A Predictive Model of Learning Independence: Integration of Social Platform and Self-Regulation in College Students

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Abstract: *In modern research in education, learning independence plays a very important role, especially in the digital era where flexibility implies alignment of endurance. Although most universities in Indonesia use online learning, the consequences of this in the form of academic independence are still unknown. This study intended to model learning independence built with online learning and self-regulation in University of PGRI Mpu Sindok students. The study was conducted among 120 students divided into high and low groups using a quasi-experimental design with group randomization. The multiple linear regression analysis result was the model $Y = 0.4923 + 0.6745X_1 + 0.2289X_2$, where Y signifies learning independence, X_1 signifies the Intuitiveness of using social learning platforms, and X_2 signifies self-regulation. Overall, the model provided significant results $p < 0.0001$ and explained 50.27% of students' learning independence variation. There is an absence in the impact of using X_2 self-regulation simultaneously as using X_1 self-regulation. This empiricism concentrates on creating experimental strategies that use self-regulation with technological and educational tools in order to increase students' academic independence-validated in line with the digital era.*

***Key Words**:* learning independence, social platform, self-regulation, predictive model

Introduction

Independence in learning is one of the focuses of modern education research. The importance of this topic is due to the instrumental role of developing students who can keep up with the changes in the world. Researchers define learning independence, learning independence is defined as a university student's capacity to take the initiative, set his/her learning objectives, choose appropriate learning strategies and evaluate the results of their learning (Konstantinidis et al., 2022). Learning independence is especially important in higher education because students must manage their time and resources effectively, particularly when completing complex academic tasks (Romero-Pérez & Sánchez-Lissen, 2022). Students with high learning independence have better academic performance (Trajectories et al, 2024). Their grade point average averages 0.5 points more than those with low learning independence. Moreover, in terms of long-term studies, Chen found that independence during college has a positive effect on career success and lifelong learning (Chen, 2022).

With the proliferation of technology and the availability of information, learning independence is increasingly important. Digital learning environments and online platforms are transforming education, so students must be more independent and proactive as some take their first steps toward realizing the full potential of the learning stage (Bjelobaba et al., 2023). Reviewing the UNESCO global survey, from respondents show that 78% believe that learning independence is the most important skill in supporting the digital age (Dadaczynski et al., 2021) . This development aligns with the World Economic Forum's "The Future of Jobs" report in 2023, with the top five candidate skills employers are looking for independent learning ability (Queralt, 2023). Therefore, researchers emphasize the importance of curriculum in enhancing students' learning ability. This not only helps students achieve better academic results now but also helps them be ready for the challenges on the road ahead and in the world of work.

Information and communication technology (ICT) have brought great changes to the world of education. It has changed the way students interact with each other and with subject matter (Doz et al., 2023). Researchers have shifted from traditional lecturer-centered learning models to more collaborative and learner-centered approaches in the last ten years (Bjelobaba et al., 2023). A recent report from the Organization for Economic Co-operation and Development (OECD) in 2023 showed that more than 70% of higher education institutions in OECD countries already use blended learning approaches, combining face-to-face and online learning. Social learning, such as Edmodo, Google Classroom, and Microsoft Teams, has become an important part of the contemporary education ecosystem (Banerjee et al., 2023) A study conducted by Stanford University in 2022 showed that using social learning sites can increase student engagement by 45% and improve average learning outcomes by 0.3 standard deviations (Badshah et al., 2021). In addition, according to a long-term study by the Massachusetts Institute of Technology (MIT), college students who actively engaged in social learning platforms significantly improved their ability to solve problems and think critically (Huang et al., 2024).

Social learning platforms created by major publishers have transformed teaching and created virtual places where students worldwide can collaborate and share ideas outside the classroom (Nematollahi et al., 2022). Researchers found that this model has facilitated online discussions, virtual collaborative projects, and customized preparation sessions that allow students to engage in peer learning, like group research in the classroom. UNESCO accessed 50,000 university students in a global survey published in 2023 across 100 countries. According to them, 82% of the respondents believe this model has made access to educational resources and learning tools impossible before legal online. 76% of them said that they felt closer to friends more during the experience, although seventeen days (Inan et al., 2024). However, the narrative authors also reported new problems. The indulgent digital environment exerts psychological pressure outside the classroom (Prodgers et al., 2023). Harvard University proved through its survey in 2022 that 35% of all competitive college students experience cognitive problems while together on several such platforms. Only then do the researchers advocate that changing digital literacy and information management is the key to maximizing different potentials (Weinstein, 2022).

Over the past few decades, educational research has been directed towards self-regulation in learning, also known as SRL. SRL is crucial in shaping individuals who can learn independently and successfully. SRL is an active and constructive process in which students set their own learning goals and strive to monitor, regulate, and control their cognition, motivation, and behavior, which are inevitably constrained by their goals and elements of the environmental context (Mejeh & Held, 2022). The recent meta-analysis of Lozano-Blasco et al., (2022) produced results based on 213 effect sizes of 85 empirical studies, with 38,906 participants. The study yielded a moderate positive correlation between SRL and academic achievement in college, the effect size shattering with r = 0.35. A longitudinal study of 500 college students over four years conducted by Chou & Zou (2020) showed that students with strong SRL skills were 30% more likely to graduate on time and had an average GPA of 0.5 points higher than peers with weak SRL. The findings encourage researchers to invest further effort in instilling SRL skills.

The three main components of SRL, namely planning, monitoring, and evaluation, work together to promote independent learning. Indicatively, students are likely to be efficacious in setting goals during the planning phase, selecting appropriate strategies, allocating resources during the monitoring phase, and assessing results against set goals during the evaluation phase. For example, an experimental study of 1,200 students from all departments of science conducted by Mejeh & Held (Mejeh & Held, 2022) found that the intervention of all three phases of SRL significantly improved KBL with an effect of 0.78. A large-scale IEA survey across 30 countries involving 50,000 students also found that 82% of respondents who coped with high SRL showed enhanced learning satisfaction and were ready for further learning (Li et al., 2023). Therefore, SRL modules should be included in the higher education curriculum to prepare students for the ever-changing academic and professional demands.

The main objective of this study is to create a predictive model of learning independence that addresses social learning platforms with self-regulation among PGRI Mpu Sindok University students. Based on this study, the researcher wanted to determine the way social learning platforms interplay with self-regulation components in the local environment. The master platform variables include frequency of use, types of interactions, and content quality. Self-stabilization components include goal setting, self-monitoring, and evaluation or blame. The researcher wanted to find the main factors influencing students' self-regulation—the method they used involved case analysis and in-depth analysis. Predictive models can also be generated to create more contextualized and effective provisioning interventions.

Method

In this study, the authors used a quasi-experimental design with a non-equivalent control group. For this reason, two groups were sometimes formed: an experimental group that received the social learning platform and a control group that used conventional learning. Pre-test and post-test tests were used to measure students' learning independence. At this stage, the method was used to evaluate the effectiveness of the social learning platform in assisting learning independence. It allowed for variation in the comparison between the experimental group that received the intervention and the control group that did not. The research participants were students of PGRI Mpu Sindok University. The sample size was 120 students divided into two groups of 60 people. The only possible and efficient way was to use the random sampling method. As mentioned, the period of this study was limited to two teaching semesters. That means that experts and respondents were selected using inclusion and exclusion criteria. Power analysis was used to calculate the sample size and confirm the data probability and statistical significance.

The materials. This work used three research materials. The questionnaire was designed to measure the frequency with which students use the social learning platform—this validated instrument. A test of self-regulated learning was designed to measure the level of student self-directed learning before and after the test. All the instruments were pretested for validity and reliability via an experimental study before being used in the major study. The summary of the ontological deforestation. The summary. Descriptive analysis was also employed to describe the sample characteristics. A multiple regression analysis was used to evaluate the interaction of independent variables on self-regulated learning. An independent t-test was used to compare the outcomes of the experimental and control groups. All statistical analyses are performed via the most current version of SPSS with a significance level of $p<0.05$.

This research was conducted in several stages. First, a preliminary study was conducted to identify problems and determine the focus of the research. Second, research instruments were developed, including the SL usage questionnaire, and self-regulation meter. The instruments were then validated through expert assessment and a limited group tryout. After the instrument was ready, a test was conducted to measure the extent of students' initial independence, SL usage, and self-regulation. Then, the experimental group was exposed to SL intervention combined with self-regulation strategies for one semester. The control group continued with the usual learning.

Quantitative data and qualitative data were also obtained from this intervention. While the authors monitored the class during the same period and focused on a sample of students during the intervention, they could record subjective experiences and provide additional useful information. The authors also used social network analysis to provide an overview of the patterns of student interactions within the learning platform. Posttests were tested at the end of the semester to measure the variables under study. While quantitative data was processed and analyzed based on descriptive and inferential statistics, qualitative data was analyzed using thematic coding techniques to identify salient themes.

In addition to classroom observations, in-depth interviews with a sample of students were conducted during the intervention period to obtain qualitative data. The research also obtained the results of social network analysis, which was used to map the students' movement patterns on the learning platform. The semester posttest was used as an equivalent study for post-intervention, which provided data on changes in the observed variables. During the intervention period, both quantitative and qualitative data were obtained. This study analyzed data with descriptive and inferential statistical methods on the incidence of pretest, posttest, and platform usage. Qualitative data was analyzed using thematic coding techniques to determine the themes and sub-themes in students' life experience variables.

The final data analysis involved integrating quantitative and qualitative results to develop a predictive model of learning independence. This model was then validated using cross-validation techniques to assess its generalizability. The analysis results are presented in tables, graphs, and narratives to comprehensively overview the research findings.

Results and Discussion

Descriptive Analysis

Descriptions were conducted as follows to provide an overall picture of the characteristics of the research sample. Of the 120 participants, 65% were female and 35% were male. The average age of the participants was 20.3 years, ranging between 18 and 23 years. The distribution of participants by study program was relatively even, with 25% for mathematics education, 23% for English, 22% for economics, 20% for science, and 10% for civics.

The results of the descriptive analysis for the main research variables are presented in Table 1:

Table 1. Descriptive Statistics of Research Variables

Variable Mean	Median	Std. Deviation
X1	3.9273	0.5853
X2	3.9145	0.5661
Y	3.8145	0.6214

The table 1. shows that the mean and median values for variables X_1 and X_2 are higher than for variable Y. The standard deviation of each variable is also relatively comparable, indicating a fairly consistent distribution of data.

Normality test (Shapiro-Wilk)

The classical assumption test was conducted prior to regression analysis. The results of the normality test using Shapiro-Wilk showed that variables X_1 ($W = 0.9832$, $p = 0.1641$) and X_2 ($W = 0.9901$, $p = 0.6425$) met the assumption of normality, while Y ($W = 0.9756$, $p = 0.0352$) deviated slightly from the normal distribution. The multicollinearity test yielded a VIF value of 1.0842 for both independent variables, indicating no serious multicollinearity problem. The heteroscedasticity test with the Breusch-Pagan method yields $BP = 3.9217$, $df = 2$, and $p = 0.1408$, indicating homoscedasticity.

Regression Analysis

The variables X_1 and X_2 are shown in this bar graph with their regression coefficients and t-values. It can be seen that variable X_1 has a higher coefficient and t-value than variable X_2, indicating that X_1 has a greater influence on the dependent variable (Y). Regression result is shows in figure 1.

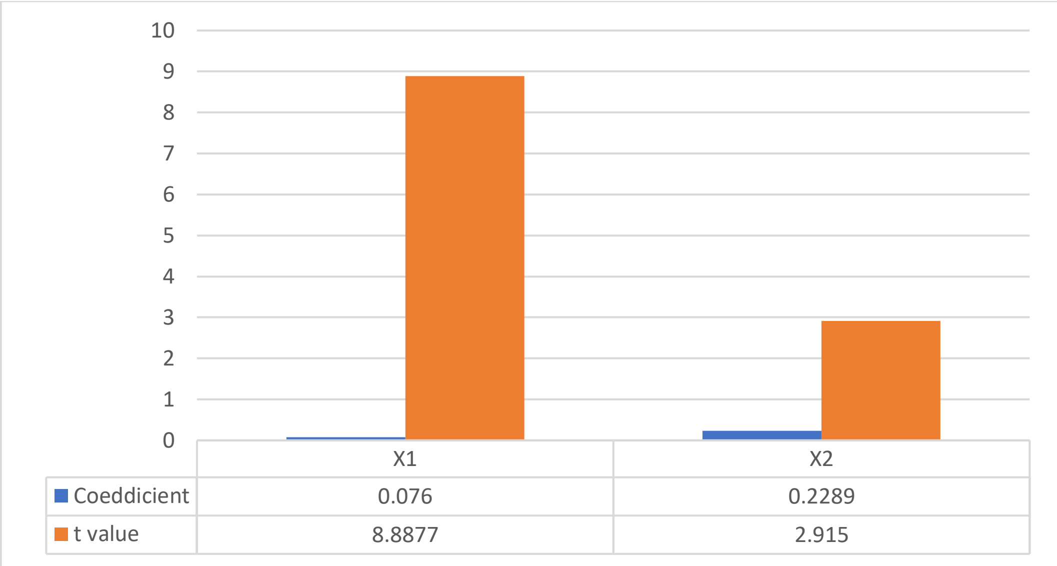

Figure 1. Regression result

The regression analysis results are presented in Table 2:

Table 2. Regression Analysis Results

Variable	Coefficient	Std Error	t-value	p-value
(Intercept)	0.4920	0.3651	1.348	0.1804
X1	0.0760	8.8877	<0.0001	
X2	0.2289	2.915	0.0043	

The whole model is significant, F 2,107 = 54.08, $p < 0.0001$. The R-squared is 0.5027, which means that the independent variables of trial use of the social learning platform and self-regulation can explain 50.27% of the variation in learning independence. An independent t-test was conducted to determine the differences between the experimental and control groups. The analysis results showed a significant difference between the two groups, where the learning independence score of the experimental group members M = 4.12, SD = 0.58 was higher than the control group M = 3.51, SD = 0.49; t 118 = 6.24, $p < 0.001$. The correlation of X_1 and X_2 to Y can be seen in figure 2.

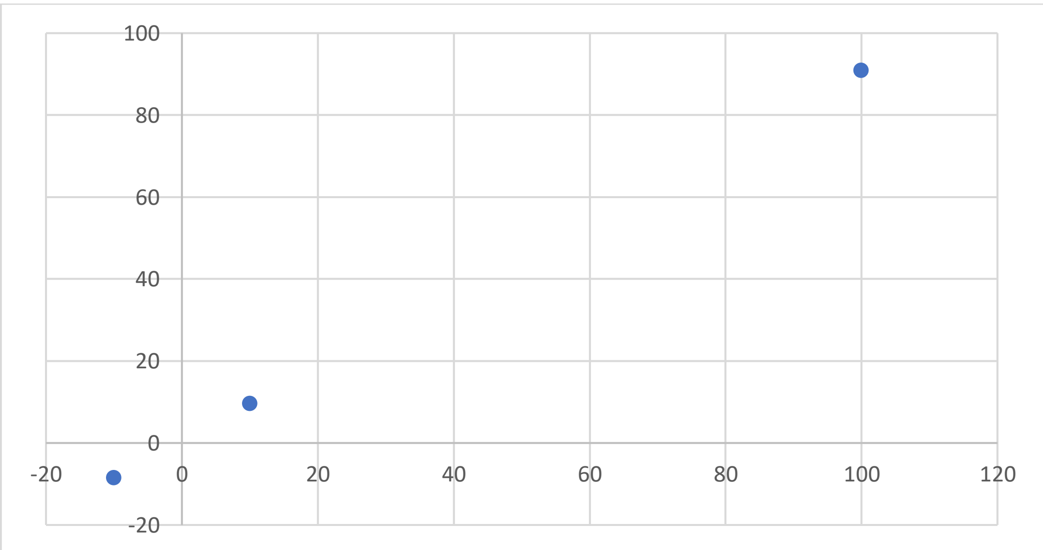

Figure 2. Correlation of X1 and X2 to Y

Additional analyses examined the change in learning independence scores from the pretest to the posttest. A paired t-test showed a significant incremental for the experimental group ($t (59) = 12.38$, $p < 0.001$) with a large effect size d of 1.60. The control group also showed incremental but with a smaller effect size ($t (59) = 5.72$, $p < 0.001$, $d = 0.74$). Social network analysis of the experimental group revealed a 37% increase in network density from the beginning of the semester; in other words, more and more students were interacting with each other on social learning platforms. The content analysis of the experimental group's forum posts showed that the increase was 45%.

Qualitative data from interviews and classroom observations have led to the following main themes: Increasing students' metacognitive awareness to undergo learning, Development of more efficient learning strategies through online collaboration, Challenges when utilizing time and motivation during online lectures, the importance of feedback and peer support to maintain learning engagement. Overall, the results showed that integrating social learning platforms and self-regulation strategies directly impacted the development of PGRI Mpu Sindok University students' learning independence. The resulting predictive model shows that the factors are correlated, with the social learning factor having a more influential factor but self-regulation also playing an important role.

Conclusion

As for future research directions, one can mention the development and testing of more specific measurement tools to evaluate the level of learning independence in the context of digital learning; identifying cultural and contextual factors that influence the effectiveness of social platforms and self-regulation strategies; more sophisticated systems and tools that will allow people to implement artificial intelligence and adaptive technologies into social learning platforms, so that these principles can support learning independence; cross-cultural comparative studies are important so that people can understand better how this model can be copied in specific situations, as well as what should be changed and adapted in terms of cultural factors.

Some of the ways in which this research orientation can be applied in the future include the development and validation of more specific measurement tools for learning independence during digital learning. In addition, a large part should include research on the way culture and other contextual variables play a role in the influence of social learning platforms and social self-regulation, and how it can improve us theoretically in the process of self-directed learning. Artificial intelligence operations, and advances in adaptive technologies included in the long term, especially the socialization aspects of self-directed learning platforms, should also be interpreted for cross-cultural research purposes, allowing us to see how the same model can be applied or modified depending on which aspects of mixed cultures are most acceptable.

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