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The Spread of Academic Boredom Model in the Context of Mathematics Lessons: Epidemiological Approach

Yenny Suzana[1]*, Budi Irwansyah[1], Mohd Afifi bin Bahurudin Setambah[2], Mulyono[3], Iyana Maulida[1]
[1]Mathematics Education Study Program, Institut Agama Islam Negeri Langsa, Indonesia
[2]Faculty of Human Development, Universiti Pendidikan Sultan Idris, Malaysia
[3]Mathematics Education Study Program, Universitas Negeri Medan
yenni@iainlangsa.ac.id

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ABSTRACT

Boredom in educational contexts seems to be a universal academic emotion, and one that is frequently experienced by students across age groups, educational needs, and ethnicity However, despite its significance in the context of mathematics lessons, academic boredom is rarely studied, especially in terms of mathematical modeling. This article proposes a dynamic model of the spread of academic boredom in the context of mathematics lessons using an epidemiological approach, taking a case study in the middle school students. This model divides the student population into four subpopulations or compartments: susceptible (S), exposed (E), infected (I), and recovered (R) from academic boredom in the context of mathematics lessons. The transition process between subpopulations or compartments is influenced by social interactions between students. By using theoretical assumptions that refer to general patterns of social behavior dynamics in adolescents and consideration of the educational context, we explore the model behavior for the spread of academic boredom in the context of mathematics lessons using sensitivity analysis and scenario-based simulation methods. The simulation results indicate that the strength of social interactions between students significantly influences the spread of academic boredom in the context of mathematics lessons. The results of this study provide insights for the policy makers in the middle school students in designing more effective strategies to mitigate academic boredom among students, especially in the context of mathematics lesson. This study opens up opportunities for further, more empirical research by incorporating actual data regarding the decisions of students why they have academic boredom.

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A. INTRODUCTION

The concept of boredom, often used in everyday life, has been associated with many different concepts such as indifference, lethargy, fatigue, and aversion (Raffaelli et al., 2018). Academic boredom is based on studies of workplace distress that continued into the 1980s and were conducted by psychologists, psychotherapists, and psychiatrists (Maroldo, 1986). Jang et al. (2009) found that Grade 9 Korean students stated that being bored was one of their unsatisfying learning experiences. These empirical findings thus suggest that boredom in educational contexts seems to be a universal academic emotion, and one that is frequently experienced by students across age groups, educational needs, and ethnicity. Tze et al. (2013) also found that boredom while studying and in class was evident among students in China. The fact that boredom is related to the learning process allows this concept to be studied in education (Acee et al., 2010). It is stated that boredom is generally a negative situation and hinders student participation, learning, and overall performance (Linnenbrink-Garcia & Pekrun, 2011). Özerk (2020), in his paper discusses academic boredom as a negative emotion that undermines goal achievement. These negative emotions include, for example, lowering intrinsic motivation (Pekrun et al., 2010), impeding academic attainment (Daniels et al., 2009), and leading to a heightened suspension rate in gifted students (Kanevsky & Keighley, 2003). However, there is a counter-argument suggesting the potential benefits of being bored (Belton & Priyadharshini, 2007). For instance, Bench & Lench (2013) argued that boredom signals an individual to make changes, given that the current activity and goal are no longer motivating. Mann & Cadman (2014) furthered this line of argument with research that suggested that individuals became more creative after being exposed to boring conditions than those who were in a control condition.

Boredom observed in students is caused by four basic reasons Eastwood et al. (2012): (a) Arousal-related, which stems from the failure to properly meet individual arousal needs, (b) Attention-related, which stems from the inability to maintain focus due to individual cognitive processes, (c) Psychodynamic: which stems from processes formed unconsciously by the individual. Suppression of the desire to do something meaningful, for example, and (d) Existential: which stems from a sense of emptiness and lack of purpose in life. Boredom is still considered a neglected emotion in psychological research compared to fear, anger, shame, and anxiety (Andreas, 2022). The causes of boredom generally originate from the individual and their environment. This requires teachers to take action, both on processes originating from students and processes originating from the educational environment. In school, boredom is associated with higher career aspirations (Krannich et al., 2019), and lower academic achievement (Camacho-Morles et al., 2021). Goetz et al. (2023) examined student boredom during exams and tests based on the emotion-control-value theory of achievement. Academic boredom experienced by students in mathematics is detrimental to learning and effective participation in the lesson. This is because students who experience greater boredom in the lesson than other students show lower behavioral and cognitive engagement in mathematics (Pekrun et al., 2011). Boredom has been studied in many learning-related studies, for example, boredom in mathematics lessons experienced by students at the junior high school level and other levels of education, even if only occasionally (Sharp et al., 2017), the relationship between boredom and health symptoms including anxiety (Sommers & Vodanovich, 2000), the relationship between academic boredom and self-efficacy (Tze et al., 2013), the relationship between boredom and student engagement (Tze et al., 2014), the causal influence of boredom on learning and achievement (Tze et al., 2016), the relationship between boredom and students' academic achievement (Sharp et al., 2018), and the relationship between academic boredom and sources of self-efficacy and anxiety in the context of mathematics lessons (Şimşek et al., 2020).

Specifically in the context of mathematics lessons, Goetz et al. (2007) assessed the experience of boredom in a group of elementary school students during a mathematics exam. Similarly, Asseburg & Frey (2013) measured the level of boredom of 9th grade students when they took a mathematics exam. Ahmed et al. (2013) also measured the level of boredom during a mathematics exam by combining it with items assessing students' boredom experienced in class and while studying. Golle et al. (2022) investigated the relationship between academic boredom, general cognitive ability, and intrinsic value in mathematics and language classes in elementary school students in Germany. Using a structural equation model. Smedsrud et al. (2022) explored gifted students' perceptions of mathematics teacher competence in Norway and examined students' boredom in school. Bekker et al. (2023) investigated the impact of demographic and contextual variables on boredom in English and mathematics in South African secondary school students. Salemi et al. (2024) tested the validity of value control theory in predicting academic boredom in first-grade high school students in mathematics using correlation and structural equation analysis methods. Schwartze et al. (2024) examined the presence and prevalence of student boredom in Bavaria (Germany) in grades V-IX (primary, middle, and high school) due to challenges in mathematics lessons using latent profile analysis. However, despite its significance in the context of mathematics lessons, academic boredom is rarely studied, especially in terms of mathematical modeling.

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 boredom 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 boredom in the context of mathematics lessons. This model categorizes the student population into four compartments: students who are susceptible, exposed, infected, and recovered to academic boredom in the context of mathematics lessons. 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 boredom 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, Kao (2002) modelling the 2001 foot and mouth disease epidemic in the UK; Vaidya et al. (2014) modeling the spread of H_1N_1; and Mamo & Koya (2015) modeling the spread of the Ebola outbreak in West Africa. 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; Oakes & Kaufman, 2017). This approach also emphasizes the importance of reducing health inequalities, not just improving the average health of the population (Diez Roux, 2022).

New diseases, information, or products, or social ills such as academic boredom in the context of mathematics lessons in the middle school 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 boredom in the context of mathematics lessons 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.

B. METHODS

This research is theoretical research focused on developing a mathematical model and analyzing its behavior. There are no field experiments, no human participants, and no empirical data collection. The research data in this study refer to the basic parameter values used in the SEIR model formulation, namely the boredom transmission rate (β), exposure-infection transition (γ), recovery rate (δ), resuscitation rate (α), and natural student dropout rate (μ). All parameter values are determined based on theoretical assumptions that refer to the general characteristics of junior high school students, such as the three-year study duration used to determine the value of μ. These values serve as a baseline for the simulation and are then varied within a realistic range in the sensitivity analysis. The subjects of this study are a hypothetical population of junior high school students modeled in aggregate within the SEIR (Susceptible, Exposed, Infected, and Recovered) compartments. The study does not involve individual or respondent data as the approach used is mathematical modelling. The population size ($N = 449$) was chosen as a reasonable quantitative representation for a medium-sized high school and is used solely for the purposes of model simulation. The state variables are explained as follows:

1. Students who are susceptible to academic boredom in the context of mathematics lessons. They are a group of students who enter the school without a strong dislike or boredom, including students who are interested the context of mathematics lessons and are infected with academic boredom every time they meet a group of students who are infected with academic boredom, symbolized by $S(t)$.
2. Students exposed to academic boredom in the context of mathematics lessons. They are a group of students enrolled in the middle school students in 2020–2025, who had close contact with susceptible students and hearing negative attitudes towards math teachers, denoted by $E(t)$. Individuals exposed to academic boredom may or may not also be infected.
3. Students infected with academic boredom in the context of mathematics lessons. They are a group of students who dislike and are bored with mathematics lessons, symbolized by $I(t)$.
4. Students who have recovered from their academic boredom in the context of mathematics lessons. They are a group of students who are aware of their purpose in studying in school, and are symbolized by $R(t)$.

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

1. The group of students who are susceptible to academic boredom [S(t)] will increase with the number of new students entering in the school at a rate of Λ, and with the number of students who are fully convinced of their purpose of studying in the school at a rate of α at each time t; this susceptible group of students will decrease due to contact with students infected with academic boredom at a rate of β at each time t where the total number of students is constant with the same entry and exit rates, namely μ.
2. The group of students exposed to academic boredom [E(t)] will increase with the number of students who have close contact with infected students at a rate of β at each time t, and will decrease at a rate of γ at each time t.
3. The group of students infected with academic boredom [I(t)] will increase at a rate of γ at each time t, and will decrease when they are aware of their purpose in studying in the school at a rate of δ at each time t.
4. The group of students who recovered from their academic boredom because they were aware of their purpose of studying in the school [R(t)] will increase at a rate of δ at each time t, and will decrease at a rate of α at each time t from the class that was made aware by the school leader at each time t.
5. The number of students in all compartments decreases by the natural rate of μ.
6. The total population of students is constant.
7. Parameter Λ = μN is the rate of acceptance of new students.

The SEIR model used in this study is based on the conceptual assumption that academic boredom is a social-psychological phenomenon that can spread through interactions between students. Pedagogically, students who initially do not experience boredom (Susceptible) can be exposed to negative perceptions of learning through informal communication, observation of peer attitudes, or collective classroom narratives. This exposure does not necessarily result in immediate boredom, but rather increases students' emotional and cognitive vulnerability, represented by the Exposed compartment. The transition to the Infected state describes the phase when boredom has become manifest as low engagement, task rejection, or apathy toward the lesson. The Recovery process (Recovered) reflects pedagogical and psychological interventions, such as improving the quality of learning, academic counseling, or reflection on learning goals, which enable students to regain motivation. Thus, the SEIR structure in this study directly corresponds to relevant psychological and pedagogical processes, making the model not only mathematical but also conceptual. Based on the assumptions and description of the model, a flow diagram of student transition between compartments is given in Figure 1.

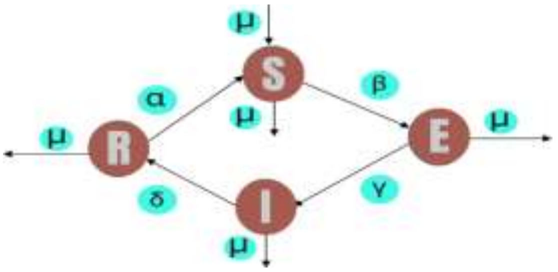

Figure 1. The Flow Diagram of Student Transition in SEIR Model

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

$$\frac{dS}{dt} = \Lambda + \alpha R - \beta SI - \mu S \tag{1}$$

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

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

$$\frac{dR}{dt} = \delta I - (\mu + \alpha)R \tag{4}$$

Each parameter in the model has clear behavioral and pedagogical implications. The β parameter represents the intensity of academic boredom transmission through social interactions between students, such as negative discussions, repeated complaints, or the normalization of apathy toward mathematics. The γ parameter describes the speed of transition from exposure to actual boredom, which can be influenced by low learning control, material difficulty, or monotonous learning experiences. The δ parameter represents the rate of student recovery or awareness, reflecting the effectiveness of educational interventions such as active learning strategies, teacher feedback, or academic counseling. The α parameter indicates the likelihood that recovered students will become vulnerable again, reflecting the transient nature of academic boredom and its recurrence if learning conditions deteriorate. The μ parameter represents the natural turnover of students due to graduation or grade changes, which structurally breaks the chain of boredom transmission in the population.

Systematic steps in the analysis of epidemiological compartmental models (such as SIR, SEIR) generally involve several sequential and interrelated main stages, including: (1) identifying compartments and relevant underlying assumptions of the formulated model; (2) formulating a mathematical model using a system of differential equations that describes the movement of individuals between compartments; and (3) 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; X. Li et al., 2024; Schiassi et al., 2021).

However, in this study, we explore the model behavior for the spread of academic boredom in the context of mathematics lesson using sensitivity analysis and scenario-based simulation methods. Sensitivity analysis is a commonly used tool, at least in traditional modeling, to examine the robustness of model results to changes in parameter values (ten 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 parameter sensitivity analysis in this study uses the One-At-a-Time (OAT) method and the Partial Rank Correlation Coefficient (PRCC) method. The OAT method is traditionally used to estimate sensitivity measures in the form of partial derivatives of model results with respect to input parameters. The parameters tested included the boredom transmission rate (β), exposure–infection transition rate (γ), recovery rate (δ), re-susceptibility rate (α), and student natural turnover rate (μ). This estimation is based on the effect of small deviations from nominal parameter values on model results. In the OAT analysis, each parameter was varied individually within a predetermined range of values, while the other parameters were maintained at baseline values. The main output indicators analyzed included the basic reproduction number of academic boredom (R_0), the peak prevalence of boredom (A_{peak}), and the final prevalence of boredom (A_{final}). According to (Yang et al., 2016), OAT can be an alternative method to variance-based methods in some initial design scenarios. Sensitivity is calculated in terms of elasticity:

$$E_p = \frac{\Delta Y/_{Y}}{\Delta p/_{p}}$$

where E_p represents the elasticity of output with respect to parameter p, Y is the model output (e.g., R_0, A_{peak}, or A_{final}), ΔY is the change in output, and Δp is the change in parameter value. The E_p value describes the magnitude of the relative change in output due to a relative change in the parameter. The PRCC method is used to measure the nonlinear but monotonic relationship between input and output. This method allows for the identification of the parameters that have the most statistical influence on the dynamics of academic boredom. This 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):

$$r_{x_j,y} = \frac{Cov\,(\widehat{x_j},\hat{y})}{\sqrt{Var(\widehat{x_j}).Var(\hat{y})}}$$

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.

Numerical simulations were performed by solving a system of ordinary differential equations. The initial conditions were set with the majority of the population in the Susceptible (S) compartment, a small proportion in the Exposed (E) and Infected (I) compartment, and no individuals in the Recovered (R) compartment. The analysis was performed on three operational scenarios: (i) a baseline scenario, which represents normal learning conditions; (ii) a high-risk scenario, characterized by an increased boredom transmission rate (β) and a decreased recovery rate (δ); and (iii) a low-risk scenario, which represents an effective pedagogical intervention with an increased δ and a decreased β. All simulations and sensitivity analyses were performed using the MATLAB numerical computing platform, so the procedures can be independently replicated by other researchers with the same parameters and initial conditions.

C. RESULT AND DISCUSSION

1. Results

This is consistent with the "average of 150 students per year" (449 ÷ 3 years). This means that the new student intake rate (Λ) in the SEIR model does reflect the constant supply of new students entering the school. So on average there are 12-13 new students "added" to the population every month. This figure is consistent with empirical data, total number of students = 449 students ≈ 150 students per year (divided into 3 classes). In other words, the SEIR model in our study, which uses the assumption of a "constant population with equal entry and exit rates ($\Lambda = \mu N$)," is indeed realistic because it aligns with the pattern of new student admissions. This figure ensures that the susceptible group (S) always receives additional new students every month. Thus, the potential for the spread of academic boredom is never completely eliminated, because there are always "new generations" entering the system.

Epidemiologically, this is analogous to the recruitment rate that maintains the continuity of dynamics, so that the system does not automatically stabilize at R = 0. From an academic managerial perspective, ≈ 12.47 new students per month indicates: 1) there is a continuous need for "academic orientation" and "attitude development" from the start. Otherwise, these new students could quickly become "susceptible sources" easily exposed to academic boredom from existing students. In essence, the figure of 12.47 per month is a mathematical translation of "a constant influx of new students," and evidence that the SEIR model in this study is calibrated to reality. Substantively, this emphasizes the importance of routine interventions every month/year, not just once when academic boredom cases are at their peak. Based on this explanation, the maximum number of students infected with academic boredom in the context of mathematics lesson is estimated to be ≈ 150 people). The results of this estimate have an impact on the sensitivity analysis, namely: a) the R_0 value is independent of the student population (N), meaning that R_o does not change; and b) the endemic equilibrium I^* and the PRCC simulation results are still affected, because I^* is proportional to the student population (N). This means that the maximum burden (absolute number of infected (I)) will increase in proportion to the cohort size.

Next, based on the results of the analytical solution of the differential equation system (1) - (4), the value of R_0 (the basic reproduction number of academic boredom) is determined by a combination of the parameters β, γ, δ, and μ. The results:

$$R_o = \frac{\beta\gamma}{(\gamma+\mu)(\delta+\mu)},$$

This number crystallizes the role of the balance between the rate of transmission (β) and the rate of 'eradication' of infection through awareness/healing (δ) and student turnover (μ);

$$S^* = \frac{N}{R_O};$$

This number is the number of students who remain susceptible in equilibrium. If R_0 is larger, then S^* will be smaller (because more are exposed);

$$I^* = \frac{\mu N(R_O - 1)}{\beta - \frac{R_O \alpha \delta}{\alpha + \mu}};$$

This number is the number of students who are stable and infected with academic boredom in the long run, provided that the mathematical condition in the denominator is met (denominator > 0). The condition that the denominator > 0 is important, to ensure a meaningful (positive) solution. Otherwise, it means that the model does not have a stable endemic equilibrium. By analogy with epidemiology: if $R_0 < 1$, then one student who is "infected with academic boredom" is not able to transmit enough to other students, so that the boredom disappears by itself; and if $R_0 > 1$, then academic boredom can persist or explode within the middle school population.

Assuming reasonable parameters for the context of the middle school, there are indications that R_0 (the basic reproduction number of academic boredom) tends to be greater than one, so that the dynamics of academic boredom have the potential to persist without intervention. We attempted to use realistic parameter assumptions, with $N = 449$ to calculate the basic reproduction number of academic boredom R_0 for three scenarios, namely:

a. The baseline scenario ($\beta = 0.20$, $\gamma = 0.40$, $\delta = 0.15$) yielded an $R_0 \approx 1.03$, indicating that the SEIR model proposed in this study is capable of predicting the existence of an endemic equilibrium with $S* \approx 436$ susceptible students and $I^* \approx 6$ students persistently affected by academic boredom in the absence of intervention.
b. The high-risk scenario ($\beta = 0.45$, $\gamma = 0.60$, $\delta = 0.10$) yielded an $R_0 \approx 3.55$, indicating a potentially much greater burden of academic boredom with $S^* \approx 127$ susceptible students and $I^* \approx 94$ infected students.
c. Low-risk scenario ($\beta = 0.08$, $\gamma = 0.20$, $\delta = 0.20$), obtained $R_0 < 1$, meaning that academic boredom tends to subside without forming endemicity.

In summary, the parameters, baseline, and range of variation for sensitivity analysis can be seen in Table 1.

Table 1. SEIR Model Parameters of Student Academic Boredom & Baseline Values & Range of Variation

Parameters	Description	Baseline (per month)	Range of variation (OAT/PRCC)
β	The rate of transmission of academic boredom	0.20	0.02 – 0.50
γ	Transition rate from E → I	0.40	0.10 – 1.00
δ	Recovery/awareness rate	0.15	0.05 – 0.50
α	Rate of return of conscious students → S	0.0278	0.01 – 0.20
μ	The rate of natural student turnover	0.0278 (≈1/36)	0,021 – 0,033 (≈1/48 –1/30)
N	Number of students	449	Fixed

Next, using the OAT method, we provide a biological/social meaning of the results of the analytical elasticity of Ro (the basic reproduction number of academic boredom), namely:

a. Elasticity with respect to parameter β = +1 (most sensitive, linear); meaning that every 1% increase in the rate of academic hate transmission (β) will increase Ro by 1%. β is the most dominant factor; the more frequent negative interactions or "bad attitude contagion" occur, the greater the potential for boredom to spread. Managerially, β is related to (e.g., gossip, internal social media, seniority).

b. Elasticity with respect to parameter $\gamma = \frac{\mu}{(\gamma+\mu)}$ (positive but decreasing if γ is much greater than μ); meaning that increasing the speed of transition from "exposed" (E) to truly "infected" (I) will increase the chance of spread, but the sensitivity is reduced if students move too quickly. The process of being "fully influenced" by boredom has its limits, if it is too fast, many students will be immediately caught/detected and can be intervened.

c. Elasticity with respect to parameter $\delta = \frac{-\delta}{(\delta+\mu)}$ (The faster the "recovery"/awareness, the more it suppresses Ro); meaning that strategies for coaching, counseling, or strengthening learning motivation will be effective in suppressing the continuation of boredom. Socially, δ can be seen as the role of teachers, school leader, or academic conselor.

d. Elasticity with respect to parameter $\mu = -\frac{\mu}{(\gamma+\mu)} - \frac{\mu}{\delta+\mu}$ (natural turnover suppresses R_0); meaning that the greater the rate of student "natural turnover" (e.g., graduation, transfer, or dropout), the more it suppresses R_0. Although "natural," this factor indicates that the student social system is always changing; thus, the sustainability of academic boredom can be weakened simply by regeneration. However, relying on turnover alone is insufficient because its effect is relatively small compared to the β parameter.

e. The parameter α does not affect R_0 (which makes sense since it only moves individuals in compartment R to compartment S (R → S) post-infection). This means that the parameter α does not change the initial transmission mechanism. The reverse cycle of students who regain consciousness and become susceptible does not affect the sustainability of the academic boredom epidemic, as long as β, γ, δ, and μ remain dominant.

The numerical solution for I* using the OAT method shows that I* generally increases with β, and decreases with δ and μ. The effect of α can be non-monotonic because α increases the backflow of individuals in compartment R to compartment S (R → S) (increasing vulnerability), but also affects the denominator in the I* formula. Using the OAT method, the results show that the rate of academic boredom transmission (β) is the most dominant or sensitive parameter with the largest positive elasticity, followed by the rate of student awareness (δ) with a fairly strong negative elasticity. The graph can be seen in Figure 2.

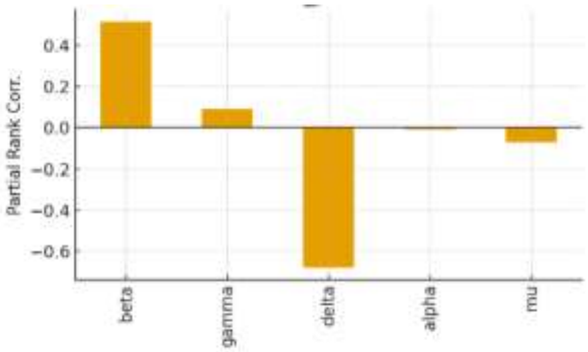

Figure 2. Peak Graph of Academic Boredom Infection via PRCC Method

Figure 2 illustrates the temporal evolution of susceptible, exposed, infected, and recovered students under baseline conditions. The increase in the infected compartment reflects the gradual accumulation of academic boredom through peer interaction, while the delayed growth of the recovered compartment highlights the time required for pedagogical interventions to take effect. For the PRCC analysis of final prevalence (I_{final}), the results show a similar pattern to I_{peak}. β remains the primary reinforcing factor, while δ is the primary suppressing factor. This indicates that the effects of these two parameters are consistent both at the peak and at the end of the dynamics. The graph can be seen in Figure 3.

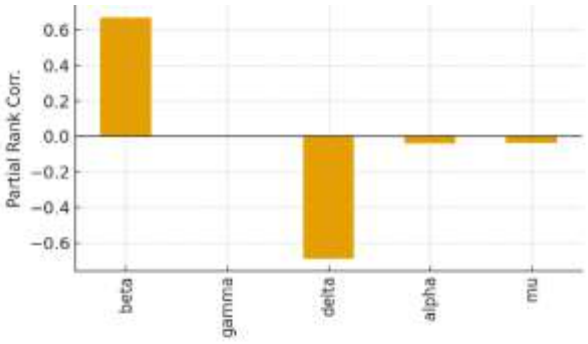

Figure 3. Final Prevalence Graph of Academic Boredom Infection

The diagram reveals that the transmission rate of academic boredom (β) exerts the strongest influence on all output indicators, indicating that peer-to-peer interactions are the primary driver of boredom dynamics. In contrast, the recovery rate (δ) shows a strong negative effect, suggesting that effective pedagogical or counseling interventions can substantially mitigate boredom prevalence. Meanwhile, for the PRCC on the basic reproduction number (R_0), the results reaffirm that β has a dominant positive correlation, while δ has a dominant negative correlation. Meanwhile, γ also plays a role in increasing R_0, although not as strongly as β. The parameters α and μ remain weak in their influence. Thus, R_0 is primarily controlled by the balance between the power of hate transmission (β) and the effectiveness of student awareness (δ). The graph can be seen in Figure 4:

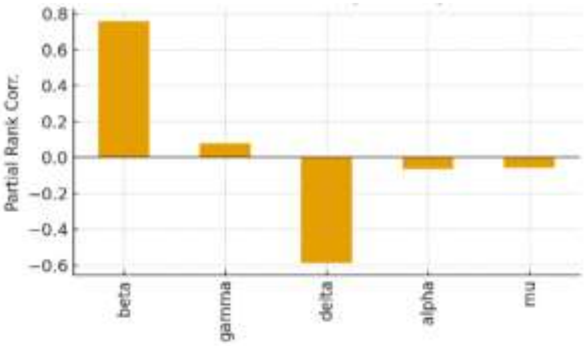

Figure 4. PRCC Graph Against the Basic Reproduction Number of Academic Boredom

PRCC analysis confirms the dominance of β as a positive contributor and δ as a negative contributor to both peak and final boredom prevalence. The consistency between OAT and PRCC results strengthens the robustness of the model conclusions. These visual results demonstrate not only statistical sensitivity but also meaningful behavioral mechanisms.

2. Discussion

The academic boredom transmission rate parameter (β) has the greatest influence on the peak number of students infected with academic boredom (I_{peak}) and the final prevalence (I_{final}) based on the analysis results using the One-At-a-Time (OAT) method. The elasticity value of β to I_{peak} is close to 1, meaning that small changes in β will have a proportional impact on the increase or decrease in cases of academic boredom. The student awareness rate parameter (δ) also makes a significant contribution in a negative direction, so that an increase in δ can reduce the number of students infected with academic boredom. Meanwhile, the parameters α (relapse tendency) and μ (natural exit) have a relatively small influence on the system dynamics. Thus, from the OAT perspective, the most effective strategy to reduce the peak of academic boredom is by suppressing the boredom transmission rate (β) and increasing the student awareness rate (δ). With N = 449, the baseline scenario shows an Ro slightly above one (≈ 1.03), meaning that academic boredom has the potential to maintain itself at a low level (around 6 students at equilibrium) if there is no additional intervention. Increasing the transmission parameters (for example, in a high-risk scenario) dramatically increases the basic reproduction number of academic boredom (Ro) and moves the system to equilibrium with a much larger proportion of infected students (≈ 94 students). Conversely, if mitigation efforts succeed in reducing β and/or increasing δ, then Ro can be reduced < 1 and academic boredom will subside in the population, with no remaining endemicity. The results of this SEIR model analysis indicate that academic policies aimed at reducing the spread of negative opinions (reducing β) - for example, through regulating class discussions, student guidance, and strengthening subject-student communication - are expected to have a significant impact on controlling the dynamics of academic boredom. This is in line with research findings (Odutayo et al., 2024). According to

Tze et al. (2016), both boredom in class and boredom while studying have a negative impact on students' learning process and achievement, this deserves the attention of educators to help reduce these undesirable impacts. In essence, education professionals should identify strategies to alleviate students' boredom in academic settings (Tze et al., 2016). In addition, student awareness and motivation programs (increasing δ), both through academic guidance and positive activities, have proven to be key factors in suppressing long-term prevalence. Overall, both the OAT and PRCC methods consistently demonstrate that controlling the β factor and increasing the δ factor are the dominant strategies for reducing the level of academic boredom among students in the context of mathematics lesson. The dominance of the transmission parameter β aligns closely with emotional contagion theory, which posits that emotions such as boredom can spread socially through observation and interaction. In classroom settings, negative narratives about mathematics, disengaged behaviors, or peer complaints may amplify collective boredom, increasing the basic reproduction number (R_0). Conversely, the recovery parameter δ reflects mechanisms emphasized in *Control–Value Theory* (Pekrun, 2024; Tze et al., 2022), where increased perceived control and task value reduce negative academic emotions. Interventions such as adaptive instruction, formative feedback, and motivational counseling effectively increase δ, thereby suppressing R_0 below unity and preventing persistent boredom dynamics. From a policy perspective, the model suggests that efforts to reduce academic boredom should prioritize limiting negative peer influence (reducing β) while simultaneously strengthening recovery mechanisms (increasing δ). School-level policies may include structured collaborative learning, teacher professional development focused on engagement strategies, and early counseling interventions. Such measures can prevent boredom from becoming a self-sustaining classroom phenomenon. By integrating mathematical modelling with educational psychology theories, this study demonstrates that academic boredom is not merely an individual experience but a socially transmissible phenomenon. The SEIR framework provides a conceptual bridge between quantitative dynamics and pedagogical intervention strategies.

D. CONCLUSION AND SUGGESTIONS

The SEIR (Susceptible–Exposed–Infected–Recovered) model proposed in this article can be used effectively to understand the dynamics of the spread of academic boredom in the context of mathematics lesson among the student population of the middle school. The results of the elasticity analysis of the analytical solution for the basic reproduction number of academic boredom (Ro) indicate that the transmission rate of academic boredom (β) is the most dominant factor, with an elasticity of +1. This means that every small increase in the β parameter will proportionally increase the Ro value, so controlling negative interactions between students (for example, the spread of gossip or negative perceptions about the mathematics lesson) becomes a top priority. The transition rate from exposure to infection (γ) also has a positive impact on Ro, although its sensitivity decreases when the γ parameter is much larger than the μ parameter. This indicates that accelerating the process of being "fully affected" by academic boredom does increase the potential for spread, but the effect tends to be limited if the transition occurs very quickly. Conversely, the recovery rate or student awareness parameter (δ) has a negative elasticity, so that a higher δ parameter will suppress

Ro. This factor emphasizes the importance of academic coaching, counseling, intervention strategies by mathematics lesson, and school leaders in accelerating the process of re-awareness of the goals of study. Similarly, the natural student attrition rate (μ) also puts pressure on Ro as regeneration or class turnover weakens the ongoing spread of academic boredom. This finding is in line with *Control–Value Theory*, which explains that boredom arises and spreads when students feel they have little control over the learning material or do not see the value of the learning task. These findings are also consistent with emotional contagion theory, which suggests that negative emotions can spread socially through imitation, spontaneous empathy, or affective resonance. In the context of the SEIR model, these mechanisms are represented by the transition rate from susceptible students to exposed and then infected with boredom (γ), as well as how negative perceptions spread through social interactions. Although γ increases the value of Ro, its sensitivity decreases when γ is much larger than μ, suggesting that rapid contagion is only significant in the early stages and will decline as the population saturates.

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