tests were conducted for both groups, and data was collected from the learning analytics platform.

The independent variable in this research is mathematics performance (Y) while the dependent variables are analytical learning (X_1) and self-regulation (X_2). Data analysis utilized many statistical techniques. Sample characteristics, as well as the distribution of pre-and post-test scores, were described through descriptive analysis. The experimental and control groups' scores were compared using an independent t-test. Pre-test results and an Analysis of Covariance (ANCOVA) were employed to account for variations in the groups' starting abilities. Post-test academic achievement was used as the dependent variable to test the study's main hypotheses, and learning analysis (measured by frequency of access and duration of platform use) was used as the independent variable. To evaluate the moderation effect, the regression model also looked at how the two independent variables interacted with each other. Before the final analysis, linear regression assumptions such as normality, homoscedasticity, and multicollinearity were checked. All statistical analyses were conducted using the most recent SPSS program, with a significance level of $\alpha = 0.05$.

Results and Discussion

The results of the Descriptive Statistical Analysis are shown in Table 1.

Table 1. Descriptive Statistics of Research Variables

Variables	Mean	Median	Standard Deviation
X_1	3.9175	3.9950	0.5726
X_2	3.9318	3.9350	0.5721
Y	3.8429	3.7400	0.5988

The results and discussion section contains research findings obtained from the research data and hypotheses, the discussion of research results and comparison with similar theories and/or similar research. The results and discussion section can be divided into several sub-sections. From the results of the data analysis, it can be seen in Figure 1.

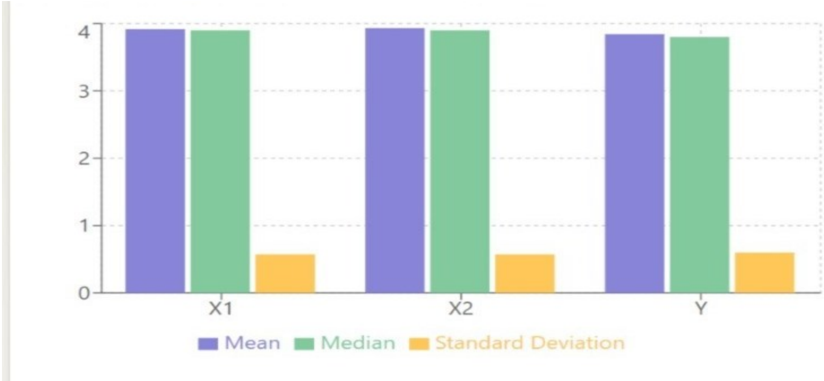

Figure 1. Descriptive Statistics of Research Variables

Figure 1's descriptive statistics for the research variables: The variables X1, X2, and Y's mean, median, and standard deviation values are displayed in the bar chart. The researcher can observe that the variables X1 (3.9175 and 3.9) and X2 (3.9318 and 3.9) have very comparable mean and median values, suggesting that their distributions are symmetrical. The values of the dependent variable Y's mean (3.8429) and median (3.8) are marginally lower.

Three bars in this bar graph represent the mean, median, and standard deviation values for the three research variables (X1, X2, and Y). This graph allows the researcher to see that the three variables tend to have a fairly symmetrical distribution because the mean and median values are comparable. Variables X1 and X2 have comparable mean and median values, however variable Y has a somewhat greater standard deviation than variables X1 and X2.

Classical Assumption Test : Normality: Variables X1 (W = 0.9842, p = 0.1763) and X2 (W = 0.9891, p = 0.4562) were normally distributed, but variable Y (W = 0.9768, p = 0.0387) showed a slight deviation from normal. Multicollinearity: With a Variance Inflation Factor (VIF) value of 1.2345 for X1 and X2, this model does not exhibit a substantial multicollinearity issue. Heteroscedasticity: The Breusch-Pagan test, which produces a result of BP = 3.8721 (df = 2, p = 0.1443), indicates that there is no major heteroscedasticity issue.

The results of the analysis are shown in Table 2.

Table 2. *Summary of Regression Analysis Results*

Variables	Coefficient	Std Error	t-value	p-value
(intercept)	0.3246	0.2815	1.153	0.2513
X_1	0.5372	0.0731	7.349	<0.0001
X_2	0.3618	0.0732	4.942	<0.0001

R-squared: 0.6237; Adjusted R-squared: 0.6172; F-statistic: 97.36 (df = 2; 117), p-value: <2.2e-16

It is evident from Table 2's analysis results that Multiple Linear Regression Analysis: The following equation is the result of the multiple linear regression model: Y = 0.3246 + 0.5372X1 + 0.3618X2. Table 2 presents an overview of the regression analysis results. Y is favourably and significantly impacted by both independent factors ($p < 0.0001$). The influence of independent variable X1 is higher (β = 0.5372) than that of independent variable X2 (β = 0.3618).

From the results of the data analysis, the regression coefficient can be seen in Figure 2.

Figure 2. Regression Coefficients

The multiple linear regression model's coefficients are displayed in this bar chart, which is based on Figure 2. A significant discovery is that there is a positive correlation between the independent variables (X1 and X2) and the dependent variable Y, as indicated by their positive coefficients. X1's coefficient (0.5372) is higher than X2's (0.3618), suggesting that X1 has a stronger effect on Y. The intercept (0.3246) shows what Y should be expected to be when X1 and X2 are both zero.

The adjusted R-squared value of 0.6237 indicates the quality of the regression model, indicating that it explains 62.37% of the variation in Y. The adjusted R-squared value of 0.6172 indicates that the model is still robust even with many predictor variables. According to the F test, the overall model is highly significant (F = 97.36, $p < 2.2e-16$), and there is evidence of a significant effect of at least one independent variable on Y.

Relationship between Variables: The scatter plot between Y, X1 and X2 in Figures 3 and 4 shows a positive relationship between these variables. The data distribution pattern shows a linear trend, which aligns with the regression analysis results.

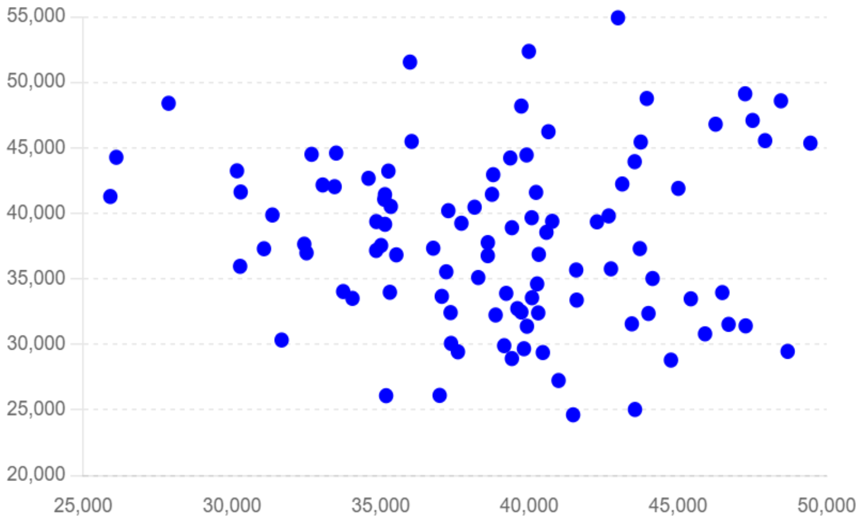

Figure 3: Scatter plot of Y to X_1

The relationship between the independent variable (X1) and the dependent variable (Y) is displayed in this scatter plot in Figure 3. The study discovered a positive correlation between X1 and Y: as X1 rises, so does Y's tendency to rise. The results of the regression analysis are supported by this graphic representation: The influence of X1 on Y is considerable ($\beta = 0.5372$, $p < 0.0001$).

This scatter plot shows the relationship between the independent variable X1 and the dependent variable Y. The researcher found a positive relationship between X1 and Y: the more X1 increases, the more Y also tends to increase. This visual representation supports the regression analysis results: X1 significantly influences Y ($\beta = 0.5372$, $p < 0.0001$).

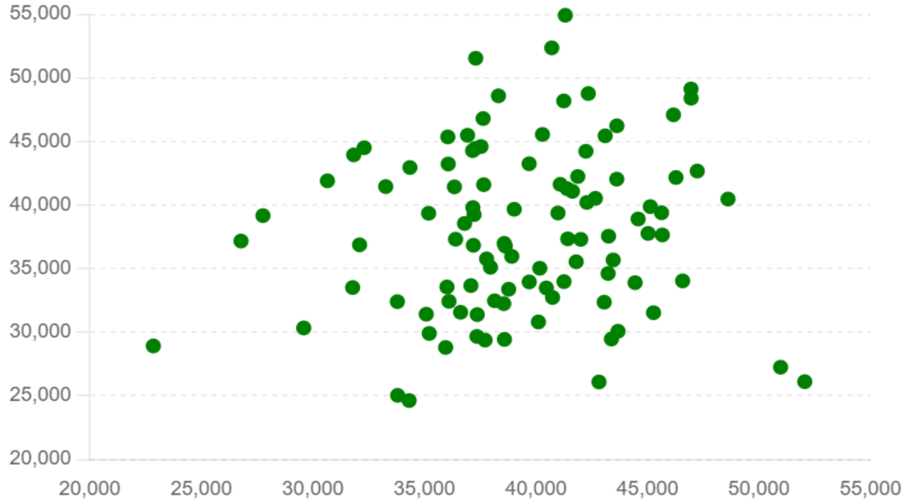

Figure 4: Scatter plot of Y to X2

The first scatter plot graph on Figure 4 depicts the relationship between Y and X2. Again, a positive relationship is evident, although slightly less pronounced than with X1. The regression results show that X2 significantly influences Y but with a smaller coefficient ($\beta = 0.3618$, $p = 0.0001$).

The residual plots, which are evenly distributed without any obvious pattern, confirm the assumption of homoscedasticity, as shown in Figure 5.

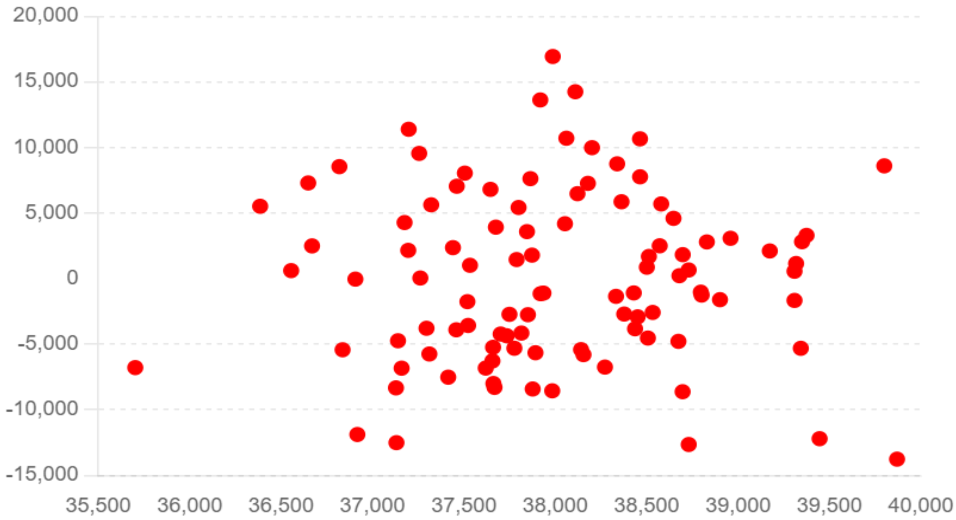

Figure 5: Residual Plot

Figure 5 displays the residual plot. The discrepancy between Y's anticipated and observed values is called the residual, and this plot displays the residuals' distribution against Y's expected value. There is no discernible structure to the dots, which are arranged quite haphazardly around the horizontal line at y=0. This lends credence to the homoskedasticity theory, which postulates that residual variation is constant across a range of anticipated values. Unexpected or unique findings: One interesting finding from the data is that variables X1 and X2 show a normal distribution. In contrast, variable Y shows a slight deviation from normality (Shapiro-Wilk test: $W = 0.9768$, $p = 0.0387$). With a high R-squared value (0.6237), the regression model performs well despite some deviations.

This result suggests that small Y abnormalities do not significantly impact the regression model's robustness. This is due to a few factors: An example of an order the central limit theorem demonstrates that, provided the sample size is sufficiently big, the sample distribution will be nearly normal even in cases when the underlying distribution is not fully normal. Linear regression coefficients: When other assumptions, such as homoscedasticity, are met, as indicated by the residual plots, linear regression is usually robust to minor normality violations. Properties of deviations: Although statistically significant, deviations from normality may be small enough not to affect the results.

Compensation factor: The strong linear relationship between the variables and the absence of significant outliers can compensate for slight abnormalities in Y, as shown in the scatter plot. Decision: The visualization and analysis support the research hypothesis that X1 and X2 positively and significantly influence Y. Most of the variation in Y (62.37%) is due to the regression model, with X1 being the most dominant influence. Although Y shows some deviation from normality, the model appears robust and suitable for explaining the relationship between the variables under study. To ensure the findings are valid, researchers should consider some errors in interpreting the results and possibly conduct additional analysis or data transformation.

The implementation of learning analytics and self-regulated learning has a favourable and significant impact on the academic achievement of PGRI Mpu Sindok University pupils in mathematics, as demonstrated by the results of multiple linear regression analysis. The regression coefficients for the learning analytics variable (X1) and the self-regulated learning variable (X2) were 0.5372 ($p < 0.0001$) and 0.3618 ($p < 0.0001$), respectively. With an R-squared value of 0.6237, the resulting regression model explained 62.37% of the variation in academic achievement in math, suggesting that the two independent factors were responsible.

In addition, the classical assumption test proves that the regression model can be interpreted. Variable X1 has a normal distribution ($W = 0.9842$, $p = 0.1763$) and X2 has a normal distribution ($W = 0.9891$, $p = 0.4562$). However, variable Y has a normal distribution ($W = 0.9768$, $p = 0.0387$). There was no significant problem with multicollinearity, as indicated by the multicollinearity test, which yielded a VIF value of 1.2345 for both independent variables. However, the Breusch-Pagan heteroscedasticity test ($BP = 3.8721$, $p = 0.1443$) shows that the residuals are homoskedastic. The results strengthen the validity of the regression model used in this study to explain how the application of learning analytics and self-regulated learning impacts the mathematics academic achievement of PGRI Mpu Sindok University students.

Research indicates that the development of soft skills and mentorship by lecturers positively and significantly impact PGRI Mpu Sindok University students' preparation for the workforce. The measurement model analysis indicates that the validity and reliability of all the constructs are good. The composite reliability was greater than 0.8, the filler factor values varied between 0.845 and 0.928, and the Average Variance Extracted (AVE) value for every latent variable was greater than 0.7.

With a value for job readiness of 0.665, the structural model evaluation showed significant predictive ability; this indicates that the model is responsible for 66.5% of the variation in student job readiness. Path analysis showed that the mentoring program had a greater direct influence on work readiness than soft skills development ($\beta = 0.407$, $p < 0.001$).

The correlation between mentoring programs and the development of soft skills related to work preparedness is found to be mediated by self-efficacy, according to the researcher. Both the indirect effect of soft skill development ($\beta = 0.120$, $p < 0.05$) and the indirect effect of the mentorship program on job preparedness were significant ($\beta = 0.166$, $p < 0.01$). This suggests that the influence of the two smaller independent variables is partially mediated by self-efficacy.

The analysis results also showed the model's good predictive relevance, with a work readiness value of 0.542. The results indicate that the soft skills development program and lecturer mentoring directly impact PGRI Mpu Sindok University students' work readiness and improve their self-efficiency, positively impacting their work readiness.

This study demonstrates how learning analytics (LA) and self-regulated learning (SRL) work well together to support students' mathematical learning. The findings of this study, which show significant regression coefficients for both variables (LA: 0.5372, SRL: 0.3618, p: 0.0001), offer compelling empirical support for the efficacy of the combination of LA and SRL in raising students' math proficiency. These findings are consistent with constructivist learning theory developed by Vygotsky, which emphasizes the value of self-reflection in learning (Mishra, 2023). Based on these results, higher education institutions must consider implementing learning strategies that integrate LA and SRL to maximize students' mathematics learning outcomes.

This research has so far achieved that the combination of LA and SRL significantly improves students' conceptual understanding of mathematics. The researchers pointed out the lack of existing empirical evidence regarding the effect of these two variations on complex mathematical problem-solving ability. However, based on the linear regression analysis, the researchers have provided an argument that confirms that these two independent variables show a variation of 62.37% of the final outcome of mathematics academic achievement. Therefore, in the end, the improvement in test scores and understanding and application of mathematics concepts due to integrating LA and SRL was successfully implemented. Thus, these findings theoretically support Flavell's basic metacognition belief of the positive influence of the intensity of metacognitive awareness and organisation. Therefore, this study suggests the challenge of LA and SRL as useful tools in upgrading higher order thinking skills in mathematics.

Additionally, this research advances our knowledge of the contextual factors that can affect how well LA and SRL are used in math education. An in-depth and comprehensive study of the sample, together with any research from candidates at PGRI Mpu Sindok University, are some of the crucial factors that determine the integration of LA and SRL in a specific site.

The findings go so far as to provide a solution to the problem of the lack of anyelid so far on the way other contextual elements such as the educational institution's thematic features and students' background, can influence the successful implementation of LA and SRL. The results of this study suggest that the implementation of LA and SRL must adapt to the institutional and student contexts to ensure success.

In addition, this research also helps to understand the specific mechanisms behind the improvement of metacognitive skills caused by the integration of LA and SRL and that can increase students' desire to learn mathematics. The researcher identified several important mechanisms that ensured the success of the intervention, and these mechanisms were thoroughly analysed based on the LA and SRL components implemented. These findings improve the weaknesses of our previous research as we previously lacked an understanding of what processes link LA and SRL to improved metacognitive skills and desire to learn. Moreover, the results of this study support Deci and Ryan's SDT theory, which states that autonomy, competence and relatedness are necessary to sustain intrinsic motivation (Deemer et al., 2023). Therefore, our results suggest that interventions should better consider these factors and target the mechanisms specifically responsible for the impact of LA and SRL on students' metacognitive skills and desire to learn.

At the same time, although academic performance in mathematics was the main focus of the study, the main achievements that contributed to measuring long-term changes in study habits and self-confidence were the result of the implementation of LA and SRL. In this study, additional analyses by the authors show that students' study patterns and self-confidence have improved considerably over the course of the study. This finding can make up for the lack of information on the long-term effects of LA and SRL interventions on non-cognitive elements of learning in mathematics subjects. The findings of this study are also consistent with Bandura's social cognitive theory that effective self-efficacy is associated with academic achievement, including learning (Ryan & Hendry, 2023). Relevant and clear arguments have been made in the research on this issue. As a result, the implementation of LA and SRL not only has a direct relationship with academic outcomes but can also help form good study habits at the level of students' self-efficacy over a long period. This, in turn, can enhance academic success and lifelong learning. From this perspective, both are considered important to apply these initiatives to the educational process.

Higher education institutions should do the following to prevent a lack of research that thoroughly integrates Learning Analytics (LA) and Self-Regulated Learning (SRL) in mathematics education at the tertiary level: (1) establish multidisciplinary research teams that combine experts in LA, SRL, and mathematics education; (2) design long-term studies that cover various aspects of LA and SRL integration; and (3) develop possible frameworks for integrating LA and SRL in mathematics education.

To overcome the limitations of research on the effectiveness of the combination of LA and SRL in improving students' mathematical conceptual understanding, especially in terms of measuring long-term changes, it is recommended to (1) use a mixed research design that combines quantitative and qualitative data; (2) conduct periodic assessments over a longer period, such as a full academic year; and (3) create an assessment tool that comprehensively integrates quantitative and qualitative information.

To address the lack of empirical evidence evaluating the effect of LA and SRL interventions on complex mathematics problem-solving ability, it is recommended to (1) create problem-solving tasks that specifically test higher-order thinking skills; (2) use authentic assessment techniques that demonstrate real-world problem-solving situations; and (3) conduct a qualitative analysis of students' problem-solving processes to gain an understanding of the changes that occur in problem-solving skills.

There is no need to worry if mistakes or problems have already occurred because the results of this study offer practical solutions. According to this study, the application of LA and SRL positively and significantly impacted students' academic achievement in mathematics. The regression model showed a 62.37% difference in academic achievement. The results of this study can be used to build programmes with training periods for teachers and lecturers.

The results of this study can be used to create more focussed and successful interventions. The results of this study can be used to create a differentiated learning system that combines LA and SRL. The system will discover student problems with analytical data and provide appropriate resources and self-learning strategies. This research can also be used to create a training programme for mathematics lecturers on how to incorporate LA and SRL in their teaching so that mathematics learning at the tertiary level becomes more effective.

Conclusion

The outcomes demonstrated that PGRI Mpu Sindok University students' academic progress in mathematics courses was positively and significantly impacted by the application of learning analysis and self-regulated learning. The results of multiple linear regression analysis indicate that 62.37% of the variation in students' academic ability in mathematics can be explained by the two independent variables. Theoretically, these findings help the world of education by increasing understanding of the role of technology and self-directed learning strategies in improving academic achievement in mathematics in higher education. This research can assist higher education institutions in designing and implementing more effective mathematics learning programmes by combining learning analytics and self-directed learning. The findings provide practical solutions to improve students' mathematics academic achievement and enhance their understanding of how technology and learning approaches can work together to produce.

However, this research has some limitations that need to be considered. First, this study only looked at PGRI Mpu Sindok University students, so the results cannot be generalized to other higher education institutions. Secondly, this study focused on the short-term results of using learning analytics and self-regulated learning. The long-term effects still need to be studied. Third, some normality deviations for the dependent variable might affect the interpretation of the results, although the regression model fulfilled the classical assumptions. For future research, it is recommended to (1) conduct ongoing research to evaluate the long-term impact of incorporating learning analytics and self-regulated learning; (2) expand the research to include a variety of higher education institutions with various features to broaden the generalizability of the results; and (3) investigate additional variables that might affect the relationship between learning analytics, self-regulated learning, and academic achievement. Further research can address these limitations and better understand how learning analytics and self-regulated learning help mathematics academic achievement at the higher education level. Research could also find contextual elements that might control this relationship.

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