JPPIPA 12(5) (2026)

Jurnal Penelitian Pendidikan IPA

http://jppipa.unram.ac.id/index.php/jppipa/index

SEICR Mathematical Modelling of Academic Stress Dynamics Among Chemistry Students in Aceh Province: An Epidemiological Approach to Sustainable Student Mental Health

Jelita Jelita[1*], Budi Irwansyah[1], Lilla Puji Lestari[2], Faidliyah Nilna Minah[3], Nuraida Nuraida[1]

[1] Institut Agama Islam Negeri Langsa, Langsa, Indonesia.
[2] Universitas Maarif Hasyim Latif Sidoarjo, Sidoarjo, Indonesia.
[3] Institut Teknologi Nasional Malang, Malang, Indonesia

Received: January 20, 2026
Revised: April 28, 2026
Accepted: June 15, 2026
Published: June 15, 2026

Corresponding Author:
Jelita Jelita
jelita@iainlangsa.ac.id

DOI: 10.29303/jppipa.v12i5.13709

Open Access

Abstract: Academic stress among higher education students is a common concern that requires thorough investigation. This study develops and analyzes a SEICR (Susceptible–Exposed–Infected–Confirmed–Recovered) mathematical model to describe academic stress dynamics among chemistry students, treating stress as a contagious phenomenon transmitted through social interactions and peer influence. The model captures the progression of students from susceptibility to stress exposure, active stress, coping intervention, and recovery while incorporating behavioral and institutional factors. A system of nonlinear ordinary differential equations is formulated and analyzed through equilibrium and stability analyses. The basic reproduction number, R_0, is derived using the Next Generation Matrix method and serves as a threshold parameter governing system dynamics. Results indicate that academic stress diminishes and approaches a stress-free equilibrium when $R_0 < 1$, whereas stress persists and becomes endemic when $R_0 > 1$. Sensitivity analysis based on the Partial Rank Correlation Coefficient (PRCC) identifies the coping transition rate (δ) as the most influential parameter in reducing stress prevalence, while the transmission rate (β) has a moderate effect. These findings suggest that intervention accessibility plays a greater role than transmission intensity in shaping stress dynamics. Therefore, mitigation strategies should emphasize early detection, timely intervention, and accessible coping support.

Keywords: Academic stress; Chemistry students; Epidemiological approach; Mathematical model; SEICR

Introduction

Academic stress represents a significant challenge to student well-being globally. The World Health Organization (WHO) defines academic stress as "a student's perception of events in the learning process as threatening to themselves, resulting in a variety of undesirable behaviors" such as worry, anxiety, or fear. Rois et al. (2021) defined stress as "the inability to cope with perceived (actual or perceived) threats to mental, physical, emotional, and spiritual well-being." Persistent academic stress manifests through symptoms including low energy, depression, difficulty concentrating, irritability, and physical discomfort (Zhang et al., 2022). A public opinion poll found that approximately 80% of college students worldwide said they experienced academic stress (Nguyen et al., 2022). This suggests that students have reached a level of academic stress that warrants in-depth investigation. Stress is understood as a crisis that affects any individual regardless of their

How to Cite:
Jelita, J., Irwansyah, B., Lestari, L. P., Minah, F. N., & Nuraida, N. (2026). SEICR Mathematical Modelling of Academic Stress Dynamics Among Chemistry Students in Aceh Province: An Epidemiological Approach to Sustainable Student Mental Health. *Jurnal Penelitian Pendidikan IPA*, *12*(5), 960–974. https://doi.org/10.29303/jppipa.v12i5.13709

developmental stage (Banerjee & Chatterjee, 2016). When examining the impact of stress, evidence has shown how stress is related to emotional, behavioral, and cognitive symptoms (Benedetto et al., 2020; Scharp & Hall, 2019). Stress has now become a serious reality referred to as a "career blocker" (Kadapatti & Vijayalaxmi, 2012). There is a significant relationship between suicidal ideation and stress levels (Windarwati et al., 2022). Depression and suicide occur due to low self-esteem (Nikitha et al., 2014). There is ample evidence linking stress to negative health conditions (Shaw et al., 2017). Huli (2014) noted that disturbed family dynamics, peer pressure, inability to cope with schoolwork, drug abuse, and lack of competence are the main reasons for stress during adolescence. Ghatol (2017) reviewed the literature on academic stress among high school students and presented the causes and symptoms of stress, as well as coping mechanisms. Their literature review indicated that the causes of stress during adolescence include disrupted family dynamics, peer pressure, learning disabilities, substance abuse, and lack of competence. From an educational psychology perspective, it is reasonable to assume that academic stress factors in schools can originate from the students themselves, as well as from their context. Several researchers have conceptualized stress factors in education in various ways. For example, student-centered factors, such as self-efficacy (Lazarus, 1999), personality (Saklofske et al., 2012), temperament (Hirvonen et al., 2019), self-regulation behavior (Boyraz et al., 2016; Fuente et al., 2020), stress management (Freire et al., 2019), student anxiety (Cassady et al., 2019; Putwain, 2019), and student goals (Cabanach et al., 2007; Rusk et al., 2011). In addition to these psychological factors, academic factors also play an important role in shaping students' responses to academic pressure. Learning motivation, scientific literacy, and effective learning strategies have been shown to enhance student engagement and learning outcomes, which may help students better cope with academic challenges and learning demands (Amala et al., 2023; Abdullah et al., 2021; Asri et al., 2021; Taupik & Fitria, 2023). Stress has been studied in many studies related to learning. Students are most affected by academic stress, because they face various types of stressors, such as academic stress and the obligation to succeed (Veena & Shastri, 2016). Academic stress in particular is considered as a process where students feel overwhelmed by academic tasks, difficulty meeting academic demands and requirements to achieve adequate performance (Frenzel et al., 2018; Karaman et al., 2019). Academic demands and requirements in the learning process such as presentations in class, excessive workload, team-based assignments, and testing situations, according to Cabanach et al. (2007) and Pozos-Radillo et al. (2014) are factors that influence academic stress. Bello & Gumarao (2012) stated that stress is not correlated with academic achievement. Tus (2020) also stated that stress and motivation do not have a significant relationship with student academic achievement. However, Alyami et al. (2017), found a relationship between self-esteem, academic self-efficacy, and perceived stress on academic achievement. Their findings are also supported by Kötter et al. (2017) who stated that stress negatively impacts academic performance and can also create a vicious cycle that continuously increases stress and decreases performance. Using structural equation modeling, Edjah et al. (2020) examined stress and its impact on academic and social life among college students in Ghana. Yuhuan et al. (2022) also used structural equation modeling to investigate the relationship between academic stress, social support, and self-regulation fatigue among a group of nursing students in Heilongjiang Province, China. In the context of mathematics, Mahato & Sen (2021) in their study compared academic stress, mathematics self-efficacy, and mathematics anxiety among high school students in India. Sathishkumar & Vannathi (2024) explored the role of reasoning ability and academic stress in mathematics achievement among high school students. Silva & Vera (2025) investigated the relationship between academic stress and mathematics scores in 9th grade students. Gupta et al. (2017) on the other hand, stated that neither perceived stress nor emotional intelligence was related to academic stress in medical students. However, perceived stress was significantly predicted by emotional intelligence. In essence, students with higher emotional intelligence showed lower stress, although neither had a significant relationship with academic achievement. Ranasinghe et al. (2017) also stated that academic stress was negatively correlated with emotional intelligence and academic achievement. Llego et al. (2018) found that the main source of stress for nursing students was academic work, where the higher the stress level, the lower their academic achievement. Therefore, various learning innovations, such as virtual laboratories, flipped learning, and problem-based learning, have been implemented to enhance students' motivation and learning outcomes, thereby supporting their readiness to cope with the complex academic demands of chemistry learning (Pane et al., 2024; Ndoa & Jumadi, 2022; Safitri et al., 2023). Despite academic stress remains a significant issue among students and continues to attract research attention. Using multilevel structural equation modeling, Hosseinkhani et al. (2020) examined the relationship between various sources of academic stress and adolescent mental health through mediator variables at the student and school levels.

However, despite its significance in the context of general chemistry, academic stress has received limited attention, particularly from a mathematical modeling perspective. Although extensive studies have examined academic stress in various educational settings, research focusing on chemistry students remains scarce. Furthermore, learning motivation, critical thinking skills, and academic resilience have been identified as important factors that support students in coping with the demands of chemistry learning (Annisa et al., 2023; Dibyantini et al., 2023; Nilyani et al., 2023). To the best of our knowledge, no previous study has specifically modeled the spread of academic stress among chemistry students using a SEICR mathematical epidemiological model.

Conventional approaches to analyze educational preferences typically utilize psychological or sociological approaches. However, in a more dynamic and collective context, a social epidemiological approach becomes relevant and powerful. By borrowing a framework from the infectious disease transmission model, the spread of academic hate among students towards a particular course can be modeled as the spread of a disease or social fever, which spreads from one individual to another through social contact and interaction. We then introduce this model as the "spread of academic stress model," a mathematical model based on a system of differential equations that categorizes the student population into several compartments according to the tendency of academic stress among chemistry students. This model categorizes the student population into five compartments: students who are susceptible, exposed, infected, confirmed, and recovered to academic stress. Transitions between compartments occur through social interactions that occur over time. Using a social context-based epidemiological approach, this study is expected to investigate how this academic stress spreads and changes within the population collectively, thus explaining how the trend of this social phenomenon is contagious and dynamically develops. Most epidemic models are primarily based on transmission through human-to-human interactions. Micro-level epidemic diffusion models first establish the population structure and construct nonlinear differential equations that describe changes in the status of population classes. These micro-level models are referred to as equation-based models (EBMs). EBMs operate on global laws defined by equations and applied to all members of a compartment. The underlying assumption of EBMs is that the population is homogeneous and governed by holistic rules. These models assume that people have a constant rate of contact, are infected with a disease with a unique rate of contagiousness, and recover at a certain rate. There are numerous examples of equation-based models used to analyze specific outbreaks or epidemics after they occur. For example, modelling the 2001 foot and mouth disease epidemic in the UK (Kao, 2002); modeling the spread of H_1N_1 (Vaidya et al., 2014); and modeling the spread of the Ebola outbreak in West Africa (Mamo & Koya, 2015). These models are used to determine lessons learned from the outbreak. Using diffusion models, we can understand how a new disease, information, or product spreads, predict its success or failure early on, and increase or decrease its chances of diffusion.

Social epidemiology has now become an accepted part of the academic intellectual landscape. However, in many ways, social epidemiology is also at risk of losing the identity that distinguished it as a discipline during its emergence (Galea & Link, 2013). According to Muntaner (2013), social epidemiology has become a field of study in Asia, Europe, Latin America, and Africa, realism is more suitable for social epidemiology than positivism, more research is needed on social mechanisms (social class relations, racial discrimination) to increase the explanatory power of social epidemiology, increased attention to causal (social) models will result in more innovative social interventions, and social interventions must be carried out in full partnership with the affected population. Compared to other subfields, social epidemiology is uniquely positioned to benefit from partnerships to help raise new questions and ensure that findings are used to inform population health interventions. Partnerships, in particular, can be formed with those implementing social policies and programs to help determine the impact of social change on health, especially given that most social programs do not measure health as an outcome (Hwang et al., 2012). Social epidemiology studies the social distribution and social determinants of health, emphasizing that all epidemiological exposures are related to social factors. This discipline is often contrasted with individualistic epidemiology, which focuses only on the causes of disease at the individual level (Bauch & Galvani, 2013; Berkman & Kawachi, 2023; Roux, 2022; Eastwood et al., 2019; Kawachi & Subramanian, 2018). The research framework in social epidemiology includes identifying relevant contexts (e.g., geographic environment, socioeconomic status), measuring contextual characteristics, analyzing across generations, and developing quasi-experimental methods to assess causal effects (Eastwood et al., 2019; Takaeb, 2021). This approach also emphasizes the importance of reducing health inequalities, not just improving the average health of the population (Roux, 2022).

New diseases, information, or products, or social ills such as academic stress among chemistry students, can spread through both indirect interactions and direct contact. Models that assume homogeneous mixing among individuals, in other words, random contact, are called population models. Population models divide the population into classes that reflect the status of individuals within the population. Network-based models consider the network within which diffusion occurs and focus on the influence of network properties on the diffusion process. Kermack & Mckendrick (1927) initially proposed the SIR epidemic model, a representative epidemic model, with three compartments: susceptible, infected, and recovered. The model expresses the status changes of the three compartments using differential equations. The epidemic model has been applied to the problem of the processes underlying word-of-mouth promotion in networks (Goldenberg et al., 2001), the spread of rumors (Kawachi, 2008), the spread of violent topics in a forum (Woo et al., 2011), financial crisis (Peckham, 2014), stock market financial network behavior (Balci, 2016), online game addiction (Li & Guo, 2019), coexistence of racism and corruption among individuals in society (Kotola & Teklu, 2022), and the spread of the game in the population (Wang et al., 2024). In education, Anwar et al. (2021) proposed the SEIRS epidemic model also for the problem of online game addiction in mathematics students. Recently, Side et al. (2024) also used the SEIRS epidemic model to address the problem of online game addiction among junior high school students in Makassar City. From several studies in the field of education that propose mathematical models using the epidemiological approach; in this study, we intend to develop a dynamic model of the spread of academic stress among chemistry students using an epidemiological approach. To develop a more complex model but appropriate to the educational context, we adapt the compartmental structure in the epidemiological approach.

Method

In this study, we consider the total population of chemistry students given time N(t) and divide it into five subpopulations or compartments, namely the susceptible, exposed, infected, confirmed, and recovered from academic stress class compartments, which are denoted by S, E, I, C, and R, respectively. The state variables are described as follows:

a. Students who are vulnerable to academic stress, namely individuals who are in an academic environment that has the potential to cause stress but have not shown symptoms or significant exposure to such stress, symbolized by S(t).
b. Students who have been exposed to academic stressors and are beginning to experience initial distress, but have not yet shown significant symptoms of stress or obvious performance impairment, symbolized by E(t).
c. Students experiencing significant academic stress, characterized by decreased performance, anxiety, or mental exhaustion. Within the context of the model, this group also acts as a source of social contagion, influencing the stress levels of other students through social interactions and the academic environment, symbolized by I(t).
d. Students who are undergoing a coping process or active efforts to manage stress, such as through counseling, social support, or time management strategies, symbolized by C(t).
e. Students who have recovered from academic stress and returned to a stable condition, and have effective adaptation skills or coping strategies to face academic pressure in the future, symbolized by R(t).

In this study, we assume and define some model parameters as follows:

a. Λ is the rate of recruitment of new students entering vulnerable classes.
b. μ is the natural rate of exit from the system, including graduation, transfer, or dropout, which is not explicitly modeled as a result of stress.
c. α is the rate of exit from compartment C due to failure of coping or severe fatigue (stress-induced dropout).
d. β is the rate of stress transmission through social interactions (social contagion rate), which represents the probability that an interaction between a vulnerable student and a stressed student results in stress exposure.
e. σ is the rate of transition from the exposure phase (E) to active stress (I).
f. $\delta(t)$ is the rate of entry into the coping phase due to institutional detection/intervention.
g. γ_1 and γ_2 are immediate rate of recovery from stressful conditions without formal intervention (self-recovery), and rate of recovery through coping/intervention processes.
h. c(t) is the intensity of interaction (e.g. increases during exams).
i. $\delta(t)$ is the intensity of campus intervention.
j. The total population size is not constant due to stress withdrawal represented by the parameter α. The total population size satisfies $N(t)=S+E+I+C+R$, which can vary over time if there is a decrease in the population size due to stress (α).

Based on the assumptions and description of the model above, a flow diagram of student transition between compartments is given in Figure 1.

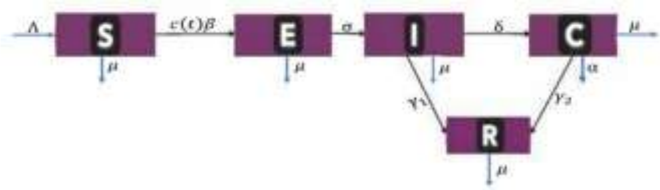

Figure 1. The compartmental flow diagram of SEICR model

By using several model assumptions, parameter definitions, and Figure 1, the dynamic system can be formulated as a system of differential equations as follows:

$$\frac{dS}{dt} = \Lambda - c(t)\beta SI - \mu S \tag{1}$$

$$\frac{dE}{dt} = c(t)\beta SI - (\sigma + \mu)E \tag{2}$$

$$\frac{dI}{dt} = \sigma E - (\delta + \gamma_1 + \mu)I \tag{3}$$

$$\frac{dC}{dt} = \delta I - (\gamma_2 + \alpha + \mu)C \tag{4}$$

$$\frac{dR}{dt} = \gamma_1 I + \gamma_2 C - \mu R \tag{5}$$

Where:

- $c(t)$: time-dependent contact levels representing variations in the intensity of academic stress.
- β : The level of academic stress transmission through social interactions (social contagion).
- σ : The level of development of an exposed individual into an individual experiencing stress.
- $\delta(t)$: The degree to which a stressed individual enters the coping phase as a result of institutional detection or intervention.
- γ_1 : Immediate level of recovery from stress without formal intervention.
- γ_2 : Level of recovery through coping or intervention mechanisms.
- A : dropout rate due to stress from stress management classes.

Systematic steps in the analysis of epidemiological compartmental models (such as SIR, SEIR) generally involve several sequential and interrelated main stages, including: identifying compartments and relevant underlying assumptions of the formulated model; formulating a mathematical model using a system of differential equations that describes the movement of individuals between compartments; conducting model analysis, including stability analysis, numerical simulations, and exploration of intervention scenarios (Bernardi et al., 2025). The identification and parameter estimation stages of the formulated model can be performed using available epidemiological data through various methods, see Beira & Sebastião (2021), Ferrández et al. (2023), Li et al. (2024), and Schiassi et al. (2021). However, in this study, we explore the model behavior for the spread of academic stress using sensitivity analysis methods. To identify the parameters that most influence the number of students in the chronic stress phase (C_{final}), a sensitivity analysis was conducted using the Partial Rank Correlation Coefficient (PRCC) method on six main parameters: $\alpha, \beta, \sigma, \delta, \gamma_1, \gamma_2$. Sensitivity analysis is a commonly used tool, at least in traditional modeling, to examine the robustness of model results to changes in parameter values (Broeke et al., 2016). Sensitivity analysis is a widely used tool in computational modeling, used for various purposes, such as better understanding the relationship between parameter values in a mathematical model and its results, and identifying parameters whose changes in value imply greater variation in model results, among other purposes (Galvão & Lobosco, 2020). The PRCC method is used to measure the nonlinear but monotonic relationship between input and output. The PRCC method appears to be the best choice, because it provides a measure of monotonicity between parameters and model output after removing the linear effects of all parameters except the parameter of interest. The PRCC method is based on calculating the partial correlation coefficient between the ranks of each parameter and the rank of the objective function value (Marino et al., 2008):

$$r_{x_j,y} = \frac{\mathrm{Cov}\,(\hat{x}_j, \hat{y})}{\sqrt{\mathrm{Var}(\hat{x}_j).\mathrm{Var}(\hat{y})}} \tag{6}$$

A higher positive PRCC indicates that the parameter has a greater positive control on the response variable of interest, while a higher (absolute value) negative PRCC indicates a greater negative control (Jiang et al., 2012). This method provides a measure of the sensitivity of the objective function to each parameter, while taking into account the interactions between parameters. Rank-transformed data are used to take into account possible nonlinearity in the data. This approach is therefore computationally efficient and can be applied to large-scale models with many parameters. To calculate the PRCC sensitivity coefficient, a set of random points in the parameter set is sampled using the Sobol low discrepancy sequence, as described in previous work (Sorokin et al., 2019; Sorokin & Goryanin, 2023). The PRCC sensitivity coefficient is then calculated as a partial correlation coefficient between each parameter and the objective function value, with the influence of other parameters controlled for.

Result and Discussion

Simulation of Student Academic Stress Dynamics

National empirical data shows that academic stress is a widespread phenomenon among Indonesian students. Based on a 2019–2020 survey by ILMPI (Indonesian Psychology Student Association), out of more than 5,000 respondents, 1,470 students experienced persistent anxiety, 1,235 experienced prolonged fatigue, and 907 showed symptoms of sadness that disrupted daily activities. This shows that academic stress is multidimensional: it is not just a single symptom, but includes anxiety, burnout, and emotional distress. In the context of the model, this reinforces that the I(t) compartment is not simply "mild stress," but a significant (clinical/behavioral) condition. In line with these findings, Ambarwati et al. (2019) reported that the prevalence of academic stress among Indonesian students ranges from 36.7 to 71.6%, indicating varying levels of stress depending on the academic and social context of the campus. This indicates the variability of the system, which depends on the campus environment, academic load, or social support. In the model, this actually supports the use of c(t), β as a contextual & dynamic parameter. Furthermore, 72.4% of students experience stress due to academic workload, future concerns, and financial uncertainty; this indicates a multi-driver system, meaning stress is not only from "social contact." In the model, this can be interpreted as an increase in c(t), or an increase in β. These three data points confirm that our proposed SEICR model is relevant, as stress is systemically distributed; there is "social contagion" where students influence each other; and a Coping (C) compartment is necessary, as not everyone recovers immediately; there is an adaptation process. This strongly justifies the SEICR model we propose in this study. Based on data (Humaira & Astuti, 2024), where from a total of 180 students (15% low, 72.8% medium, and 12.2% high), this data is based on stress levels, not epidemiological compartments. Therefore, we conducted a rational mapping.

Table 1. Mapping to SEICR

Category	Model
Low (15%)	S (susceptible)
Medium (72.8%)	E (exposed)
High (12.2%)	I (active stress)

Because it is "moderate" (already under pressure), then E is suitable "high" which proves that stress → I. By calculating the initial value, where the total is 180, we obtain: S_0 = 15% × 180 = 27; E_0 = 72.8% × 180 = 131, and I_0 = 12.2% × 180 = 22. And because the data only has 3 categories, we use C_0 = 0 and R_0 = 0. So, the final initial condition (S_0, E_0, I_0, C_0, R_0) = (27, 131, 22, 0, 0). Next, using time t ∈ [0.24], the realistic parameters for the initial simulation of the SEICR model are β=0.002; c(t)=10; σ = 0.3; δ = 0.2; γ_1 = 0.1; γ_2 = 0.15; μ = 0.01; α = 0.02, and $\Lambda=\mu N$. Under these conditions: E will be high at the beginning (because it is 72% of the population); I will rise first (transition from E → I); C starts to rise after that (effect of δ (intervention)); and R rises slowly (effect of γ_1 and γ_2).

The initial conditions were derived from empirical data reported by Humaira & Astuti (2024), where 15% of students experienced low stress, 72.8% moderate stress, and 12.2% high stress. These categories were mapped into the SEICR framework as susceptible, exposed, and stressed compartments, respectively.

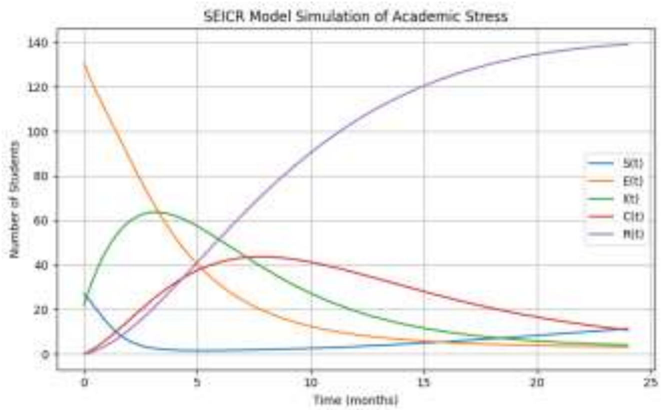

Figure 2. Temporal dynamics of the SEICR model

The simulation results (Figure 2) show that the dynamics of academic stress follow a gradual transition pattern from exposure to an active stress state before finally recovering through coping and recovery mechanisms. In the initial phase (t = 0–3 months), the Exposed (E) compartment dominates the population because most students are at a moderate level of stress. This condition reflects the presence of extensive academic pressure that has not yet fully developed into severe stress. Over time, there is an increase in the Stressed (I) compartment due to the transition from E→I at a rate of σ. The peak number of individuals in the I compartment generally occurs in the middle phase of the simulation (around the 4th to 8th month), which indicates a critical period where academic pressure reaches maximum intensity. Contextually, this phase can be associated with exam periods, assignment deadlines, or cumulative academic pressure. After reaching a peak, the number of individuals in compartment I begins to decline as the Coping compartment (C) increases. This indicates that the detection and intervention rate δ plays an important role in shifting students from stressful conditions to the adaptation process. The increase in C(t) reflects the effectiveness of counseling services, social support, and individual coping strategies. However, the presence of the parameter α (dropout due to stress) causes some individuals to leave the system before reaching full recovery. This indicates that coping is not always successful, especially in cases of severe stress. The Recovered (R) compartment increases gradually throughout the simulation period as a result of two recovery pathways: direct recovery from stress (γ_1) and recovery through coping (γ_2). The contribution of the coping pathway (γ_2) tends to be more dominant in the long term, which emphasizes the importance of structured interventions over spontaneous recovery. By the end of the simulation period (month 24), the system tends to reach a quasi-steady state, where the number of stressed individuals decreases, the recovered population increases, and stress exposure remains but at a more controlled level. Despite the increasing number of individuals recovering, the Exposed (E) compartment did not completely disappear. This suggests that academic stress persists in the system, primarily due to ongoing academic pressure, social interactions between students, and external factors such as future uncertainty. In other words, the system did not return to a stress-free equilibrium, but rather to an endemic state.

The simulation results provide several important implications: a) Early intervention (reducing σ) can prevent severe stress spikes, b) Increasing detection and access to coping (δ) significantly reduces the number of individuals in active stress, c) Coping effectiveness (γ_2) is a key factor in increasing the population's recovery rate, and d) Reducing systemic stress (β, c(t)) is necessary to reduce the overall spread of stress. The simulation results demonstrate that academic stress behaves as a persistent and dynamically evolving phenomenon within the student population. The inclusion of a coping compartment provides a more realistic representation of behavioral adaptation, highlighting that effective intervention strategies are crucial to preventing the escalation of stress into severe conditions.

Equilibrium Point

The SEICR model with recruitment rate Λ and exits rate μ is given by the following differential system:

$$\frac{dS}{dt} = \Lambda - c(t)\beta SI - \mu S \quad (1)$$

$$\frac{dE}{dt} = c(t)\beta SI - (\sigma + \mu)E \quad (2)$$

$$\frac{dI}{dt} = \sigma E - (\delta + \gamma_1 + \mu)I \quad (3)$$

$$\frac{dC}{dt} = \delta I - (\gamma_2 + \alpha + \mu)C \quad (4)$$

$$\frac{dR}{dt} = \gamma_1 I + \gamma_2 C - \mu R \quad (5)$$

The SEICR system under consideration has an equilibrium point (balance point) which is obtained by setting the time derivative equal to zero, namely:

$$\frac{dS}{dt} = \frac{dE}{dt} = \frac{dI}{dt} = \frac{dC}{dt} = \frac{dR}{dt} = 0 \quad (6)$$

The stress-free equilibrium point occurs when no individual experiences exposure or stress, namely: E = I = C = 0.

From the system:

$$\frac{dS}{dt} = \Lambda - \mu S = 0 \Rightarrow S^* = \frac{\Lambda}{\mu}$$

$$\frac{dR}{dt} = -\mu R = 0 \Rightarrow R^* = 0$$

So, we get: $E_0 = \left(\frac{\Lambda}{\mu},\ 0,\ 0,\ 0,\ 0\right)$.

The endemic equilibrium point occurs when academic stress persists in the population, namely: $E^*, I^*, C^* \neq 0$.

From the equation E: $0 = c\beta S^* I^* - (\sigma + \mu)E^*$,

$$E^* = \frac{c\beta S^* I^*}{\sigma + \mu} \quad (7)$$

From the equation I; $0 = \sigma E^* - (\delta + \gamma_1 + \mu)I^*$; substitution E*: $\sigma\left(\frac{c\beta S^* I^*}{\sigma+\mu}\right) = (\delta + \gamma_1 + \mu)I^*$, and divided by $I^* \neq 0$: $\frac{c\beta\sigma S^*}{\sigma+\mu} = \delta + \gamma_1 + \mu$, we get:

$$S^* = \frac{(\sigma + \mu)(\delta + \gamma_1 + \mu)}{c\beta\sigma} \quad (8)$$

From the population balance relationship: $\frac{dS}{dt} = 0 \Rightarrow \Lambda = c\beta S^* I^* + \mu S^*$; we get:

$$I^* = \frac{\Lambda - \mu S^*}{c\beta S^*} \quad (9)$$

$$E^* = \frac{c\beta S^* I^*}{\sigma + \mu} \quad (10)$$

$$C^* = \frac{\delta I^*}{\gamma_2 + \alpha + \mu} \quad (11)$$

$$R^* = \frac{\gamma_1 I^* + \gamma_2 C^*}{\mu} \quad (12)$$

An endemic point exists if: $I^* > 0$; $\Lambda - \mu S^* > 0$. Substituting S*, we obtain the following condition $R_0 > 1$. If $R_0 < 1$, academic stress disappears (DFE is stable), and If $R_0 > 1$, stress persists (endemic). The meaning is, academic stress is not a temporary phenomenon, but can become a systemic condition in the student population.

This model recognizes two equilibrium points: a disease-free equilibrium where no academic stress persists, and an endemic equilibrium where stress persists in the student population. The existence of an endemic equilibrium depends on the basic reproduction number R_0, which indicates that academic stress can persist as a systemic phenomenon when $R_0 > 1$.

Basic Reproduction Number (R0)

Using the Next Generation Matrix (NGM) method (Diekmann et al., 2010), the infectious compartment is considered to consist of E, I, and C. The new infection matrix F (appearing only at E) at the DFE point are formulated as: $\mathcal{F} = \begin{bmatrix} c\beta SI \\ 0 \end{bmatrix}$, and transition terms V: $\mathcal{V} = \begin{bmatrix} (\sigma+\mu)E \\ (\delta+\gamma_1+\mu)I - \sigma E \end{bmatrix}$.

Evaluation at $S = S^* = \frac{\Lambda}{\mu}$, $E = I = 0$:

Matrix $F = D\mathcal{F} \mid_{DFE}$ is: $F = \begin{bmatrix} \frac{\partial(c\beta SI)}{\partial E} & \frac{\partial(c\beta SI)}{\partial I} \\ 0 & 0 \end{bmatrix}_{DFE} = \begin{bmatrix} 0 & c\beta S^* \\ 0 & 0 \end{bmatrix}$; and matrix $V = D\mathcal{V} \mid_{DFE}$ is: $V = \begin{bmatrix} \sigma+\mu & 0 \\ -\sigma & \delta+\gamma_1+\mu \end{bmatrix}$.

We get invers V^{-1}:

$$V^{-1} = \frac{1}{(\sigma+\mu)(\delta+\gamma_1+\mu)} \begin{bmatrix} \delta+\gamma_1+\mu & 0 \\ \sigma & \sigma+\mu \end{bmatrix}$$

Using the Next Generation Matrix method, we obtain: $K = FV^{-1}$

$$K = \begin{bmatrix} \frac{c\beta S^*\sigma}{(\sigma+\mu)(\delta+\gamma_1+\mu)} & \frac{c\beta S^*}{\delta+\gamma_1+\mu} \\ 0 & 0 \end{bmatrix} \quad (13)$$

The basic reproduction number R_0 is defined as the largest eigenvalue (spectral radius) of the matrix FV^{-1}. Through substitution and simplification, we obtain the spectral radius: $R_0 = \rho(K) = \frac{c\beta S^*\sigma}{(\sigma+\mu)(\delta+\gamma_1+\mu)}$, substitution $S^* = \frac{\Lambda}{\mu}$, we get:

$$R_0 = \frac{c\beta\Lambda\sigma}{\mu(\sigma+\mu)(\delta+\gamma_1+\mu)} \quad (14)$$

Biologically, R_0 is the average number of "stress-exposed" freshmen generated by one stressed student during their stress period, in the entire susceptible population. If $R_0 < 1$, it means that each stressed student produces < 1 new case (stress does not spread). The dynamic impact is $I(t) \to 0$, the system is heading towards DFE (stress-free), in this context coping is effective, campus intervention is successful, and the academic environment is relatively healthy. And if $R_0 > 1$, it means that one stressed student can cause more than 1 other student to be exposed (stress spreads and persists). The dynamic impact is the emergence of endemic equilibrium (stress becomes a systemic phenomenon), in this context academic pressure is high, coping is not effective enough, and the social environment reinforces stress.

Following the Next Generation Matrix approach, the infected compartments are identified as the exposed and stressed classes, since only these contribute to the generation of new infections. Although the coping class is included in the model dynamics, it does not produce new infections and therefore does not influence the basic reproduction number.

Numerical Interpretation

Since detailed empirical data are not yet available, we use representative values based on literature & initial simulation (monthly): $\beta = 0.002 \rightarrow$ stress transmission rate; $c = 10 \rightarrow$ academic interaction intensity; $\sigma = 0.30 \rightarrow$ E→I progression; $\delta = 0.20 \rightarrow$ entry into coping; $\gamma_1 = 0.10 \rightarrow$ immediate recovery; $\mu = 0.01 \rightarrow$ exit the system; $N = 180 \Rightarrow \Lambda = \mu N = 1.8$:

$$R_0 = \frac{(10)(0.002)(1.8)(0.3)}{(0.01)(0.3+0.01)(0.2+0.1+0.01)} \approx 11.24$$

The R_0 value of 11.24 > 1 (this is the worst-case scenario / initial baseline) indicates that one student experiencing academic stress can, on average, trigger more than 11 other students to be exposed to stress during their stressful period. These results align with previous Indonesian data (Ambarwati et al., 2019) and Into The Light (2022), which showed a prevalence of 36–71%; 72.4% of students experiencing stress; and a predominance of the "moderate" category in data on Chemistry students in Aceh Province. This means that our proposed SEICR model successfully represents empirical reality Since the R0 value is > 1, the stress-free equilibrium point of our proposed SEICR model becomes unstable (academic stress has a high propagation power), and it can be concluded that the system has an endemic equilibrium point. This means that stress does not disappear from the population, and there will always be students under stress (social interactions and academic pressure play a dominant role). The academic environment allows stress to spread continuously, thus becoming a systemic phenomenon among students. This analysis shows that academic stress management can be achieved through: a) reducing the level of stressful interactions (c,β) → for example, by reducing the workload or competitive pressure; b) increasing detection and intervention (δ) → counseling services, psychological screening; c) increasing coping effectiveness (γ1,γ2) → stress management training.

Sensitivity Analysis

The following table presents the Partial Rank Correlation Coefficient (PRCC) values for each parameter in the SEICR model against the variable C(t) at the end of the simulation period (24 months, n = 200). The PRCC values illustrate the strength and direction of the relationship between each parameter and the number of students experiencing chronic stress.

From the results in the Table 2, it appears that the β parameter has the strongest positive influence on the increase in the number of students experiencing chronic stress, while γ_2 and μ have the greatest negative influence on this variable. Therefore, academic stress management strategies should focus on two complementary approaches: a) reducing the rate of stress transmission (β) through learning policies that de-emphasize competitive pressure and strengthen a supportive academic climate; b) increasing the rate of recovery (γ_2 and α) through optimizing counseling services, academic mentoring, and mental health promotion programs for students.

Table 2. PRCC values for parameters in SEICR model

Parameters	PRCC Value	Interpretation	Insight
β	0.21	The level of academic stress transmission through social interactions (social contagion)	Academic stress is more controlled by intervention than by the spread of
σ	−0.43	The level of development of an exposed individual into an individual experiencing stress	Fast transition reduces accumulation
γ_1	-0.37	Immediate level of recovery from stress	Without formal intervention
γ_2	-0.02	Level of recovery through coping or intervention mechanisms	Coping is not effective on its own, meaning it must be supported by δ (access to coping)
δ	−0.72	The sooner students enter the coping phase, the greater the overall reduction in stress.	Very strong results for policy: early detection + intervention = the key
α	0.01	Dropout rate due to stress from stress management classes	Dropout does not affect core dynamics much
μ	-0.30	The natural rate of exit from the system, including graduation, transfer, or dropout	is not explicitly modeled as a result of stress

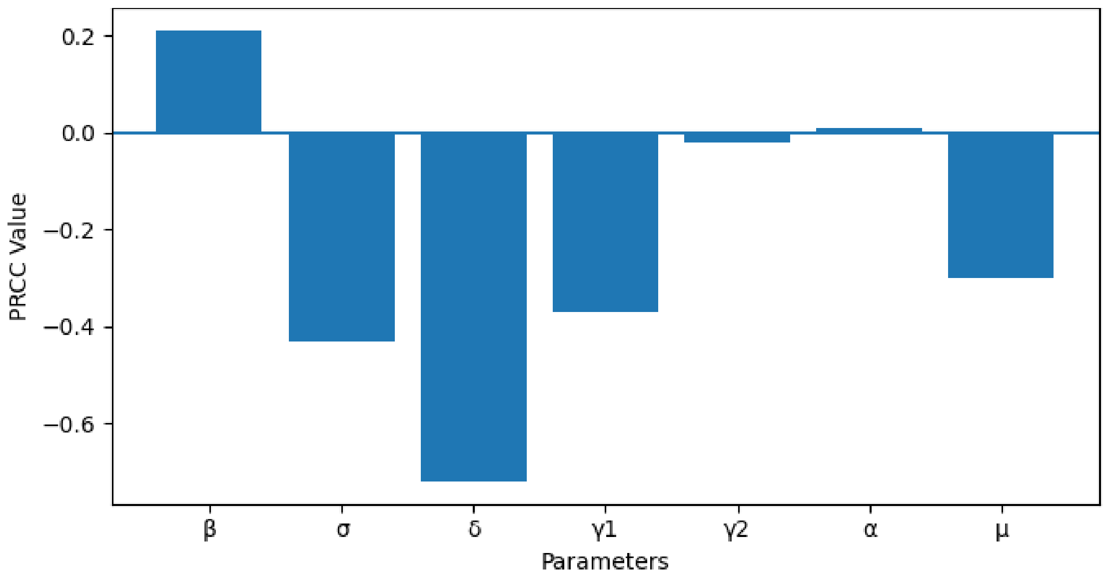

Figure 3. PRCC sensitivity analysis of SEICR model

The Figure 3 shows the results of a PRCC sensitivity analysis of SEICR model after 24 months using 200 sample parameter variations.

The PRCC value is the largest (negative, around −0.7), the parameter δ, representing the transition rate from a stressed individual to a coping compartment, shows the strongest negative correlation with stress prevalence. This means that the sooner students enter the coping phase, the greater the reduction in stress in the system. This suggests that early detection and access to intervention are the most crucial factors. The σ development rate also shows a relatively strong negative effect, with a rapid transition from the early phase to active stress, and reduced accumulation in the "exposed" phase. This indicates that the system does not "accumulate" latent stress, but moves rapidly towards resolution (coping/recovery). γ_1 and μ have a moderate effect, where γ_1 (direct recovery) can reduce stress, and μ (exit system) can reduce the proportion of stress. This means that natural recovery is important, but not the main factor. The transmission parameter β shows a weak positive correlation (only a small effect), this is interesting; it differs from classical epidemics, and suggests that the spread of stress is not the dominant factor, but rather internal processes & interventions. The parameter γ_2 has a negligible effect. This means that coping effectiveness alone is not sufficient; what matters is access to coping (δ); and this is a very powerful insight in our model. α is not significant; that is, dropout/late intervention does not significantly affect core dynamics. The sensitivity analysis suggests that academic stress dynamics are primarily controlled by intervention accessibility rather than transmission intensity. Unlike classical epidemic systems where transmission dominates, this model reveals that the accessibility and speed of intervention (δ) play a far more critical role in controlling academic stress. These findings align with various national surveys (Ambarwati et al., 2019; Humaira & Astuti, 2024).

Overall, the findings suggest that academic stress should be understood as an adaptive systems phenomenon, not simply a transmissible process. Therefore, effective intervention strategies should prioritize early detection and accessibility, rather than simply efforts to reduce exposure.

Conclusion

This study developed a SEICR-based mathematical model to analyze the dynamics of academic stress among university students using an epidemiological framework. The model incorporates key behavioral transitions, including exposure, stress manifestation, coping, and recovery, allowing a more realistic representation of stress progression in academic environments. The analytical results show that the system is governed by a threshold parameter, the basic reproduction number R_0. When $R_0 < 1$, academic stress diminishes over time and the system converges to a stress-free equilibrium. Conversely, when $R_0 > 1$, stress persists and stabilizes at an endemic level, indicating that academic stress can become a sustained systemic phenomenon within the student population. The numerical estimation of R_0 suggests that, under typical conditions, the system tends toward the endemic regime. Sensitivity analysis further reveals that the model is primarily driven by intervention-related parameters rather than transmission alone. In particular, the transition rate into coping (δ) is identified as the most influential factor in reducing stress prevalence, while the transmission parameter (β) plays a comparatively minor role. This finding highlights that academic stress behaves differently from classical infectious diseases, where transmission dominates system dynamics. Additionally, the results indicate that faster progression through early stress stages (σ) may reduce the accumulation of latent stress, emphasizing the importance of timely identification and response. The relatively weak influence of recovery effectiveness (γ_2) suggests that access to intervention is more critical than the intervention process itself. Overall, this study demonstrates that academic stress should be understood as an intervention-driven dynamic system. Effective mitigation strategies should prioritize early detection, rapid transition to coping mechanisms, and accessible institutional support systems. These findings provide a quantitative foundation for designing evidence-based policies to manage academic stress in higher education settings. This work contributes to the growing body of research by reframing academic stress as a controllable dynamic process, where timely intervention plays a more decisive role than exposure reduction. Future research may extend this model by incorporating behavioral heterogeneity, stochastic effects, and real-time data calibration.

Acknowledgments
We are grateful for the assistance and support provided by the Mathematics Laboratory Manager at the Integrated Laboratory, Institut Agama Islam Negeri Langsa.

Author Contributions
Conceptualization, methodology, software, data curation, J.J.; writing—original draft preparation, J.J. and B.I.; writing—review and editing, L.P.L. and F.N.M.; supervision, J.J. and N.N. All authors have read and agreed to the published version of the manuscript.

Funding
This research received no external funding.

Conflicts of Interest
The authors declare no conflict of interest.

References

Abdullah, N., Khaldun, I., & Musman, M. (2021). The Influence of Pocketbook to Improve Student Learning Outcomes and Motivation on Electron Configuration Material. *Jurnal Penelitian Pendidikan IPA*, *7*(3), 298–304. https://doi.org/10.29303/jppipa.v7i3.647

Alyami, M., Melyani, Z., Johani, A. A., Ullah, E., Alyami, H., Sundram, F., Hill, A., & Henning, M. (2017). The Impact of Self-Esteem, Academic Self-Efficacy and Perceived Stress on Academic Performance: A Cross-Sectional Study of Saudi Psychology Students. *The European Journal of Educational Sciences*, *4*(4), 51–68. https://doi.org/10.19044/ejes.v4no3a5

Amala, I. A., Sutarto, S., Putra, P. D. A., & Indrawati, I. (2023). Analysis of Scientific Literacy Ability Junior High School Students in Science Learning on Environmental Pollution. *Jurnal Penelitian*

Pendidikan IPA, *9*(3), 1001–1005. https://doi.org/10.29303/jppipa.v9i3.1816
Ambarwati, P. D., Pinilih, S. S., & Astuti, R. T. (2019). Gambaran Tingkat Stres Mahasiswa. *Jurnal Keperawatan Jiwa*, *5*(1), 40–47. https://doi.org/10.26714/jkj.5.1.2017.40-47
Annisa, D., Sutrisno, H., & Widjajanti, E. (2023). Academic Resilience in Chemistry During Covid-19: A Systematic Review. *Jurnal Penelitian Pendidikan IPA*, *9*(11). https://doi.org/10.29303/jppipa.v9i11.4354
Anwar, A., Syam, R., Pratama, M. I., & Side, S. (2021). SEIRS Model Analysis for Online Game Addiction Problem of Mathematics Students. *Journal of Physics: Conference Series*, *1918*(4), 042024. https://doi.org/10.1088/1742-6596/1918/4/042024
Asri, Y. N., Mursyidah, D. S., & Rizqi, V. (2021). Application of Project-Based Learning Through a STEM Approach to Improve Learning Outcomes During a Pandemic. *Jurnal Penelitian Pendidikan IPA*, *7*(4), 719–722. https://doi.org/10.29303/jppipa.v7i4.819
Balci, M. A. (2016). Fractional Virus Epidemic Model on Financial Networks. *Open Mathematics*, *14*(1), 1074–1086. https://doi.org/10.1515/math-2016-0098
Banerjee, N., & Chatterjee, I. (2016). Academic Stress, Suicidal Ideation & Mental Wellbeing Among 1st Semester & 3rd Semester Medical, Engineering & General Stream Students. *Researchers World: Journal of Arts, Science and Commerce*, *7*(3), 74–83. https://doi.org/10.18843/rwjasc/v7i3/09
Bauch, C. T., & Galvani, A. P. (2013). Social Factors in Epidemiology. *Science*, *342*(6154), 47–49. https://doi.org/10.1126/science.1244492
Beira, M., & Sebastião, P. (2021). A Differential Equations Model-Fitting Analysis of COVID-19 Epidemiological Data to Explain Multi-Wave Dynamics. *Scientific Reports*, *11*, 16312. https://doi.org/10.1038/s41598-021-95494-6
Bello, D. L., & Gumarao, M. (2012). Stress, Coping Strategies, and Academic Performance of Dentistry Students. *AUP Research Journal*, *19*(2), 37–58.
Benedetto, M. D., Towt, C. J., & Jackson, M. L. (2020). A Cluster Analysis of Sleep Quality, Self-Care Behaviors, and Mental Health Risk in Australian University Students. *Behavioral Sleep Medicine*, *18*(3), 309–320. https://doi.org/10.1080/15402002.2019.1580194
Berkman, L. F., & Kawachi, I. (2023). A Historical Framework for Social Epidemiology. In L. F. Berkman & I. Kawachi (Eds.), *Social Epidemiology* (2nd ed., pp. 1–16). Oxford University Press. https://doi.org/10.1093/oso/9780195083316.003.0001
Bernardi, E., Lorenzi, T., Sensi, M., & Tosin, A. (2025). Heterogeneously Structured Compartmental Models of Epidemiological Systems: From Individual-Level Processes to Population-Scale Dynamics. *Studies in Applied Mathematics*, *155*(2), e70091. https://doi.org/10.1111/sapm.70091
Boyraz, G., Granda, R., Baker, C. N., Tidwell, L. L., & Waits, J. B. (2016). Posttraumatic Stress, Effort Regulation, and Academic Outcomes Among College Students: A Longitudinal Study. *Journal of Counseling Psychology*, *63*(4), 398–410. https://doi.org/10.1037/cou0000102
Broeke, G. T., Voorn, G. V., & Ligtenberg, A. (2016). Which Sensitivity Analysis Method Should I Use for My Agent-Based Model? *Journal of Artificial Societies and Social Simulation*, *19*(1), 5. https://doi.org/10.18564/jasss.2857
Cabanach, R. G., Rodríguez, S., Valle, A., & Millán, I. P. y P. G. (2007). Metas Académicas y Vulnerabilidad al Estrés en Contextos Académicos. *Aula Abierta*, *36*(1–2), 3–16.
Cassady, J. C., Pierson, E. E., & Starling, J. M. (2019). Predicting Student Depression with Measures of General and Academic Anxieties. *Frontiers in Education*, *4*, 11. https://doi.org/10.3389/feduc.2019.00011
Dibyantini, R. E., Amdayani, S., Siregar, M. I., & Syafriani, D. (2023). Application of STEM-PjBL Based Chemistry Module to Improve Science Literacy and Student Learning Motivation. *Jurnal Penelitian Pendidikan IPA*, *9*(Special Issue), 95–102. https://doi.org/10.29303/jppipa.v9iSpecialIssue.5872
Diekmann, O., Heesterbeek, J. A., & Roberts, M. G. (2010). The Construction of Next-Generation Matrices for Compartmental Epidemic Models. *Journal of the Royal Society, Interface*, *7*(47), 873–885. https://doi.org/10.1098/rsif.2009.0386
Eastwood, J. G., Kemp, L. A., Garg, P., Tyler, I., & Souza, D. E. D. (2019). A Critical Realist Translational Social Epidemiology Protocol for Concretising and Contextualising a "Theory of Neighbourhood Context, Stress, Depression, and the Developmental Origins of Health and Disease (DOHaD)", Sydney Australia. *International Journal of Integrated Care*, *19*(3), 3962. https://doi.org/10.5334/ijic.3962
Edjah, K., Ankomah, F., Domey, E., & Laryea, J. E. (2020). Stress and Its Impact on Academic and Social Life of Undergraduate University Students in Ghana: A Structural Equation Modeling Approach. *Open Education Studies*, *2*(1), 86–98. https://doi.org/10.1515/edu-2020-0100

Ferrández, M., Ivorra, B., Redondo, J., Ramos, A., & Ortigosa, P. (2023). A Multi-Objective Approach to Identify Parameters of Compartmental Epidemiological Models - Application to Ebola Virus Disease Epidemics. *Communications in Nonlinear Science and Numerical Simulation*, *120*, 107165. https://doi.org/10.1016/j.cnsns.2023.107165

Freire, C., Ferradás, M. D. M., Núñez, J. C., Valle, A., & Vallejo, G. (2019). Eudaimonic Well-Being and Coping with Stress in University Students: The Mediating/Moderating Role of Self-Efficacy. *International Journal of Environmental Research and Public Health*, *16*(1), 48. https://doi.org/10.3390/ijerph16010048

Frenzel, A. C., Becker-Kurz, B., Pekrun, R., Goetz, T., & Lüdtke, O. (2018). Emotion Transmission in the Classroom Revisited: A Reciprocal Effects Model of Teacher and Student Enjoyment. *Journal of Educational Psychology*, *110*(5), 628–639. https://doi.org/10.1037/edu0000228

Fuente, J. D. L., Amate, J., González-Torres, M. C., Artuch, R., García-Torrecillas, J. M., & Fadda, S. (2020). Effects of Levels of Self-Regulation and Regulatory Teaching on Strategies for Coping with Academic Stress in Undergraduate Students. *Frontiers in Psychology*, *11*, 22. https://doi.org/10.3389/fpsyg.2020.00022

Galea, S., & Link, B. G. (2013). Six Paths for the Future of Social Epidemiology. *American Journal of Epidemiology*, *178*(6), 843–849. https://doi.org/10.1093/aje/kwt148

Galvão, M. F., & Lobosco, M. (2020). A System for the Automation of One-at-a-Time Sensitivity Analysis in ODE Systems. *Revista Mundi Engenharia, Tecnologia e Gestão*, *5*(2), 21–171. https://doi.org/10.21575/25254782rmetg2020vol5n21171

Ghatol, S. D. (2017). Academic Stress Among Higher Secondary School Students: A Review. *International Journal of Advanced Research in Education & Technology*, *4*(1), 38–41.

Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth. *Marketing Letters*, *12*(3), 211–223. https://doi.org/10.1023/A:1011122126881

Gupta, R., Singh, N., & Kumar, R. (2017). Longitudinal Predictive Validity of Emotional Intelligence on First Year Medical Students Perceived Stress. *BMC Medical Education*, *17*(1), 139. https://doi.org/10.1186/s12909-017-0979-z

Hirvonen, R., Yli-Kivistö, L., Putwain, D. W., Ahonen, T., & Kiuru, N. (2019). School-Related Stress Among Sixth-Grade Students – Associations with Academic Buoyancy and Temperament. *Learning and Individual Differences*, *70*, 100–108. https://doi.org/10.1016/j.lindif.2019.01.012

Hosseinkhani, Z., Hassanabadi, H. R., Parsaeian, M., Karimi, M., & Nedjat, S. (2020). Academic Stress and Adolescents Mental Health: A Multilevel Structural Equation Modeling (MSEM) Study in Northwest of Iran. *Journal of Research in Health Sciences*, *20*(4), e00496. https://doi.org/10.34172/jrhs.2020.30

Huli, P. R. (2014). Stress Management in Adolescence. *Quest Journals Journal of Research in Humanities and Social Science*, *2*(7), 40–47.

Humaira, S., & Astuti, W. (2024). Gambaran Stress Akademik pada Mahasiswa Indonesia Bagian Timur di Provinsi Aceh. *INSIGHT: Jurnal Penelitian Psikologi*, *2*(4), 796–809. Retrieved from https://ojs.unimal.ac.id/index.php/jpt/index

Hwang, S. W., Stergiopoulos, V., O'Campo, P., & Gozdzik, A. (2012). Ending Homelessness Among People with Mental Illness: The at Home/Chez Soi Randomized Trial of a Housing First Intervention in Toronto. *BMC Public Health*, *12*(1), 787. https://doi.org/10.1186/1471-2458-12-787

Jiang, Y., Zhuang, Q., Schaphoff, S., Sitch, S., Sokolov, A., Kicklighter, D., & Melillo, J. (2012). Uncertainty Analysis of Vegetation Distribution in the Northern High Latitudes During the 21st Century with a Dynamic Vegetation Model. *Ecology and Evolution*, *2*(3), 593–614. https://doi.org/10.1002/ece3.85

Kadapatti, M. G., & Vijayalaxmi, A. H. M. (2012). Stressor of Academic Stress- A Study on Pre-University Students. *Indian Journal of Science and Research*, *3*(1), 171–175.

Kao, R. (2002). The Role of Mathematical Modelling in the Control of the 2001 FMD Epidemic in the UK. *Trends in Microbiology*, *10*(6), 279–286. https://doi.org/10.1016/S0966-842X(02)02371-5

Karaman, M. A., Lerma, E., Vela, J. C., & Watson, J. C. (2019). Predictors of Academic Stress Among College Students. *Journal of College Counseling*, *22*(1), 41–55. https://doi.org/10.1002/jocc.12113

Kawachi, I., & Subramanian, S. V. (2018). Social Epidemiology for the 21st Century. *Social Science and Medicine*, *196*, 240–245. https://doi.org/10.1016/j.socscimed.2017.10.034

Kawachi, K. (2008). Deterministic Models for Rumor Transmission. *Nonlinear Analysis: Real World Applications*, *9*(5), 1989–2028. https://doi.org/10.1016/j.nonrwa.2007.06.004

Kermack, W., & Mckendrick, À. (1927). A Contribution to the Mathematical Theory of Epidemics. *Proceedings of The Royal Society A: Mathematical,*

Physical and Engineering Sciences, *115*, 700–721. https://doi.org/10.1098/RSPA.1927.0118
Kotola, B. S., & Teklu, S. W. (2022). A Mathematical Modeling Analysis of Racism and Corruption Codynamics with Numerical Simulation as Infectious Diseases. *Computational and Mathematical Methods in Medicine*, *2022*, 9977727. https://doi.org/10.1155/2022/9977727
Kötter, T., Wagner, J., Brüheim, L., & Voltmer, E. (2017). Perceived Medical School Stress of Undergraduate Medical Students Predicts Academic Performance: An Observational Study. *BMC Medical Education*, *17*(1), 256. https://doi.org/10.1186/s12909-017-1091-0
Lazarus, R. S. (1999). The Cognition–Emotion Debate: A Bit of History. In T. Dalgleish & M. J. Power (Eds.), *Handbook of Cognition and Emotion* (pp. 3–19). John Wiley & Sons. https://doi.org/10.1002/0470013494.ch1
Li, T., & Guo, Y. (2019). Stability and Optimal Control in a Mathematical Model of Online Game Addiction. *Filomat*, *33*(17), 5691–5711. https://doi.org/10.2298/FIL1917691L
Li, X., Swallow, B., & Chadwick, F. (2024). A Novel Approximate Bayesian Inference Method for Compartmental Models in Epidemiology Using Stan. *arXiv Preprint*. https://arxiv.org/abs/2401.12156
Llego, J., Gabriel, E., & Corpus, J. (2018). A Correlational Study on the Stress Level and Academic Performance of Nursing Students. *Journal of Nursing Practice*, *4*(2), 198–207. https://10.13140/RG.2.2.13693.41441
Mahato, R. C., & Sen, S. (2021). Academic Stress, Self-Efficacy and Anxiety: A Study on Mathematics of Higher Secondary Level Students in Purulia District of West Bengal, India. *International Journal of Creative Research Thoughts*, *9*(5), 4836–4847.
Mamo, D., & Koya, P. (2015). Mathematical Modeling and Simulation Study of SEIR Disease and Data Fitting of Ebola Epidemic Spreading in West Africa. *Journal of Multidisciplinary Engineering Science and Technology*, *2*(1), 106–114.
Marino, S., Hogue, I. B., Ray, C. J., & Kirschner, D. E. (2008). A Methodology for Performing Global Uncertainty and Sensitivity Analysis in Systems Biology. *Journal of Theoretical Biology*, *254*(1), 178–196. https://doi.org/10.1016/j.jtbi.2008.04.011
Muntaner, C. (2013). Invited Commentary: On the Future of Social Epidemiology--A Case for Scientific Realism. *American Journal of Epidemiology*, *178*(6), 852–857. https://doi.org/10.1093/aje/kwt143
Ndoa, Y. A. A., & Jumadi, J. (2022). Increasing Learning Motivation Through the Application of Physics E-Module Based on Flipped Learning. *Jurnal Penelitian Pendidikan IPA*, *8*(3), 1223–1230. https://doi.org/10.29303/jppipa.v8i3.1556
Nguyen, M. T., Nguyen, T. G., Tran, T. T. A., Nguyen, T. T. N., Le, D. D., Nguyen, T. T. B., Hoang, H. H., Ho, T. L. D., & Tran, B. T. (2022). Network Analysis of Psychological Factors Related to Academic Pressure Faced by Medical Students in the Central and Highland Regions of Vietnam. *Medical Education Online*, *27*(1), 2007577. https://doi.org/10.1080/10872981.2021.2007577
Nikitha, S., Jose, T. T., & Valsaraj, B. P. (2014). A Correlational Study on Academic Stress and Self-Esteem Among Higher Secondary Students in Selected Schools of Udupi District. *Journal of Health and Allied Sciences NU*, *4*(1), 6–9. https://doi.org/10.1055/s-0040-1703742
Nilyani, K., Asrizal, A., & Usmeldi, U. (2023). Effect of STEM Integrated Science Learning on Scientific Literacy and Critical Thinking Skills of Students: A Meta-Analysis. *Jurnal Penelitian Pendidikan IPA*, *9*(6), 65–72. https://doi.org/10.29303/jppipa.v9i6.2614
Pane, E. P., Lubis, N. F., & Simarmata, G. (2024). Application of Interactive Virtual Lab Media Based on a STEM Approach in Improving Students' Scientific Literacy and Learning Motivation. *Jurnal Penelitian Pendidikan IPA*, *10*(12), 10736–10744. https://doi.org/10.29303/jppipa.v10i12.8589
Peckham, R. (2014). Contagion: Epidemiological Models and Financial Crises. *Journal of Public Health*, *36*(1), 13–17. https://doi.org/10.1093/pubmed/fdt083
Pozos-Radillo, B. E., Preciado-Serrano, M. D. L., Acosta-Fernández, M., Aguilera-Velasco, M. D. L. Á., & Delgado-García, D. D. (2014). Academic Stress as a Predictor of Chronic Stress in University Students. *Psicologia Educativa*, *20*(1), 47–52. https://doi.org/10.1016/j.pse.2014.05.006
Putwain, D. W. (2019). An Examination of the Self-Referent Executive Processing Model of Test Anxiety: Control, Emotional Regulation, Self-Handicapping, and Examination Performance. *European Journal of Psychology of Education*, *34*(2), 341–358. https://doi.org/10.1007/s10212-018-0383-z
Ranasinghe, P., Wathurapatha, W. S., Mathangasinghe, Y., & Ponnamperuma, G. (2017). Emotional Intelligence, Perceived Stress and Academic Performance of Sri Lankan Medical Undergraduates. *BMC Medical Education*, *17*(1), 41. https://doi.org/10.1186/s12909-017-0884-5
Rois, R., Ray, M., Rahman, A., & Roy, S. K. (2021). Prevalence and Predicting Factors of Perceived Stress Among Bangladeshi University Students Using Machine Learning Algorithms. *Journal of*

Health, Population and Nutrition, *40*(1), 50. https://doi.org/10.1186/s41043-021-00276-5

Roux, A. V. D. (2022). Social Epidemiology: Past, Present, and Future. *Annual Review of Public Health*, *43*, 79–98. https://doi.org/10.1146/annurev-publhealth-060220-042648

Rusk, N., Tamir, M., & Rothbaum, F. (2011). Performance and Learning Goals for Emotion Regulation. *Motivation and Emotion*, *35*(4), 444–460. https://doi.org/10.1007/s11031-011-9229-6

Safitri, R., Hadi, S., & Widiasih, W. (2023). Effect of the Problem Based Learning Model on the Students Motivation and Learning Outcomes. *Jurnal Penelitian Pendidikan IPA*, *9*(9), 7310–7316. https://doi.org/10.29303/jppipa.v9i9.4772

Saklofske, D. H., Austin, E. J., Mastoras, S. M., Beaton, L., & Osborne, S. E. (2012). Relationships of Personality, Affect, Emotional Intelligence and Coping with Student Stress and Academic Success: Different Patterns of Association for Stress and Success. *Learning and Individual Differences*, *22*(2), 251–257. https://doi.org/10.1016/J.LINDIF.2011.02.010

Sathishkumar, G., & Vannathi, S. (2024). The Role of Reasoning Ability and Academic Stress in Mathematics Achievement Among Higher Secondary Students. *Alochana Chakra Journal*, *13*(1), 227–234.

Scharp, K. M., & Hall, E. D. (2019). Examining the Relationship between Undergraduate Student Parent Social Support-Seeking Factors, Stress, and Somatic Symptoms: A Two-Model Comparison of Direct and Indirect Effects. *Health Communication*, *34*(1), 54–64. https://doi.org/10.1080/10410236.2017.1384427

Schiassi, E., Florio, M. D., D'Ambrosio, A., Mortari, D., & Furfaro, R. (2021). Physics-Informed Neural Networks and Functional Interpolation for Data-Driven Parameters Discovery of Epidemiological Compartmental Models. *Mathematics*, *9*(17), 2069. https://doi.org/10.3390/math9172069

Shaw, M. P., Peart, D. J., & Fairhead, O. J. W. (2017). Perceived Stress in University Students Studying in a Further Education College. *Research in Post-Compulsory Education*, *22*(3), 442–452. https://doi.org/10.1080/13596748.2017.1362534

Side, S., Jannah, M., Saman, A., Pratama, M. I., & Sanusi, W. (2024). Optimal Control and Analysis of the SEIRS Model on the Problem of Online Game Addiction: A Case Study Among Class VIII Students of the State Junior High Schools in Makassar City. *IAENG International Journal of Applied Mathematics*, *54*(2), 316–326.

Silva, M. M., & Vera, J. (2025). Relationship between Academic Stress and Math Scores in Grade 9 Students. *Journal of Mathematics and Statistics Studies*, *6*(3), 77–82. https://doi.org/10.32996/jmss.2025.6.3.7

Sorokin, A., & Goryanin, I. (2023). FBA-PRCC. Partial Rank Correlation Coefficient (PRCC) Global Sensitivity Analysis (GSA) in Application to Constraint-Based Models. *Biomolecules*, *13*(3), 500. https://doi.org/10.3390/biom13030500

Sorokin, A., Sorokina, O., & Armstrong, J. D. (2019). RKappa: Software for Analyzing Rule-Based Models. In W. Hlavacek (Ed.), *Modeling Biomolecular Site Dynamics* (pp. 363–390). Humana Press. https://doi.org/10.1007/978-1-4939-9102-0_17

Takaeb, A. E. L. (2021). Understanding Research Methods for Social Epidemiology: A Narrative Review. *Indonesian Journal of Health Sciences Research and Development*, *3*(2), 126–135. https://doi.org/10.36566/ijhsrd/vol3.iss2/91

Taupik, R. P., & Fitria, Y. (2023). Learning Motivation and Computational Thinking Ability of Elementary School Students in Learning Science. *Jurnal Penelitian Pendidikan IPA*, *9*(9), 7665–7671. https://doi.org/10.29303/jppipa.v9i9.4826

Tus, J. (2020). Academic Stress, Academic Motivation, and Its Relationship on the Academic Performance of the Senior High School Students. *Asian Journal of Multidisciplinary Studies*, *8*(5), 29–37.

Vaidya, N., Morgan, M., Jones, T., Miller, L., Lapin, S., & Schwartz, E. (2014). Modelling the Epidemic Spread of an H1N1 Influenza Outbreak in a Rural University Town. *Epidemiology and Infection*, *143*(8), 1610–1620. https://doi.org/10.1017/S0950268814002568

Veena, N., & Shastri, S. (2016). Stress and Academic Performance. *International Journal of Indian Psychology*, *3*(4), 71–82.

Wang, T., Ye, G., Liu, X., Zhou, R., Li, J., & Wang, T. (2024). SIAR: An Effective Model for Predicting Game Propagation. *Lecture Notes in Electrical Engineering*, *1134*,325–336. https://doi.org/10.1007/978-981-99-9342-0_31

Windarwati, H. D., Lestari, R., Wicaksono, S. A., Kusumawati, M. W., Ati, N. A. L., Ilmy, S. K., Sulaksono, A. D., & Susanti, D. (2022). Relationship between Stress, Anxiety, and Depression with Suicidal Ideation in Adolescents. *Jurnal Ners*, *17*(1), 30–37. https://doi.org/10.20473/jn.v17i1.31216

Woo, J., Son, J., & Chen, H. (2011). An SIR Model for Violent Topic Diffusion in Social Media. *Proceedings of 2011 IEEE International Conference on Intelligence and Security Informatics*, 15–19. https://doi.org/10.1109/ISI.2011.5984043

Yuhuan, Z., Pengyue, Z., Dong, C., Qichao, N., Dong, P., Anqi, S., Hongbo, J., & Zhixin, D. (2022). The Association between Academic Stress, Social Support, and Self-Regulatory Fatigue Among Nursing Students: A Cross-Sectional Study Based on a Structural Equation Modelling Approach. *BMC Medical Education*, *22*(1), 827. https://doi.org/10.1186/s12909-022-03829-2

Zhang, C., Shi, L., Tian, T., Zhou, Z., Peng, X., Shen, Y., Li, Y., & Ou, J. (2022). Associations between Academic Stress and Depressive Symptoms Mediated by Anxiety Symptoms and Hopelessness Among Chinese College Students. *Psychology Research and Behavior Management*, *15*, 547–556. https://doi.org/10.2147/PRBM.S353778