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Mathematical model of student learning behavior with the effect of learning motivation and student social interaction

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Abstract

This study aims to determine the mathematical model of student learning behavior. The model is built by analogizing the spread of learning behavior with infectious diseases, which is called the SEIR model. The survey was conducted through filling out a questionnaire on the learning behavior of junior high school students with a population of 1,143 students. The results of the simulation model show that the peak of students' vulnerability to changes in learning behavior increases rapidly in the first two days and will be stable when passing the 150th day. The results of the simulation of the SEIR mathematical model with an incubation period of 365 days found that student learning behavior in Non-Boarding Schools will be stable in on day 198, while in Boarding Schools it will be stable on day 201. Infection cases in Boarding Schools fell to 0 on day 25 while in Non-Boarding Schools decreased on day 21, meaning that infections occurring in Boarding Schools were slower and more resistant long, meaning that the influence of the social environment is very significant on student learning behavior. This study also serves as material for policy formulation for the Aceh Provincial Government regarding the junior high school curriculum.

Keywords: Learning Behavior, Peers, SEIR Models, Social Interactions

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The student's internal state is the main predictor in determining student learning outcomes (Jovanović et al., 2021). There is a significant relationship between academic achievement and motivation (Abdelrahman, 2020). One of the most important principles in learning is motivation (Al-Osaimi & Fawaz, 2022). Students' independent learning behavior is controlled by learning needs, ways of learning and motivation to learn (Wang and Zhang, 2022). Student motivation is an antecedent of engagement (Singh et al., 2022). Students with a good level of motivation have practical implications for aspects of student self-study behavior (Opelt & Schwinger, 2020).

Self-learning behavior recommends that students learn outside the classroom through pedagogical activities that link classroom learning with other learning resources in the environment (Hsieh & Hsieh, 2019). So that the pattern or student learning behavior in the form of private lessons or student social interactions outside the classroom has positive results in increasing students' non-cognitive factors (Ömeroğulları et al., 2020). Non-cognitive factors of students in the form of motivation, deep learning, teamwork, self-efficacy, meta-cognition, and expected values directly or indirectly affect students' academic success (Imbrie et al., 2008). The non-cognitive factors referred to refer to the motivational factors of student learning. This is because there is a strong relationship between students' non-cognitive variables and student academic achievement (Chen & Hastedt, 2022).

The test results found that students' use of resources showed a very potent positive relationship between independent learning behavior and overall resource use (Hsieh & Hsieh, 2019). Independent learning behavior facilitates emotional regulation skills and student development related to positive student-teacher relationships and students' cognitive processing to increase motivation and academic success (Graziano et al., 2007). Unclear understanding during independent learning can cause students to experience initial assessment failures. This can affect students' motivation, self-confidence, and ongoing academic performance (Chandler & Potter, 2012).

A positive learning environment and learning motivation provide good knowledge to achieve learning goals. Goal orientation, self-efficacy, and motivation are important variables that influence student learning behavior (Geitz et al., 2016). Learning behavior is a learning activity carried out repeatedly with good and bad qualitative assessments depending on the responses obtained from learning activities (Aiello et al., 2020). Learning behavior can be influenced by learning support from parents and teachers, cultural capital in the family, and teacher commitment to support student learning (Stoeger et al., 2014). Mentoring from the teacher can mediate learning behavior and positive emotions among students in the school environment (Schweder & Raufelder, 2019). The teacher's role can also support the success of the parent-school partnership. The teacher's role in communicating creates active participation in school (Levinthal et al., 2021).

The school environment is one aspect affecting learning behavior (Costa & Steffgen, 2020; Haghighi & Jusan, 2012; Varachanon, 2015; Wang et al., 2020). Learning strategy is one of the distinguishing elements of students in learning (Lanza Escobedo & Sánchez Souto, 2015). The quality of the learning strategies provided influences students' expectations about the future, which in turn can encourage students to achieve higher academic goals (Mazzetti et al., 2020). Academic success has strong implications for students' education and learning strategies. So, there is a significant relationship between student achievement, learning styles, and learning behavior (Magdalena, 2015).

Learning behavior is a learning habit that is pursued by individuals repeatedly and spontaneously (Geitz et al., 2016; Jebaseelan, 2016; Schweder & Raufelder, 2019). Learning behavior can be interpreted by the mental readiness that students have in learning which is shown by students through intelligence, active and creative thinking, students' love of ongoing learning and having better psychological adjustments (Saxena, 2002). Learning behavior is a pattern of training that is developed stably (Wu et al., 2021). Learning behavior is related to the willingness to understand, use strategies and direct involvement in order to acquire knowledge (Geitz et al., 2016). There is a strong relationship between learning and human behavior, where the results of the study found that human behavior is modeled as an interaction between the three main sets of action, cognition and emotion (Perrusquía et al., 2021). The learning behavior of students aged 9-19 years is influenced by endurance, concentration, independence and perseverance (Lohbeck et al., 2016). Learning effectiveness is the main goal that can be used to measure the construction of learning behavior (Xia & Qi, 2022). Learning effectiveness and learning environment affect learning behavior (Nikolovski et al., 2021; Streicher et al., 2021).

Based on the data of previous researchers about learning behavior, it is known that student learning behavior is strongly influenced by the learning process, study habits, interest in learning, learning strategies, learning styles, self-efficacy, learning orientation, learning motivation, and students' social interactions outside the classroom (Geitz et al., 2016; Jebaseelan, 2016; Mary & Jebaseelan, 2014; Politzer & McGroarty, 1985; Rahman et al., 2012; Saxena, 2002; Schweder & Raufelder, 2019). This statement refers to Vygotsky's sociocultural theory which states that social interaction with adults and peers who are more educated can facilitate children's potential for learning (Langford, 2004). This shows that learning is a sociocultural process that occurs through negotiation and meaningful interaction (scaffolding) among students (Rahimi, 2013). Classmates and interpersonal relationships (interactions) influence students' opportunities to learn (Sitthirak, 2022). This study elaborates on the relevance between Bandura's theory and Vygotsky's theory. This is because in social learning theory it is emphasized that individual behavior is formed through imitating behavior in the environment, where individuals observe behavior in the environment as a model to be imitated which is then used as their behavior (Bandura, 1977).

Good learning behavior can develop discipline and improve students' academic competence otherwise poor learning behavior can cause students to become frustrated in implementation the learning process (Aiello et al., 2020; Schmidt et al., 2020; Seemiller & Gould, 2020). This is considered dangerous for the achievement of learning objectives and the learning process that takes place in the classroom. The problem that occurs is that each student has a different response to learning activities. Thus, it is necessary to study more in-depth information related to the model of changing student learning behavior. The main objective of mathematical modeling is a form of competence to simplify the development of mathematical understanding, model construction activities, organize problems, interpret solutions, validate solutions and present solutions (Hidayat et al., 2020). Mathematical models can help detect the spread of student learning behavior in the real world.

Thus, there is a strong need for math management modeling of student learning behavior to obtain a measuring tool to minimize and control the infection spike in cases of deviant learning behavior among students. A mathematical model is a description of how the real world works using symbols, equations, and mathematical formulas (Ahmed et al., 2021). Mathematical models are commonly used in medicine, agriculture, management and social sciences (Dourado-Neto et al., 1998; Pack & Murray-Smith, 1972; Pokhariyal & Rodrigues, 1993; Tabatabaie et al., 2018). In line with that, this paper answers the research questions what is the form of the construction of the Mathematical Model of Student Learning Behavior?

The spread of learning behavior among students can be analogous to the spread of infectious disease outbreaks in an area which can be formed into an epidemic model. The epidemic model in question is the Susceptible-Exposed-Infectious-Recovered (SEIR) model (Khedher et al., 2021; Kiarie et al., 2022; Liu, Saeed, et al., 2022). The SEIR mathematical prediction model can help in predicting the future course of the outbreak and evaluating strategies that can effectively control the epidemic (Kiarie et al., 2022). The SEIR model is a widely used epidemiological model to predict the increase in infection (Sampath & Bose, 2022). The SEIR model is widely used to describe the dynamic process of epidemic spread with consideration of infection exposure during travel and quarantine (Liu, Ong, et al., 2022).

The SEIR model was developed to estimate the parameters of the daily incidence and death time series for the Ebola outbreak in the Democratic Republic of Congo in 1995 (Lekone & Finkenstädt, 2006). Through this study, the researchers expanded the algorithm further and integrated it numerically into cases of student learning behavior at school. Therefore, this model requires a transformation or redefinition related to the adjustment of understanding related to the method of dissemination and prediction of the length of the dissemination process as a basis for controlling and preventing the spread of deviant learning behavior among students. Students' social interaction outside the classroom and learning motivation are two important factors that have the potential to dampen the peak magnitude of the spread of student learning behavior as a whole. The SEIR model was developed to track deployment peaks (Youkta & Paramanik, 2021).

Increased levels of social contact are often associated with an increased risk of horizontal disease transmission (Hock & Fefferman, 2012). Patterns of contact between schoolchildren are relevant for modeling disease spread and for evaluating control measures (Stehlé et al., 2011). Heterogeneity in the network of contacts has a major influence in determining whether a pathogen can become an epidemic or survive at an endemic level (Prem et al., 2017). Human epidemic modeling and pandemic control policy planning based on social distancing methods (Read et al., 2008). Social network analysis offers important insights into how to conceptualize and model social interactions and has the potential to enhance understanding of disease epidemics (Liljeros et al., 2003). Thus, this reduction in social interaction has the potential to change transmission rates, even in conditions of constant close proximity (Stockmaier et al., 2018).

The peak degree of endemic is usually indicated by the Basic Reproductive Number (R0), which is defined as the average number of secondary infections produced by a typical case of infection in a population to which each person is susceptible (Delamater et al., 2019). The basic reproduction rate of a disease cannot be measured directly and must be estimated from models of disease transmission (Kiarie et al., 2022). Likewise, the basic reproduction number of a student's learning behavior cannot be measured directly and must be estimated from the factors that cause changes in student learning behavior. Based on the literature review that researchers have done in previous research, several factors that influence learning behavior used in making mathematical models such as motivation or interest in learning (Canivez & Beran, 2011; Rahman et al., 2012; Wang & Zhang, 2022), and learning interaction or collaborative learning style, environmental exposure or learning environment (Canivez & Beran, 2011; Changthong et al., 2014; Danovitch et al., 2021; de Rivera et al., 2021; Ginevra et al., 2015; Hadjar et al., 2021; Wang & Zhang, 2022; Xia & Qi, 2022).

Research related to the mathematical model of student learning behavior specifically has never been done before. Therefore, researchers are interested in discussing the problem of models that describe student learning behavior with the relationship between learning behavior in the classroom, student motivation and social interaction of students outside the classroom. So that through this research it is expected to be able to predict and control the spread of deviant learning behavior among students at school. This research has a major contribution to the development of science and technology, namely the developed model can be used as a measuring tool to predict, minimize, and control spikes in cases of deviant learning behavior among students. This study also became material for the formulation of the Aceh Provincial Government's policy regarding the junior high school curriculum by prioritizing learning activities that support a conducive learning atmosphere, a good social interaction system, and the provision of consistent learning motivation from the school and parents to students.

METHODS

Data Source

The data in this study were obtained from the results of a survey conducted in two types of schools with different education systems, namely Non-Boarding Schools and Boarding Schools. The survey has undertaken by distributing learning behavior questionnaires to students while learning was taking place about student learning behavior in the classroom, students' social interactions outside the classroom, and learning motivation. Measurement of learning behavior is a series of comprehensive, complex, and exploratory activities, so the questionnaire used in this study needs to be developed and re-validated with Subject-Matter Experts (SMEs) from the study population by considering the diversity factors in students. Validation testing is carried out through 1) content validity, 2) construct validity, and 3) criterion validity (Perko, 2013).

Content validation was carried out by six experts, namely one professor in the field of educational evaluation, two experts in the field of instrument evaluation and psychology, and three junior high school teachers in the field of guidance and counseling. Content validation was carried out on 115 item items, content validity was calculated using the Aiken's V method and 65 valid statement items were obtained. The average value of the coefficient V of each item is Co(V) = 0.80, R(V) = 0.82, and Cl(V) = 0.82. Questionnaire validation was followed by construct validation to determine the characteristics of student learning behavior that could not be observed directly. Construct validity was analyzed using two factor analyses, namely Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). EFA was carried out using a trial sample of 406 samples, while the CFA test used a trial sample of 318 samples.

EFA revealed the KMO of 0.805, 0.789, and 0.759, respectively. The results of the CFA test resulted in 48 valid items and indicated a fit model. Sub-scale A consisted of 17 items (RMSEA = 0.062; GFI = 0.922; CFI = 0.953; NFI = 0.919; and TLI = 0.939). Sub-scale B contained 19 items (RMSEA = 0.037; GFI= 0.940; CFI=0.971; NFI=0.911; dan TLI=0.964) and sub-scale C had 12 items (RMSEA = 0.035; GFI= 0.967; CFI=0.987; and TLI = 0.983). The questionnaire used in this study is the result after testing the validity and reliability of the student learning behavior questionnaire, which consists of 48 questions.

The results of filling out the learning behavior questionnaire are then compared with the student achievement scores, namely the mid-semester grades and the students' final semester scores. The study was conducted for 10 months. The sample taken in this study amounted to 1.170 students from a total population of 1.755 students. The sample consisted of 162 samples for testing the validity of the criteria, 406 samples for testing construct validity through EFA analysis, 318 samples were used for testing CFA analysis, and 284 samples for testing the mathematical model of student learning behavior. The sample selection was carried out through random sampling technique. The samples taken have represented the entire population. The minimum sample size should be 100 or at least 200 for accuracy reasons (Kline, 2016; Nevitt & Hancock, 2001). In line with this, Meyers (2006) stated that the appropriate sample size depends on the number of items available; ten items require 200 samples, 25 items require 250 samples, 90 items require 400 samples, and so on. So that for empirical trials carried out on a sample of at least 6 times the number of statement items.

Model Formulation

The model used in the spread of student learning behavior is analogous to the infectious disease model, namely the SEIR (Susceptible Exposed Infected Recovered) model (Khedher et al., 2021; Kiarie et al., 2022; Liu, Saeed, et al., 2022). The student population is distributed into six compartments, namely: Susceptible (S) is vulnerable students who did not interact socially outside the classroom (S1) and vulnerable groups of students who interacted socially outside (S2), Exposed (E), Infected (I) namely Infected students do not have social interactions outside (I1) and infected students have social interactions outside (I2), and Recovered (R).

The sub-population is grouped in this way with the assumption that learning behavior is influenced by teaching methods and learning content (Xia & Qi, 2022). Active participation of students in the learning process is a form of student involvement in the academic field (AlQaheri & Panda, 2022). The role of peers, and learning in groups have an impact on students' social environment (Tannert & Gröschner, 2021). Social interaction of students outside the classroom has positive results on increasing students' non-cognitive factors (Ömeroğulları et al., 2020). A good level of motivation has practical implications for student learning behavior (Opelt & Schwinger, 2020).

The SEIR compartmental deterministic model can be presented in a differential equation model. A differential equation can be defined as an equation that contains the derivative or differential of one or more dependent variables on one or more independent variables of some unknown function (Marta & Braselton, 2004). Based on the number of independent variables involved, the differential equation is shared into two, namely ordinary differential equations, if the equation only contains regular derivatives (Hata, 2017; Marta & Braselton, 2004). The SEIR model is used by epidemiologists to study disease dynamics and the effect of control interventions (Lekone & Finkenstädt, 2006). Therefore, researchers assume that through the SEIR model it can also be studied the dynamics of changes in student learning behavior and interventions for controlling deviant learning behavior among students.

The mathematical model of student learning behavior is formulated based on the following assumptions:

a) The student population is closed and homogeneous.
b) Students who have not been affected by deviant behavior and have low learning motivation enter the compartment of students who are prone to not interacting socially outside the classroom (S1).
c) Vulnerable students with good social interactions outside the classroom (S2) will be re-placed to (S1) if they stop social interaction outside the classroom.
d) Infection with deviant behavior occurs when there is interaction with infected students, either directly or indirectly.
e) The recovered student (R) cannot be infected again.

Schematically the process of spreading student learning behavior is illustrated in the form of a diagram in Figure 1.

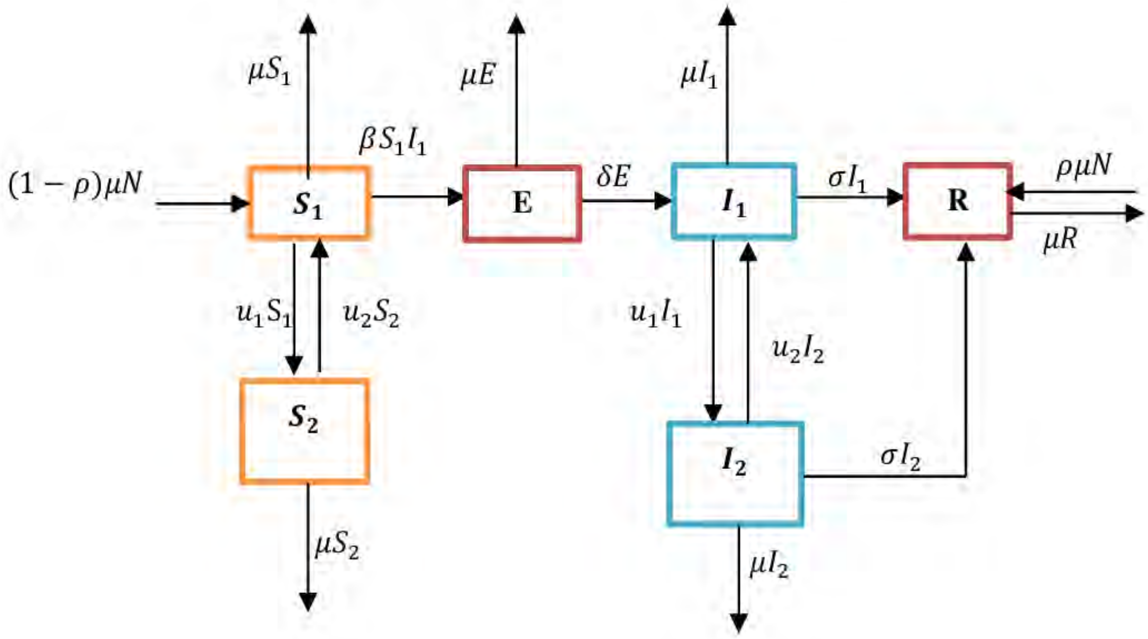

Figure 1. A flowchart that describes the dynamics of the spread of student learning behavior

Based on this description, the following interpretation of the 4-D non-linear ordinary differential equation model (Atangana & Araz, 2021) is obtained:

$$\frac{dS_1}{dt} = (1-\rho)\mu N + u_2 S_2 - (\mu + u_1)S_1 - \beta S_1 I_1$$
$$\frac{dS_2}{dt} = u_1 S_1 - (\mu + u_2)S_2$$
$$\frac{dE}{dt} = \beta S_1 I_1 - (\mu + \delta)E$$
$$\frac{dI_1}{dt} = \delta E + u_2 I_2 - (\mu + u_1 + \sigma)I_1$$
$$\frac{dI_2}{dt} = u_1 I_1 - (\mu + u_2 + \sigma)I_2$$
$$\frac{dR}{dt} = \sigma I_1 + \sigma I_2 + \rho\mu N - \mu R$$

With value $\boldsymbol{N} = \boldsymbol{S_1} + \boldsymbol{S_2} + \boldsymbol{E} + \boldsymbol{I_1} + \boldsymbol{I_2} + \boldsymbol{R}$, so therefore $\frac{\boldsymbol{dN}}{\boldsymbol{dt}} = \boldsymbol{0}$, so that $\boldsymbol{N(t)} = \boldsymbol{k}$, for $\boldsymbol{k}$ positive month number, because $\boldsymbol{N(t)}$ konstan.

The system of equations is then transformed into a non-dimensional model. The proportion of the number of students in each compartment can be expressed in the following equation:

$$s_1 = \frac{S_1}{N}, s_2 = \frac{S_2}{N}, e = \frac{E}{N}, i_1 = \frac{I_1}{N}, i_2 = \frac{I_2}{N}, r = \frac{R}{N}$$

So that it is obtained:

$$s_1 + s_2 + e + i_1 + i_2 + r = \frac{S_1}{N} + \frac{S_2}{N} + \frac{E}{N} + \frac{I_1}{N} + \frac{I_2}{N} + \frac{R}{N} = 1$$

Furthermore, the non-dimensional models formed are:

$$\frac{ds_1}{dt} = (1-\rho)\mu + u_2 s_2 - (\mu + u_1)s_1 - \beta s_1 i_1$$
$$\frac{ds_2}{dt} = u_1 s_1 - (\mu + u_2)s_2$$
$$\frac{de}{dt} = \beta s_1 i_2 - (\mu + \delta)e$$
$$\frac{di_1}{dt} = \delta e + u_2 i_2 - (\mu + u_1 + \sigma)i_1$$
$$\frac{di_2}{dt} = u_1 i_1 - (\mu + u_2 + \sigma)i_2$$
$$\frac{dr}{dt} = \sigma i_1 + \sigma i_2 + \rho\mu N - \mu R$$

Since the number of students in compartment r does not affect the rate of change in the number of students in other compartments, then the r can be temporarily ignored from the system.

$$\frac{ds_1}{dt} = (1-\rho)\mu + u_2 s_2 - (\mu + u_1)s_1 - \beta s_1 i_1$$
$$\frac{ds_2}{dt} = u_1 s_1 - (\mu + u_2)s_2$$
$$\frac{de}{dt} = \beta s_1 i_2 - (\mu + \delta)e$$
$$\frac{di_1}{dt} = \delta e + u_2 i_2 - (\mu + u_1 + \sigma)i_1$$
$$\frac{di_2}{dt} = u_1 i_1 - (\mu + u_2 + \sigma)i_2$$

Definitions of variables and parameters are described in detail in Table 1 and Table 2.

Table 1. List of Variables of Student Learning Behavior Distribution Model

Variable	Definition	Condition	Unit
$N(t)$	Total student population at time t	$N(t) \geq 0$	student
$S_1(t)$	The number of students susceptible to infection did not engage in social interaction outside the classroom at the t time	$S_1(t) \geq 0$	student
$S_2(t)$	The number of infected students socially interacting outside the classroom at the t time	$S_2(t) \geq 0$	student
$E(t)$	Number of latent students at time t	$E(t) \geq 0$	student
$I_1(t)$	The number of infected students did not interact socially outside the classroom at the t time	$I_1(t) \geq 0$	student
$I_2(t)$	The number of infected students interacting socially outside the classroom at the t time	$I_2(t) \geq 0$	student
$R(t)$	Number of students recovered at time t	$R(t) \geq 0$	student

Table 2. List of Parameters used in SEIR model of Student Learning Behavior

Parameters	Definition	Condition	Unit
μ	Natural birth and death rates of the student population	$\mu \geq 0$	$\frac{1}{day}$
β	The rate at which students are prone to become latent students after interacting with infected students	$\beta \geq 0$	$\frac{1}{individu - day}$
δ	Transfer rate from latent students to infected students	$\delta \geq 0$	$\frac{individu}{day}$
σ	Individual healing rate	$\sigma \geq 0$	$\frac{individu}{day}$
ρ	Proportion of the number of vulnerable students who have good learning motivation	$0 \leq \rho \leq 1$	
$(1-\rho)$	The proportion of vulnerable students who have low learning motivation	$0 \leq \rho \leq 1$	
u_1	The rate of student social interaction outside the classroom	$u_1 \geq 0$	$\frac{1}{day}$
u_2	The release rate of students' social interactions outside	$u_2 \geq 0$	$\frac{1}{day}$

Equilibrium Point and Basic Reproductive Number

From the resulting equation system, there are two equilibrium points, namely the equilibrium point free from deviant learning behavior and the endemic equilibrium point (deviant learning behavior consistently exists, but is limited to a certain scope) (Ahmed et al., 2021). The epidemic model deals with the value of symmetry and asymmetry from different points of view (Rangasamy et al., 2022). Equilibrium point is a point that does not change with time. It means when $t = 1,2,\dots,n$ the point value will remain and do not change.

Point $x^* = (x_1{}^*, x_2{}^*, \dots, x_n{}^*)$ is called the equilibrium point of the system$x = f(x)$ if it meets $f(x_1{}^*, x_2{}^*, \dots, x_n{}^*) = 0$ (Penny, 2000).

$$(1-\rho)\mu + u_2 s_2 - (\mu + u_1)s_1 - \beta s_1 i_1 = 0$$
$$u_1 s_1 - (\mu + u_2)s_2 = 0$$
$$\beta s_1 i_2 - (\mu + \delta)e = 0$$
$$\delta e + u_2 i_2 - (\mu + u_1 + \sigma)i_1 = 0$$
$$u_1 i_1 - (\mu + u_2 + \sigma)i_2 = 0$$

Free Equilibrium Point Effect of Student Learning Behavior

The equilibrium point free from the influence of learning behavior is the equilibrium point when there is no deviant learning behavior in the student population, so $i_1 = i_2 = 0$. With $e = 0, s_2 = \frac{u_1 s_1}{(\mu+u_2)}$, dan $s_1 = \frac{(1-\rho)(\mu+u_2)}{(\mu+u_1+u_2)}$, then the equilibrium point is obtained free from the influence of deviant learning behavior system of equations, namely: $E_1(s_1, s_2, e, i_1, i_2) = \left(\frac{(1-\rho)(\mu+u_1)}{\mu+u_1+u_2}, \frac{u_1(1-\rho)}{(\mu+u_1+u_2)}, 0,0,0\right)$.

Endemic Equilibrium Point in a Specific Sphere

The equilibrium point in a certain scope means the equilibrium point when the group of students who are "influenced" by learning behavior is not zero or when deviant learning behavior spreads in the student population. Endemic learning behavior means that in the student population there are always students who have deviant learning behavior, so that I am obtained at the endemic equilibrium point, namely $I_1^* > 0$ and $I_2^* > 0$.

With $i_2 = \frac{u_1 i_1}{(\mu+u_2+\sigma)}$, $s_2 = \frac{u_1 s_1}{(\mu+u_2)}$ and $e = \frac{\beta s_1 i_2}{(\mu+\delta)}$ obtained the equation $s_1 = \frac{(\mu+\sigma)(\mu+u_1+u_2+\sigma)(\mu+\delta)}{\beta\delta(\mu+u_2+\sigma)}$ so that the equation becomes $s_2 = \frac{u_1(\mu+\sigma)(\mu+u_1+u_2+\sigma)(\mu+\delta)}{\beta\delta(\mu+u_2)(\mu+u_2+\sigma)}$. The substitution of the equation obtained with the endemic equilibrium point is $E_2(s_1{}^*, s_2{}^*, e, i_1{}^*, i_2{}^*)$ with: $E_1(s_1, s_2, e, i_1, i_2) = \left(\frac{(1-\rho)(\mu+u_1)}{\mu+u_1+u_2}, \frac{u_1(1-\rho)}{(\mu+u_1+u_2)}, 0,0,0\right)$.

The endemic equilibrium point is $E_2(s_1{}^*, s_2{}^*, e, i_1{}^*, i_2{}^*)$ namely:

$$s_1{}^* = \frac{(\mu+\sigma)(\mu+u_1+u_2+\sigma)(\mu+\delta)}{\beta\delta(\mu+u_2+\sigma)}$$

$$s_2{}^* = \frac{u_1 s_1{}^*}{(\mu+u_2)}$$

$$e^* = \frac{\beta s_1{}^* i_2{}^*}{(\mu+\delta)}$$

$$i_1{}^* = \frac{\mu}{\beta}\left(\frac{\beta\delta n(1-\rho)(\mu+u_2) - d(\mu+\sigma)(d+\sigma)c}{(\mu+\sigma)(d+\sigma)c(\mu+u_2)}\right) i_2{}^* = \frac{u_1 i_1{}^*}{(\mu+u_2+\sigma)}$$

Basic Reproductive Number (R0)

The basic reproduction number is the expected value of a new (secondary) case caused by a contaminated student (primary case) in a population of susceptible students. If $R0 < 1$, then the deviant behavior does not affect the population, but if $R0 > 1$ then the deviant behavior is very likely to spread.

By taking the infected subsystem is e, i_1, and i_2 This linear system is represented by the Jacobi (J):

$$J_{(s_1,s_2,e,i_1,i_2)} = \begin{bmatrix} -(\mu+\delta) & \frac{\beta(1-\rho)(\mu+u_2)}{(\mu+u_1+u_2)} & 0 \\ \delta & -(\mu+u_1+\sigma) & u_2 \\ 0 & u_1 & -(\mu+u_2+\sigma) \end{bmatrix}$$

Decomposition matrix Jacobi (J) to be $J = F - V$, with F is Transmission matrix and V is the Transmission matrix obtained $A = (\mu+\delta)(\mu+u_1+u_2+\sigma)$ and $B = (1-\rho)(\mu+u_2)$, next with the eigenvalues of the matrix (FV^{-1}) obtained $\lambda_{1,2} = 0$ and $\lambda_3 = \frac{\beta\delta(1-\rho)(\mu+u_2)(\mu+u_2+\sigma)}{(u_1+u_2+\mu)(\mu+\delta)A)}$.

Since the basic reproduction number is obtained from the spectral radius or the largest value of the eigenvalues, we get:

$$R_0 = \frac{\beta\delta(1-\rho)(\mu+u_2)(\mu+u_2+\sigma)}{(u_1+u_2+\mu)(\mu+\delta)A)}$$

with $A = (\mu+\delta)(\mu+u_1+u_2+\sigma)$.

RESULTS AND DISCUSSION

In this section, a discussion of the results of the SEIR model in forecasting the situation of the spread of learning behavior of Boarding School and Non-Boarding School Middle School students is discussed in 350 days. The 365-day period is taken as the model simulation stage, this is because the incubation period for the spread of student learning behavior can be seen from the peer effect, where social interaction outside the classroom becomes strong and stable after the first year (Cheng, 2020). Students infected with deviant learning behavior can recover within 1 semester or 6 months or 180 days (Hasan & Bagde, 2013). The persistence of the effect of direct social interaction implies different predictions, depending on the frequency of interactions with peers.

Therefore, researchers made observations with a series of activities ranging from validation of questionnaires to model simulations within 365 days. Activities carried out for 365 days have been included in several other publications that are not described in this article. The model simulation was carried out using the MATLAB program by providing values for each parameter. This simulation is given to provide a geometric picture related to the results that have been analyzed. Simulation is the application of a model to obtain strategies that help solve problems or answer questions related to the system (Velten, 2009).

Parameter Values

The parameter values used utilized from the results of previous research, the results of a survey of student learning behavior, and student achievement in the middle and end of the semester. The average age of the students taken is 16 years. The rate of spread of student learning behavior is fixed by the length of student intensive contact in a day, which is a maximum of 14 hours/day. The effect of students' social interactions outside the classroom on academic achievement depends on how long the peer relationship lasts (Cheng, 2020). If peers do not interact frequently, the effect of peers on academic performance will decrease over time (Hasan & Bagde, 2013).

The incubation period for the spread of student learning behavior can be seen from the peer effect, where social interactions outside the classroom become strong and stable after the first year (Cheng, 2020). The incubation period for the spread of student learning behavior is 365 days. Students infected with deviant learning behavior can recover within one semester or six months or 180 days (Hasan & Bagde, 2013). The distribution of the parameter values for the spread of student learning behavior is presented in Table 3.

Table 3. The parameter values for the last week of the month (final clarification output).

Variable	Source	Score	
		Non-Boarding School	Boarding School
μ		0.0243	
β	(Cheng, 2020)	0.0714	
δ	(Cheng, 2020; Hasan & Bagde, 2013)	0.0027	
σ	(Hasan & Bagde, 2013)	0.0055	
ρ	Survey LBQ	0.33	0.3732
$(1-\rho)$	Survey LBQ	0.67	0.6267
u_1	Survey LBQ	0.823	0.4437
u_2	Survey LBQ	0.176	0.556

Equilibrium Point Free of Deviant Behavior

School students obtained the value of $R_0 = 0.00701622 < 1$, the independent equilibrium point of learning behavior is $E_{(s_1,s_2,e,i_1,i_2)} = (0.1311, 0.5388, 0, 0, 0)$. Because $R_0 < 1$, then learning behavior will not spread. Simulation at the equilibrium point is free of deviant behavior E_1 with initial value $s_1(0) = 0.0211, s_2(0) = 0.1830, e(0) = 0.380, i_1(0) = 0.0211, i_2(0) = 0.0633$.

Numerical simulation on Boarding School students, obtained the value of $R_0 = 0.04829 < 1$. Because $R_0 < 1$, then learning behavior will not spread. The learning behavior free equilibrium point is $E_{(s_1,s_2,e,i_1,i_2)} = (0.3549, 0.2708, 0, 0, 0)$. Simulation at the disease-free equilibrium point E_1 with initial value $s_1(0) = 0.1408, s_2(0) = 0.1267, e(0) = 0.3661, i_1(0) = 0.0492, i_2(0) =$

0.0070. The results of the model simulation can be presented in Figure (a) Non-Boarding School Junior High School, (b) zoom from (a), (c) Boarding School Model Simulation, (d) zoom from (c) in Figure 2.

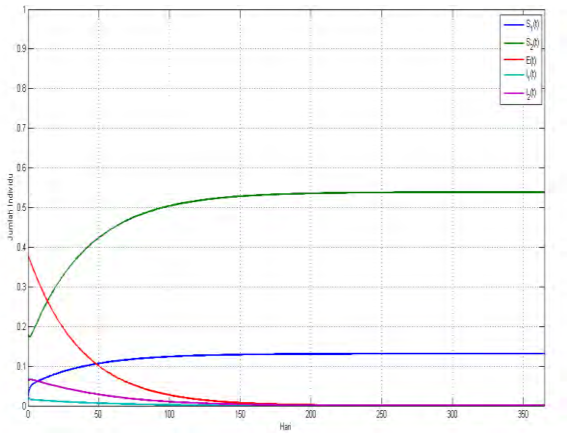

Figure 2a. Middle School Non-Boarding School.

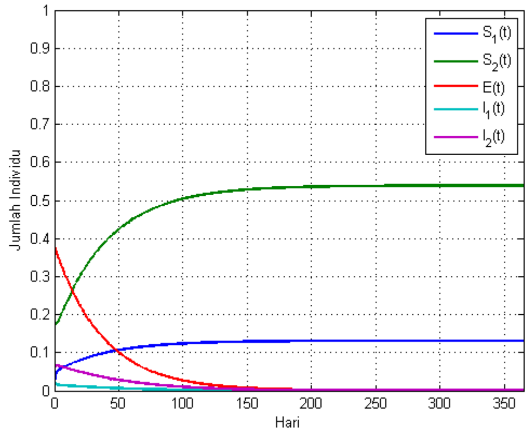

Figure 2b. Zoom from (a).

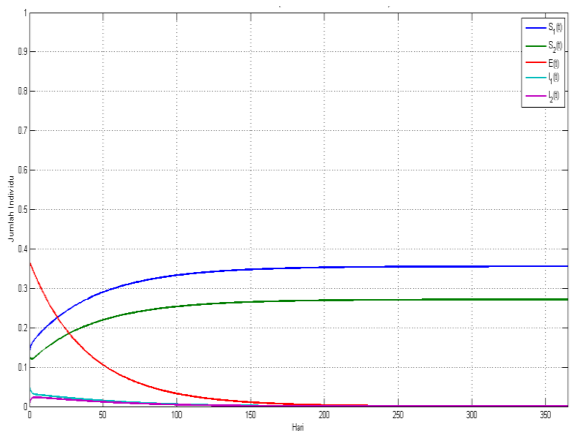

Figure 2c. Middle School Boarding School.

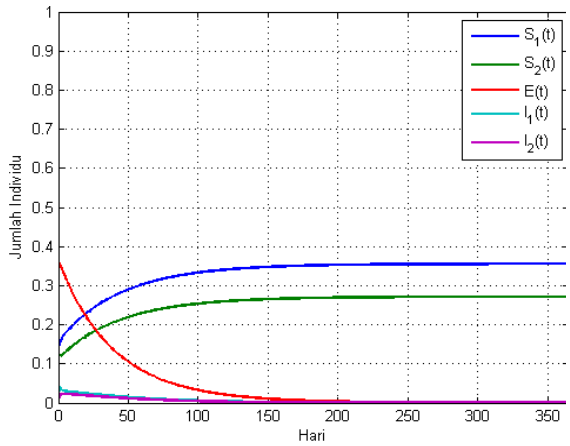

Figure 2d. Zoom from (c).

Figure 2. Disease Free Model: (a) Junior High School Non-Boarding School, (b) zoom from (a), (c) Junior High School Boarding School, (d) zoom from (c).

The value of β from Non-Boarding School and Boarding School has the same value, so it can be said that the level of vulnerability to being a group of exposed students is the same. As can be seen in Figures 2 (a) and (c), the peak of vulnerable students from both the Boarding School and the Non-Boarding School increased rapidly in the first two days and gradually stabilized by the time it passed the 150th day.

As seen in Figures 2 (b) and (d), the peak of the increase in vulnerable students in Non-Boarding School Junior High School was reached on the 250th day. The number of vulnerable respondents who do not have social interaction outside the classroom (S1) is 18 students, vulnerable students have social interaction outside of class (S2) as many as 77 students and the number of students recovering is 47 students. Whereas Boarding School Junior High School's was reached on the 200th day. The number of respondents who are vulnerable to not having social interaction outside the classroom (S1) are 50 students, vulnerable students have social interaction outside the classroom (S2) are 39 students and the number of students recovering is 53 students.

Furthermore, Figure 2 (b) shows the population of Non-Boarding School students in the vulnerable category exposed to changes in learning behavior on the 365th day reaching 13.11% of students socially interacting outside the classroom and 53.88% of students who do not interact socially outside the classroom. Meanwhile, for the population of Boarding School students, vulnerable students who come from the vulnerable student compartment do not interact socially outside the classroom (S1) reaching 35.5%. This means that students in Boarding School Junior High Schools are more susceptible to exposure to changes in learning behavior compared to Non-Boarding School Junior High Schools.

On the other hand, the increase in vulnerable students was different from the group of students, where from the Non-Boarding School Middle School the vulnerable group of students that increased sharply came from the vulnerable student compartment not socially interacting outside the classroom (S1), while in the Boarding School Junior High School the increase in vulnerable students occurred in the secondary school compartment. students are vulnerable to social interaction outside the classroom (S2). This finding is in line with previous research which found that adolescents (10-20 years old) gave an average of 39% of their resources to strangers and 51% to friends (Crone & Achterberg, 2022a). Adolescent students with wider social interactions are more willing to help unfamiliar peers than adolescents who attend boarding schools (Sabato et al., 2021).

This study shows that exposure to deviant learning behavior for boarding school students is more strongly influenced by students' social interactions outside the classroom compared to non-boarding school students. The boarding school experience brings positive results, including independence and the ability to adapt to others, which is easier for boarding school students to do (Hartman, 2022).

The results of interviews with students revealed that students in boarding schools generally experienced alienation from their mothers and fathers which contributed to poorer mental health among adolescents. Boarding school is significantly associated with estrangement from mother and father, mental health, symptoms of depression and anxiety (Chen et al., 2020; Xing et al., 2021).

From Figures 2 (a) and (b) the latent student compartment decreased from the beginning of the simulation to the end of the simulation with the final value of 2.828×10^{-5} , that is, it can be said 0 for Non-Boarding School. As for the Boarding School, it reached a value of 0 in 1,022 days with a final score of 3.100×10^{-5}.

Endemic Equilibrium Point

Numerical simulation for non-boarding school junior high school students with grades of $R_0 > 1$, if the parameter value is enlarged from the previous value to the value of $\beta = 0.755$, value $\delta = 0.735$, $\sigma = 0.555$, $u_2 = 0.756$, $u_1 = 0.0012$ and $\rho = 0.03$, Then the basic reproduction number of the system is $R_0 = 1.3775$. Meanwhile, for SMP Boarding School the parameter values used are $\beta = 0.755$, $\delta = 0.735$, $\sigma = 0.555$, $u_2 = 0.776$, $u_1 = 0.003$ and $\rho = 0.05$, then value $R_0 = 1.3826$. Because $R_0 > 1$, then student learning behavior will spread in other words there will be an epidemic.

Simulation results with parameter values β, δ, u_2 zoomed in and parameter values u_1 and ρ minimized, then the simulation for SMP Non Boarding School with an initial value of $s_1(0) = 0.0211, s_2(0) = 0.1830, e(0) = 0.380, i_1(0) = 0.0211, i_2(0) = 0.0633$ can be presented in Figures 2 (a) and (b). As for the SMP Boarding School with an initial score of $s_1(0) = 0.0211, s_2(0) = 0.1830, e(0) = 0.380, i_1(0) = 0.0211, i_2(0) = 0.0633$ presented in Figures 3 (c) and (d).

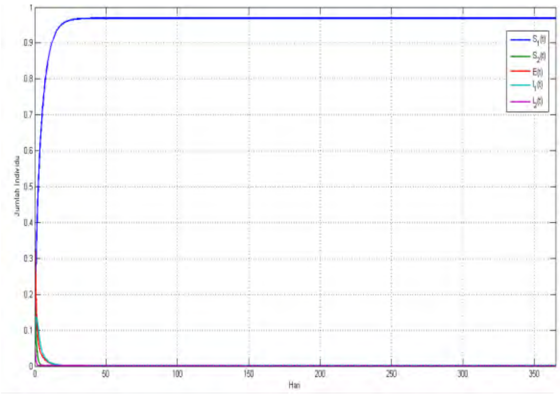

Figure 3a. Middle School Non-Boarding School.

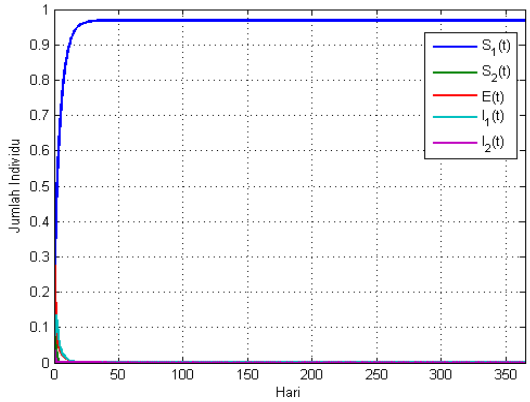

Figure 3b. Zoom from (a).

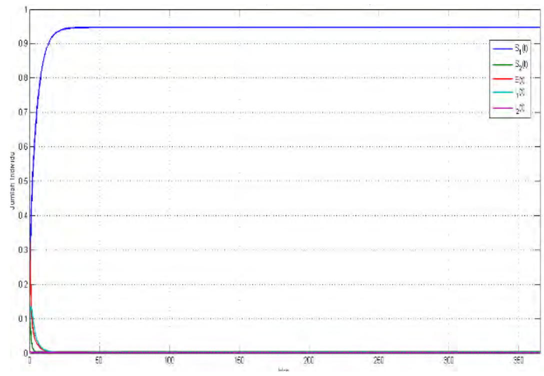

Figure 3c. Middle School Boarding School.

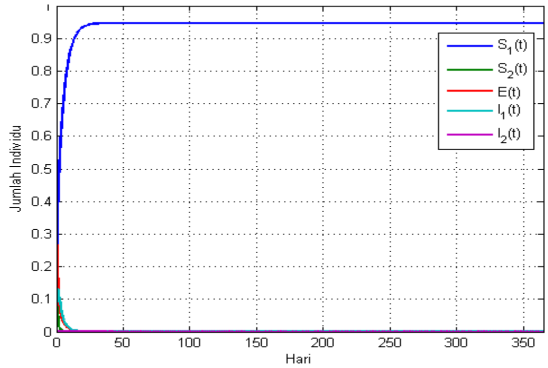

Figure 3d. Zoom from (c).

Figure 3. Endemic Model: (a) SMP Non-Boarding School, (b) zoom from (a), (c) SMP Boarding School, (d) zoom from (c).

Figure 3 shows that the population of infected students who do not have social interactions outside the classroom has increased, while the population of infected students who have social interactions outside the classroom remains constant. The group of infected students who had no social interaction outside the classroom peaked at 1,022 days and then dropped to zero and stabilized at that point.

Furthermore, Figure 4 shows SMP Non-Boarding School and SMP Boarding School for I_1 (Figure 4a) and I_2 (Figure 4b). as shown in Figure 4(a) I_1 and I_2 increased faster than Infections in SMP Boarding Schools. There were fewer daily infections at SMP Boarding Schools, meaning that the duration of the pandemic remained longer than at SMP Non-Boarding Schools. On T_i Cases of infection in learning behavior in Non-Boarding School Junior High Schools fell to 0 on the 21st day, while in Boarding School Junior High Schools on the 25th day.

The results of the model simulation concluded that infections that occur in SMP Boarding Schools are slower and more durable. Numerical studies show that the speed of spread of infection is very significant for the two schools. The distribution of student learning behavior in Non-Boarding School Junior High Schools is expected to be stable on the 198th day, while in Boarding School Junior High Schools it will be stable on the 201st day.

In this study, it was found that students who were included in the infected student compartment (I1 and I2) from the two schools were found not only first-year students but also final-year students. This is Contrary to the findings of previous researchers who found that the peer effect will only affect student academic achievement in the first year (Hasan & Bagde, 2013; Sacerdote, 2013).

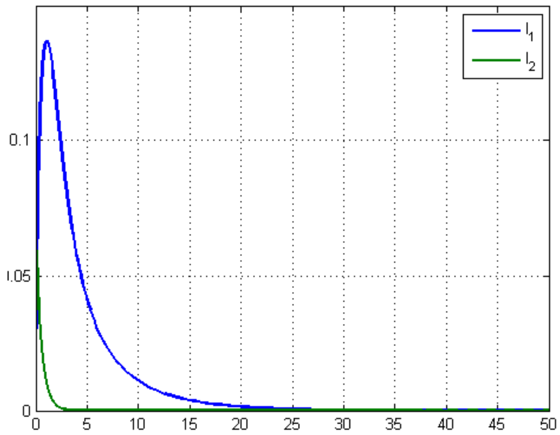

Figure 4a. Middle School Non-Boarding School.

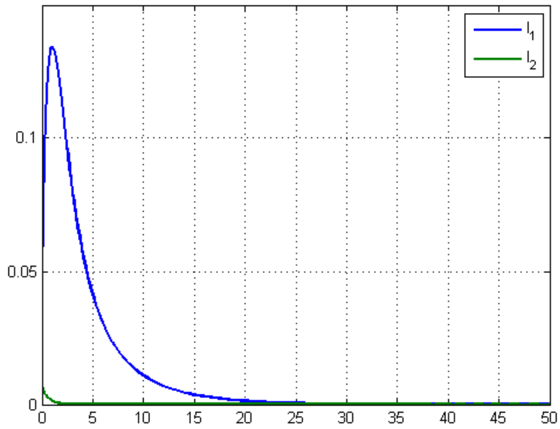

Figure 4b. Middle School Boarding School.

Figure 4. Changes in Infection Rate Changes in Student Learning Behavior.

The survey results can be seen in Table 4. The results also showed that infected students had low learning motivation. This research was conducted during the COVID-19 pandemic, so the COVID-19 crisis was felt to have a major impact on students' learning motivation (Alban Conto et al., 2021). School closures during the pandemic are closely related to lower levels of academic motivation among 12-16 year-olds (Crone & Achterberg, 2022b; Lemay et al., 2021). The bigger effect appears due to the low parental support in the student's learning process while at home. Parents and teachers need to prepare students to be more resilient and enable students to develop the ability to remain optimistic and motivated to succeed in learning. Intrinsic and extrinsic learning motivation can arise from a strong commitment from students to learn (Rahiem, 2021).

Table 4. Results of the Student Learning Behavior Survey Affected by Deviant Behavior

Level	Average Learning Behavior of Junior High School students	Average Social Interaction Outside Class	Average Student Learning Motivation	Midterm Exam Scores	Final Exams Score
Junior high school 6 Banda Aceh					
	1.94	3.5	2.56	87.70	53.33
I1	1.18	2.7	1.56	86.53	58.57
	2.00	3.6	1.44	90.90	57.14
	1.53	4.5	1.22	75.93	70.29
	1.18	4.9	1.00	88.05	60.71
	1.65	4.1	1.94	91.95	62.86
	1.24	4.6	2.39	82.95	46.67
I2	1.44	4.8	1.94	86.48	57.62
	2.06	4.1	1.00	75.95	48.57
	1.29	4.4	2.78	88.00	68.57
	1.53	4.2	1.44	76.90	49.05
	1.76	4.4	2.11	68.37	52.86
Junior high school 19 Banda Aceh					
	2.41	2.8	1.8	80	84.29
I1	1.76	1.3	1.9	71.5	72.29
	1.06	2.8	3.7	66.5	66.00

	2.06	2.0	3.1	71	63.14
	1.18	2.7	2.8	75	73.90
	1.76	2.8	3.2	61	75.00
	1.06	1.3	3.1	63	61.80
I2	1.71	3.4	1.3	61	78.10

The COVID-19 pandemic situation has had a major impact on student learning behavior. Some of the very detrimental impacts on the world of education are the "loud and disturbing" learning environment at home, does not support student productivity, low ability to absorb information from instructors to students, lack of structure for involvement with peers, lack of motivation to try hard to learn and increased stress (Nagy et al., 2021; Pandya & Lodha, 2022; Viola & Nunes, 2022) The stress felt by students during the COVID-19 pandemic was due to the lack of student social contact (Van de Velde et al., 2021). Therefore, this implies that there is a need for a better curriculum system arrangement related to student social interaction policies outside the classroom and student motivation to learn.

CONCLUSION

The mathematical model of learning behavior that is constructed is the SEIR model which describes the evolution of the outbreak of deviant learning behavior among students. SEIR model with temporal evolution of Susceptible, Exposed, Infected, and Recovered. Susceptible and Infected groups are divided into two subpopulations, namely S1, S2, I1, and I2. The test results found that the peak of vulnerable students (S) increased rapidly in the first two days and would be stable when passing the 150th day. There are differences in the stability points of vulnerable masters' students in the two schools, namely the Boarding School, the master's group of students began to stabilize at the time of passing the 250th day, while the boarding school was stable after passing the 200th day. The group of infected students (I) in SMP Boarding Schools I1 and I2 increased faster than infections that occurred in Non-Boarding Schools, so there were fewer daily infections, meaning that the duration of the pandemic at SMP Boarding Schools was slower and more durable.

From previous studies, it is known that the peer effect only affects students' academic achievement in the first year and can last until the third semester, while in the fourth semester there is no partial roommate effect remaining (Hasan & Bagde, 2013; Sacerdote, 2013). The results of the study contributed to a new concept, namely the study found that the peer effect can still affect academic achievement and student learning behavior until students complete their final studies in the sixth semester. The survey results found that there were at least the Susceptible (14 students), and Exposed (115 students) groups, which were still in the vulnerable student compartment and latent deviant learning behavior. Likewise, there are still five final-year students who fall into the category of Infected deviant learning behavior.

The findings of this study are key in developing informed mitigation strategies to ensure that the pandemic of the spread of deviant learning behavior is brought under control. SEIR parameters were obtained from OLS based on real data, so it was estimated that student learning behavior in Non-Boarding School Junior High School was stable on the 198th day and stable on the 201st day of Boarding School Junior High School. This implies that there is a need for schools to continue to create a conducive learning atmosphere, a good social interaction system and the provision of consistent learning motivation from the school to students. However, due to the limitations of the research, it only took samples from two types of schools with different education systems with schools located in the same area, so it could not be generalized and used as a basis for decision making. Therefore, it is suggested that further research is needed that accommodates a larger sample by taking junior high schools in a wider area.

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Declarations

Author Contribution	:	M: Conceptualization, Writing - Original Draft, Editing and Visualization; RJ: Formal analysis, and Methodology; MR: Validation and Supervision; M: Writing - Review & Editing
Funding Statement	:	The authors state that they are not aware of any competing financial interests or personal relationships that are likely to influence the work reported in this study.
Conflict of Interest	:	The authors declare no conflict of interest.
Additional Information	:	There is no additional information for this paper.

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