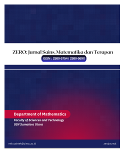
Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 9, Number 2, 2025
DOI: 10.30829/zero.v9i2.25834
Page: 631-640



Modeling Student Organizational Engagement in Higher Education Using an Adapted SIR Dynamic System

[1] M. Ivan Ariful Fathoni
Mathematics Education, Universitas Nahdlatul Ulama Sunan Giri, Bojonegoro, Indonesia

[2] Izzatul Mufidah
Mathematics Education, Universitas Nahdlatul Ulama Sunan Giri, Bojonegoro, Indonesia

Article Info

Article history:

Accepted, 15 November 2025

Keywords:

Dynamic System;
Numerical Simulation;
Organization;
SIR Model;
Stability.

ABSTRACT

Student involvement in organizations is essential for developing leadership, collaboration, and broader competencies in higher education. This study analyzes the dynamics of student organizational engagement using an adapted SIR (Susceptible–Infective–Recovered) mathematical model, where the three compartments respectively represent non-members (S), active members (I), and former members (R). Parameters including recruitment rate ($\alpha = 0.045$), disengagement rate ($\beta = 0.004$), and reactivation rate ($\gamma = 0.002$) were selected and calibrated based on prior studies in educational and social diffusion modeling. Numerical simulations conducted in MATLAB indicate convergence toward a stable equilibrium with approximately 52% non-members, 35% active members, and 13% former members, depending on parameter variation. The results also show that increasing recruitment by 50% or reducing disengagement by half accelerates system stabilization and raises the equilibrium proportion of active members by up to 20%. These findings provide quantitative insight into how organizational participation evolves dynamically and offer practical implications for universities to design data-informed policies that enhance recruitment, sustain engagement, and improve student leadership development over time.

Corresponding Author:

M. Ivan Ariful Fathoni
Mathematics Education,
Universitas Nahdlatul Ulama Sunan Giri, Bojonegoro, Indonesia
Surel: fathoni@unugiri.ac.id

1. INTRODUCTION

Student organizations in higher education play a crucial role in developing leadership, teamwork, and communication skills that enhance students' academic performance and employability [1], [2], [3]. Active participation in such organizations fosters self-efficacy, social interaction, and a sense of belonging that support student retention and holistic development [2], [4], [5]. However, recent studies have shown a decline in participation levels, especially in the post-pandemic period, due to shifting student priorities, lack of institutional support, and bureaucratic barriers [6], [7], [8], [9]. Research by Lv [10] and Gretzinger and Hicks [7] found that unclear organizational goals and limited engagement continuity across student cohorts reduce motivation to participate. These findings suggest that despite their recognized benefits, sustaining student involvement remains a significant challenge in higher education.

Most previous studies on student engagement have employed survey-based or descriptive approaches that only capture static relationships between participation and outcomes[4], [11], [12]. While these approaches identify factors influencing involvement, they cannot represent the temporal and systemic evolution of student participation. Recent developments in applied mathematics and behavioral science demonstrate that dynamic system modeling can effectively describe how social phenomena such as motivation, collaboration, and behavioral diffusion evolve over time [13], [14]. One widely used approach is the Susceptible Infective Recovered (SIR) model, which, although originally designed for epidemiological analysis [11], [15], has been successfully adapted to model information diffusion and behavioral contagion [14], [16], [17]. This framework enables the representation of student involvement as a social diffusion process influenced by peer interaction and recruitment dynamics.

Although the SIR framework has been applied in various educational and social contexts, including learning performance modeling and social contagion studies [11], [14], [15], [16], [18], [19], its application to student organizational engagement remains limited. Prior works have focused mainly on academic outcomes or individual learning behavior, without analyzing the dynamic transition of students among different levels of participation within organizations [4], [12]. Furthermore, few models incorporate the reactivation of former members or the influx of new students, both of which are critical to sustaining the continuity of campus organizations [10], [18], [19]. Addressing these limitations requires a dynamic approach capable of illustrating how engagement spreads, stabilizes, or declines through continuous social interaction and membership change.

Therefore, this study aims to formulate and analyze an adapted SIRS-based mathematical model to describe the dynamics of student organizational engagement in higher education. In this model, students are categorized as susceptible (S) or non-members, infective (I) or active members, and recovered (R) or former members who have disengaged. The model identifies equilibrium points, analyzes their stability using the Jacobian and eigenvalue criteria, and performs numerical simulations to observe participation patterns. The novelty of this research lies in extending the SIR modeling approach to the educational context, providing a quantitative tool to analyze engagement dynamics. The expected contribution of this study is to bridge mathematical modeling and educational management by offering theoretical and practical insights for designing recruitment and retention strategies that strengthen student involvement in campus organizations.

2. RESEARCH METHOD

This study employs a compartmental Susceptible Infected Recovered (SIR) framework in a novel context, where student organization involvement is modeled as a contagion process rather than a disease. SIR type models have been used in non health domains such as information and behavior diffusion [16], but this study applies the approach specifically to higher education. Figure 1 illustrates the conceptual flow of the model, where S represents susceptible students who have not yet been involved, I represent active members who can transmit involvement through peer influence, and R represents former members who have disengaged. The standard SIR structure is extended by incorporating demographic turnover and feedback loops. Inflow terms such as new student admissions add to S, while outflow terms such as graduation or dropout remove individuals from each compartment. The model also introduces a reintegration pathway, where individuals in R can return to the susceptible group through renewed exposure to active members, analogous to waning immunity in epidemiological models [20]. These extensions capture the continuous inflow of new students and the reactivation of former members, reflecting campus dynamics more accurately than a closed population system.

Model parameters including recruitment rate, disengagement rate, and reactivation rate were determined based on prior SIR based studies and secondary educational data [20]. Because these values were assumed and not derived from empirical measurements, they represent theoretical estimates and are recognized as a major limitation of this study. Dimensional consistency was verified to ensure that parameter units were compatible, but no sensitivity testing was performed to assess robustness [21]. Equations describing the model are presented in the subsequent section on model formulation, where each rate of change is defined mathematically.

Equilibrium points were determined by setting the rate of change in each compartment to zero, and local stability was analyzed through linearization using the Jacobian matrix [21]. A stable equilibrium mathematically indicates that small perturbations in participation will return to a balanced state. In educational terms, a stable equilibrium represents a sustained level of organizational engagement across semesters, while instability indicates that small variations in recruitment or retention may lead to long term decline or fluctuation in participation. The system was implemented and simulated in MATLAB using the built in ODE45 Runge Kutta solver, allowing observation of temporal changes in the proportions of susceptible, active, and former members. Figure 1 presents the conceptual compartmental diagram that summarizes the transitions among these three groups.

3. RESULT AND ANALYSIS

3.1 Model Formulation

In this study, the model employed is the standard SIR epidemic model (Susceptible–Infective–Recovered), adapted to the context of student organizational engagement. The student population is divided into three compartments: (i) susceptible (S), representing students who have not yet participated in any organization; (ii) infective (I), representing students currently active in organizational activities and capable of influencing their peers to join; and (iii) recovered (R), representing students who were once involved but are no longer active members. The model assumes homogeneous mixing within the student body, meaning each susceptible individual has an equal probability of being influenced by active members, while transitions from I to R occur due to disengagement or graduation. Figure 1 illustrates the conceptual SIR model (S → I → R → S), with labeled transitions representing recruitment (α), disengagement (β), and reactivation (γ). Axis and legend labels have been added for clarity.

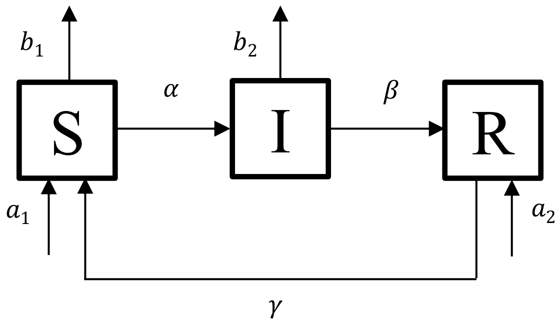


Figure 1. Conceptual SIR model of student organization engagement (S → I → R → S)

$$\frac{dS}{dt} = a_1 - b_1 S - \alpha SI + \gamma RI \tag{1}$$

$$\frac{dI}{dt} = \alpha SI - b_2 I - \beta I \tag{2}$$

$$\frac{dR}{dt} = \beta I - \gamma RI + a_2 \tag{3}$$

P:arameters :

- α : The transition rate of students from S to I is due to the influence of the interaction between students who have not been involved in the organization and those who have been involved in the organization. involved and those already involved who are involved in the organization
- β : The transition rate of students from I to R is because students stop organizing because their term of office has expired or their own awareness.
- γ : The level of student transition back from R to S, namely students who previously stopped then back active in the organization.
- a_1 : Rate of entry of new students into population S (e.g. new students who have never joined an organization)
- b_1 : The rate at which students leave the S group because they graduate or are not interested in organizing at all organization
- a_2 : The rate of return of students who have been active in organizations because they are interested in organizing
- b_2 : The exit rate of students from group I because they graduate or no longer want to organize.

3.2 Equilibrium Point

The equilibrium point represents the steady-state condition of student involvement, where recruitment, disengagement, and reactivation processes are balanced. The equilibrium point can be determined by several steps, and one of them is by setting the left-hand side of equation (1-3) equal to zero, $\frac{dS}{dt} = \frac{dI}{dt} = \frac{dR}{dt} = 0$. Thus, the following algebraic system is obtained, which represents the steady-state conditions of the model where the rates of change for each compartment vanish. Solving this system produces the equilibrium points, which describe the long-term distribution of students across the compartments.

Through further mathematical derivation, the system is shown to admit only one biologically feasible equilibrium point, denoted as

$$\begin{aligned} E &= (S^*, I^*, R^*) \\ &= \left(\frac{b_2 + \beta}{\alpha}, \frac{a_1\alpha + a_2\alpha - b_1(b_2 + \beta)}{\alpha b_2}, \frac{a_1\alpha\beta + a_2\alpha\beta + a_2\alpha b_2 - b_1 b_2 \beta - b_1\beta^2}{\gamma(a_1\alpha + a_2\alpha - b_1 b_2 - b_1\beta)}\right) \end{aligned} \tag{4}$$

Equation (4) can be simplified and concluded as

$$S^* = \frac{b_2 + \beta}{\alpha}, I^* = \frac{a_1 + a_2 - \dfrac{b_1(b_2 + \beta)}{\alpha}}{b_2}, R^* = \frac{\beta}{\gamma} + \frac{a_2}{\gamma I^*}$$

The existence of this equilibrium requires that all components are non-negative and finite, which is satisfied when the parameter values for recruitment, peer influence, disengagement, and reintegration remain within meaningful ranges. In particular, the conditions $S^* > 0, I^* \geq 0,$ and $R^* \geq 0$ must hold to ensure the feasibility of the equilibrium in the context of student organizational engagement. This unique equilibrium point reflects the steady proportion of students who remain susceptible, actively involved, and disengaged in the long run. The existence condition for the equilibrium point (4) is $a_1 + a_2 > \frac{b_1(b_2+\beta)}{\alpha}$. The equilibrium distribution provides the foundation for analyzing the system's stability, reflecting whether student engagement will persist, decline, or fluctuate over time.

3.3 Jacobian Matrix and Local Stability

To determine the local stability of the endemic equilibrium, point E, the nonlinear system is linearized. Linearization requires the Jacobian matrix, constructed from the first-order partial derivatives of the system with respect to each compartment. The Jacobian expresses how small perturbations around the equilibrium evolve, and its eigenvalues indicate whether the system returns to equilibrium or diverges. The general form of the Jacobian for this model is

$$J(S, I, R) = \left[\frac{\partial f_i}{\partial x_j}\right]_{i,j=1}^{3} = \begin{bmatrix} -b_1 - \alpha I & -\alpha S + \gamma R & \gamma I \\ \alpha I & \alpha S - (b_2 + \beta) & 0 \\ 0 & \beta - \gamma R & -\gamma I \end{bmatrix}$$

Evaluating at the endemic equilibrium $E = (S^*, I^*, R^*)$ and applying the steady-state relations $\alpha S^* - (b_2 + \beta) = 0$ and $\beta - \gamma R^* = -\frac{a_2}{I^*}$, we obtain

$$J(E) = \begin{bmatrix} -b_1 - \alpha I^* & \dfrac{a_2}{I^*} - b_2 & \gamma I^* \\ \alpha I^* & 0 & 0 \\ 0 & -\dfrac{a_2}{I^*} & -\gamma I^* \end{bmatrix}$$

The characteristic polynomial of this matrix is expressed as

$$\chi(\lambda) = \lambda^3 + A_1\lambda^2 + A_2\lambda + A_3$$

with coefficients obtained through direct expansion:

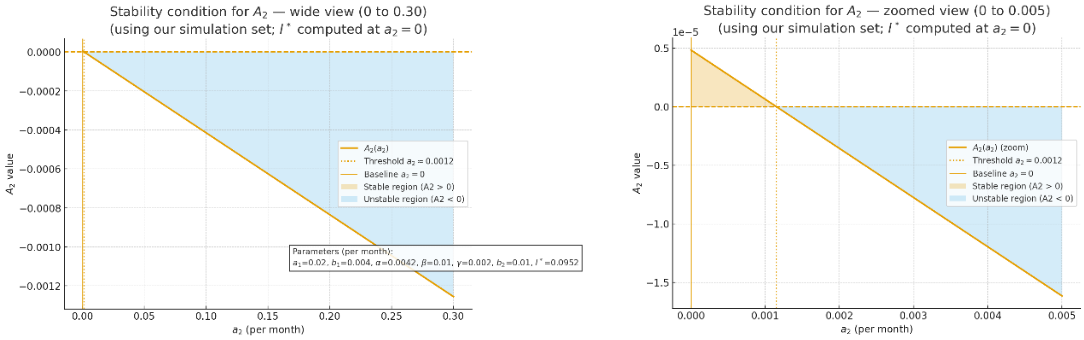
$$\begin{aligned} A_1 &= b_1 + (\alpha + \gamma)I^* \\ A_2 &= \alpha\gamma(I^*)^2 + \alpha b_2 I^* + b_1\gamma I^* - \alpha a_2 \\ A_3 &= \alpha b_2 \gamma (I^*)^2 \end{aligned}$$

The Routh–Hurwitz stability criterion states that the equilibrium point is locally asymptotically stable if $A_1 > 0, A_2 > 0, A_3 > 0,$ and $A_1A_2 > A_3$. In this model, the existence of the endemic equilibrium guarantees $I^* > 0$, ensuring $A_1 > 0$ and $A_3 > 0$. The condition $A_2 > 0$ further requires that the disengagement inflow parameter a_2 does not exceed a critical threshold:

$$\alpha a_2 < \alpha\gamma(I^*)^2 + \alpha b_2 I^* + b_1\gamma I^*$$

This inequality indicates that the background flow into the disengaged group must remain sufficiently small compared to the combined effects of peer recruitment (α), reactivation (γ), and turnover from the active group (b_2). The final inequality $A_1A_2 > A_3$ is satisfied under the same condition, thereby confirming the local asymptotic stability of E.

A stable equilibrium mathematically indicates that participation rates return to balance after small disturbances. In educational terms, stability reflects sustained organizational engagement across semesters, while instability implies that minor disruptions in motivation or peer influence may lead to long-term decline. The stability analysis reveals that the equilibrium distribution of students among susceptible, active, and disengaged groups is resilient to small disturbances if peer influence and reactivation dominate the baseline tendency to become inactive. In practical terms, organizational involvement will remain stable over time if student recruitment and pathways for re-engagement are strong, while structural causes of disengagement (represented by a_2) are limited.



(a) Wide View (b) Zoomed View

Figure 2. Stability condition illustration for parameter A_2

The illustration graph in Figure 2 shows the stability conditions based on the parameters a_2.

1. The orange area shows the domain of values a_2 where $A_2 > 0$, so the system is locally asymptotically stable.
2. The blue area indicates the domain where $A_2 < 0$, so the stability condition fails to be satisfied.
3. The orange line is the value of A_2 against a_2, while the dotted orange line is the zero axis as the stability limit.

Conversely, if a_2 is too large, the equilibrium may lose stability, and the system could drift toward reduced participation.

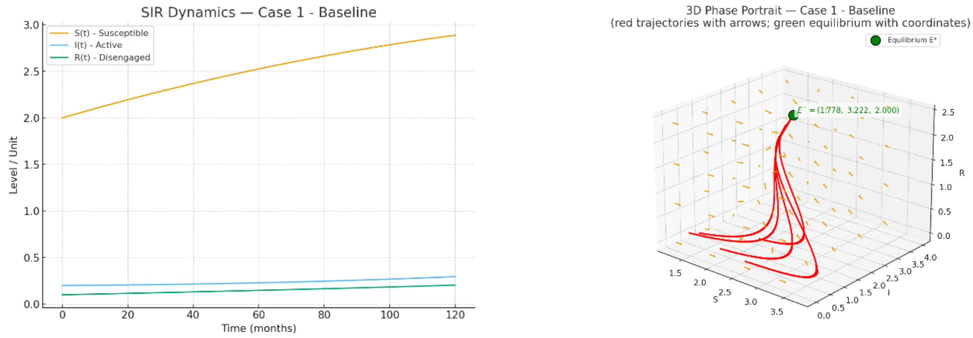
These results are consistent with dynamic behavioral diffusion studies in education, such as those by Zhang et al. [11] and Saqr et al. [13], which emphasize that peer influence and interaction strength are critical for sustaining engagement

3.4 Numerical Simulation

This section presents the simulation results of the SIR model using MATLAB. The simulation was performed under several parameter scenarios to observe the dynamic behavior of student organizational involvement. Each simulation represents the proportion of susceptible, active, and former members over time. In order to conduct numerical simulations of the proposed SIR model, it is necessary to specify realistic values for the parameters involved. Since direct empirical measurements of organizational dynamics are rarely available, parameter choices were informed by related studies in social contagion, educational modeling, and student retention, complemented with reasonable assumptions. Parameter values are shown in Table 1.

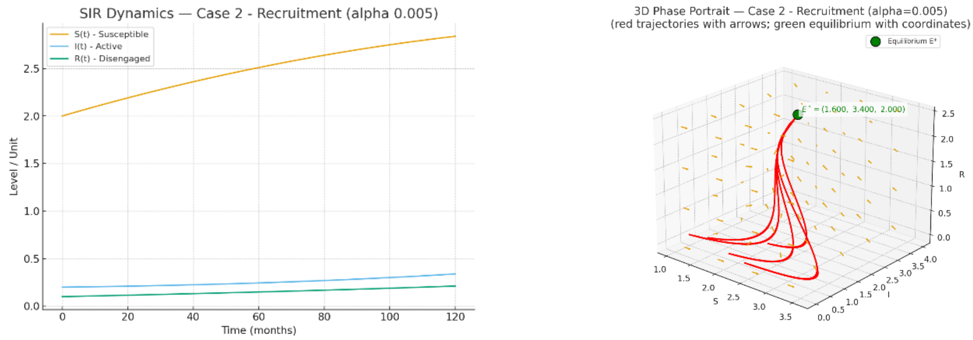
Table 1. Parameter Value

Parameter	Value/Range	Baseline used (per month)	Basis (Reference/ Assumption)
a_1	≈0.20–0.25 per year	0.02	Typical annual intake in 4–5 year programs (NCES) [22]
b_1	≈0.05 per year	0.004	Status dropout rate 5% per year (NCES) [22]
α	0.001–0.005 per month	0.0045	Social contagion models: Herrera et al. [23]; Obasuyi et al. [24]
β	0.01–0.10 per year	0.004	Membership attrition 10–20% annually [25]; also Herrera et al. [23], Obasuyi et al. [24]
γ	0.001–0.01 per month	0.002	Assumed, by analogy to waning immunity in epidemiology
a_2	≈0 (negligible)	0	No data, assumed zero unless surveys suggest otherwise
b_2	0.05–0.20 per year	0.01	Average membership duration 5–10 years, comparable to b_1



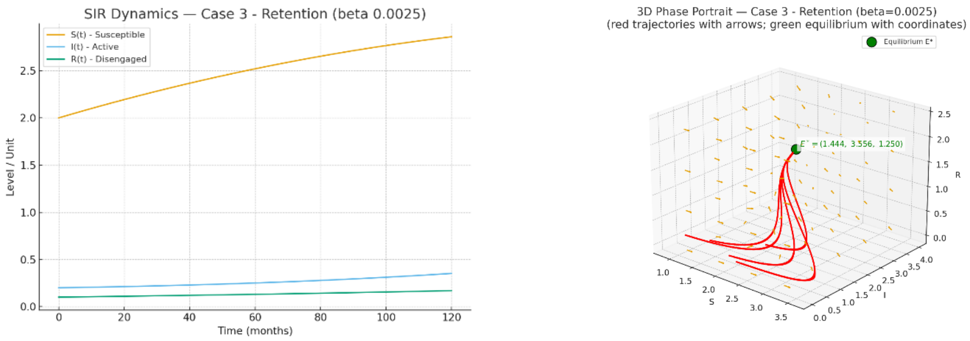
(a) SIR Dynamics (b) Phase Portrait

Figure 3. Case 1 Simulation (Baseline)



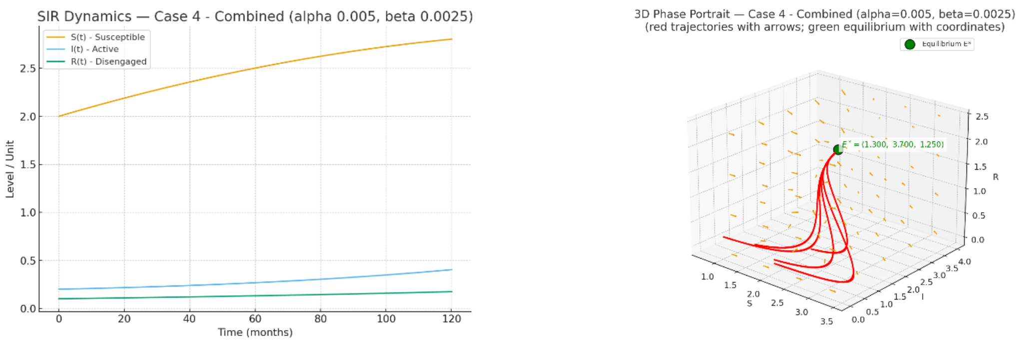
(a) SIR Dynamics (b) Phase Portrait

Figure 4. Case 2 Simulation (Recruitment Campaign)



(a) SIR Dynamics (b) Phase Portrait

Figure 5. Case 3 Simulation (Improved Retention)



(a) SIR Dynamics (b) Phase Portrait

Figure 6. Case 4 Simulation (Combined Strategy)

Table 2. Cases in simulation

No.	Cases	Scenarios
1	Baseline (Control)	This scenario uses the parameter set presented in Table 1 without any intervention. It represents the natural dynamics of student participation under current conditions, serving as a benchmark for comparison.
2	Recruitment Campaign	In this case, the peer recruitment rate α is increased by 50% ($\alpha = 0.005$), reflecting strategies such as social media promotion, campus-wide campaigns, or orientation events. The aim is to examine whether stronger peer influence can accelerate the growth of active membership.
3	Improved Retention	Here the disengagement rate β is reduced by 50% ($\beta = 0.0025$), representing interventions such as incentives, academic credit, or organizational support that encourage students to remain active. The goal is to test how much extending the average membership duration can stabilize participation.
4	Combined Strategy	This scenario simultaneously increases α ($\alpha = 0.005$) and decreases β (0.0025), integrating both recruitment and retention strategies. It represents a comprehensive organizational effort and is expected to produce the most sustainable increase in active student involvement.

The study sets the simulation time unit to months. The authors adopt a baseline parameter set consistent with Table 1. The model assumes $a_2 = 0$ unless otherwise stated. The simulations compute the trajectories of SSS, III, and RRR using MATLAB (ode45) with tight tolerances (RelTol = 10^{-8}, AbsTol = 10^{-10}) The authors choose initial conditions that reflect realistic shares of non-members, active members, and previously disengaged students at the start of a term. The procedure tests robustness by starting from a higher initial active fraction. The next section introduces four policy-relevant cases in Table 2 to isolate and combine the effects of recruitment and retention on the active student population. The simulation will be made in four cases as explained below in Figure 3-6. All simulation results for cases one through four show population changes over time, until all three populations stabilize at a certain point. This result is also evident in the 3D phase portraits of the three variables, where t resulting trajectories lead to a single, stable equilibrium point.

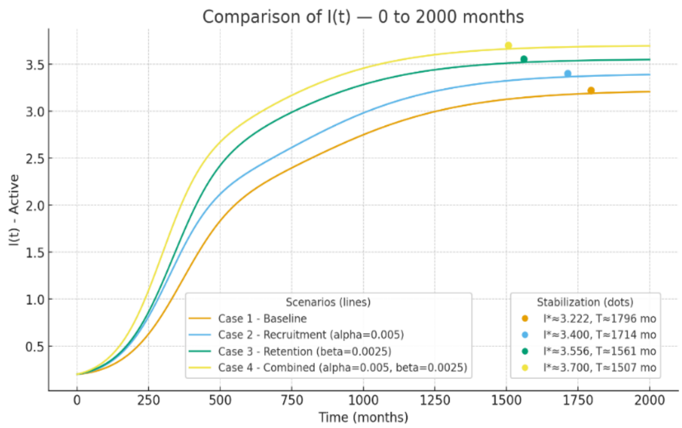


Figure 7. Comparison of $I(t)$

The comparison plot (0–2000 months) presents four trajectories of the active-member population $I(t)$, and the legend reports each curve's equilibrium level I^* and its stabilization time T (first reach of $\sim 99\%\ I^*$), see Figure 7. The baseline rises from the initial condition and plateaus at a moderate I^*, which represents business-as-usual conditions where peer recruitment and disengagement offset one another. Increasing recruitment (higher α) shifts the curve upward and left; $I^*(t)$ grows faster and stabilizes earlier at a higher I^*. Improving retention (lower β) also raises I^*, although the early slope is gentler. The combined strategy (higher α and lower β) dominates the comparison, achieves the largest I^* and the shortest T, and indicates that recruitment and retention act as complementary rather than substitutable levers. The 3D phase portraits (S–I–R) and the stabilization markers together show local asymptotic stability; once interventions operate, transient shocks decay and trajectories return to the same equilibrium. The stability-condition figure for parameter a_2 further shows that keeping a_2 close to zero preserves the stable region and prevents erosion of I^*.

Across all scenarios, the trajectories of susceptible, active, and former members eventually stabilize, indicating that the system reaches an asymptotic equilibrium. The rate at which equilibrium is achieved depends primarily on β and α, while γ influences the long-term retention of engagement. These results demonstrate that peer recruitment and reactivation have a stronger impact on participation sustainability compared to disengagement alone. The dynamic behavior observed in this model is consistent with previous educational diffusion studies, such as Zhang et al. [11] and Saqr et al. [13], where peer influence plays a critical role in maintaining engagement stability. Similarly, Goosen et al. [17] and Obasuyi et al. [24] applied SIR-based approaches in behavioral diffusion contexts, showing that recruitment and reactivation mechanisms are key drivers for sustained participation.

3.5 Policy Implications

In practical terms, the baseline calls for immediate action to raise recruitment intensity early in the term through orientation drives, student ambassador referrals, and bring a friend event, while removing structural barriers so that new students begin as potential joiners and while tracking referral to onboarding conversion. The recruitment case requires pairing the campaign with retention measures such as clear role definitions, mentoring, recognition or micro credentials, and flexible scheduling to ensure that the influx of new members does not lead to disengagement. The retention case benefits from light recruitment activities including class visits and peer challenges to avoid a slow start while maintaining low attrition through continuous support and early warning monitoring. The combined case should synchronize a front-loaded recruitment surge with consistent retention programs, introduce moderate re engagement channels such as pause and return options or alumni and buddy callbacks, ensure onboarding capacity aligns with campaign peaks, and continuously monitor recruitment and attrition metrics to iteratively adjust performance toward the most effective participation trajectory.

4. CONCLUSION

This study modeled student organizational engagement using an adapted SIR framework to analyze recruitment, retention, and reactivation dynamics. The simulations demonstrate that increasing recruitment accelerates early participation growth, improving retention strengthens long term stability, and combining both strategies produce the highest and most sustained active membership. Within the context of Indonesian higher education, these findings highlight the importance of integrating early recruitment campaigns with continuous retention initiatives while minimizing administrative barriers and tracking participation metrics regularly. Such coordinated strategies can help universities maintain organizational vitality and foster stronger student engagement ecosystems. Some parameter values, particularly recruitment and disengagement rates, were informed by previous studies and institutional observations, while others were assumed to enable theoretical simulation. The model also assumes homogeneous interaction among students and excludes stochastic variations in motivation and peer influence. These simplifications limit the empirical precision of the results, meaning that the simulations should be viewed as conceptual illustrations rather than quantitative forecasts. Future research should calibrate parameters with real participation data, incorporate heterogeneous or network-based interaction structures, and include stochastic or sensitivity analyses to enhance model realism. Extending this work toward data driven or agent-based modeling would strengthen its policy relevance and provide universities with more accurate decision support tools for managing student organizational engagement.

5. REFERENCES

[1] A. A. Bush, K. M. Buhlinger, and J. E. McLaughlin, "Identifying shared values for school-affiliated student organizations," *Am J Pharm Educ*, vol. 81, no. 9, p. 6076, 2017, doi: https://doi.org/10.5688/ajpe6076.

[2] M. Xiao, K. D. Bradley, and J. Lee, "Exploring the relationship between student involvement and first-to-second year retention at four-year postsecondary institutions," *Mid-Western Educational Researcher*, vol. 32, no. 3, pp. 191–205, 2020.

[3] A. W. Astin, "Student involvement: A developmental theory for higher education," in *College student development and academic life*, Routledge, 2014, pp. 251–262.

[4] J. E. Symonds *et al.*, "Momentary student engagement as a dynamic developmental system.," *Journal of Theoretical and Philosophical Psychology*, vol. 45, no. 4, pp. 393–410, 2024, doi: https://doi.org/10.1037/teo0000288.

[5] P. Haber-Curran and D. E. Pierre, "Student involvement as a catalyst for leadership identity development," *New Dir Stud Leadersh*, vol. 2023, no. 178, pp. 75–86, 2023, doi: https://doi.org/10.1002/yd.20556.

[6] I. R. and A. P. University of California, "Extracurricular participation and student success." Accessed: Nov. 13, 2025. [Online]. Available: https://www.ucop.edu/institutional-research-academic-planning//_files/extracurricular-activities-impact-on-

[7] E. Gretzinger and M. Hicks, "Why Campus Life Fell Apart," The Chronicle of Higher Education. Accessed: Nov. 13, 2025. [Online]. Available: https://www.chronicle.com/article/why-campus-life-fell-apart

[8] A. Mowreader, "Data: Students Less Involved on Campus Post-Pandemic," Inside Higher Ed. Accessed: Nov. 13, 2025. [Online]. Available: https://www.insidehighered.com/news/student-success/college-experience/2025/04/11/fewer-students-engage-college-activities-after

[9] I. Chirikov, J. Douglass, and G. Thomson, "The Multi-Engagement Model: Understanding Diverse Pathways to Student Success at Research Universities," Mar. 2025. [Online]. Available: https://escholarship.org/uc/item/3c27q1kd

[10] Y. Lv, "Study on the Dynamic Mechanism of College Student Organization," *Open J Soc Sci*, vol. 6, no. 12, pp. 158–164, 2018, doi: https://doi.org/10.4236/jss.2018.612014.

[11] H. Zhang, W. O. Apeanti, S. W. Akuamoah, D. Yaro, and P. Georgescu, "A mathematical view towards improving undergraduate student performance and mitigating dropout risks," *Nonlinear Analysis: Modelling and Control*, vol. 26, no. 5, pp. 842–860, 2021, doi: https://doi.org/10.15388/namc.2021.26.24120.

[12] N. S. Thomas, P. B. Barr, D. L. Hottell, A. E. Adkins, and D. M. Dick, "Longitudinal influence of behavioral health, emotional health, and student involvement on college student retention," *J Coll Stud Dev*, vol. 62, no. 1, pp. 2–18, 2021, doi: https://doi.org/10.1353/csd.2021.0001.

[13] M. Saqr, D. Dever, S. López-Pernas, C. Gernigon, G. Marchand, and A. Kaplan, "Complex dynamic systems in education: beyond the static, the linear and the causal reductionism," in *Advanced Learning Analytics Methods: AI, Precision and Complexity*, Springer, 2025, pp. 289–311. doi: https://doi.org/10.1007/978-3-031-95365-1_12.

[14] S. Govindankutty and S. P. Gopalan, "Epidemic modeling for misinformation spread in digital networks through a social intelligence approach," *Sci Rep*, vol. 14, no. 1, p. 19100, 2024, doi: https://doi.org/10.1038/s41598-024-69657-0.

[15] L. Duan, Z. Wang, G. Zhu, and Y. Zhang, "Relationship between the College Student and the Campus Club: An Evolutionary Game Theory Analysis," *Behavioral Sciences*, vol. 14, no. 3, p. 182, 2024, doi: https://doi.org/10.3390/bs14030182.

[16] J. Woo and H. Chen, "Epidemic model for information diffusion in web forums: experiments in marketing exchange and political dialog," *Springerplus*, vol. 5, no. 1, p. 66, 2016, doi: https://doi.org/10.1186/s40064-016-1675-x.

[17] C. Goosen, M. I. Nelson, and M. Watanabe, "Applying the SIR model: can students advise the mayor of a small community?," *CODEE Journal*, vol. 17, no. 1, p. 2, 2024, doi: https://doi.org/10.5642/codee.BPDX7295.

[18] D. Lewis, "Modeling student engagement using optimal control theory.," *J Geom Mech*, vol. 14, no. 1, p. 131, 2022, doi: http://doi.org/10.3934/jgm.2021032.

[19] M. A. Alrizqi, "From Interviews to Equations: A Multi-Phase System Dynamics Model of Engineering Student Engagement," 2025. doi: https://doi.org/10.48550/arXiv.2507.00382.

[20] J. López-de-la-Cruz and A. N. Oliveira-Sousa, "SIR models with vital dynamics, reinfection and randomness to investigate the spread of infectious diseases," 2024. doi: https://doi.org/10.48550/arXiv.2404.12776.

[21] Y. H. Workineh and S. M. Kassa, "Optimal control of the spread of meningitis: in the presence of behaviour change of the society and information dependent vaccination," *Commun. Math. Biol. Neurosci.*, vol. 2021, no. 29, p. Article-ID, 2021, doi: https://doi.org/10.28919/cmbn/5575.

[22] V. Irwin *et al.*, "Report on the Condition of Education 2024," U.S. Department of Education. Washington, DC, May 2024. Accessed: Nov. 14, 2025. [Online]. Available: https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2024144

[23] M. Herrera, G. Armelini, and E. Salvaj, "Understanding social contagion in adoption processes using dynamic social networks," *PLoS One*, vol. 10, no. 10, p. e0140891, 2015, doi: https://doi.org/10.1371/journal.pone.0140891.
[24] F. O. T. Obasuyi, "Modelling Dropout Crisis in Education Distribution for Developing Economies with Replicative 'SIR'Model," *Educational Thought*, vol. 10, no. 1, pp. 13–32, 2020.
[25] R. Church, "Membership Retention Basics: What Your Association Needs To Know," CM Services. Accessed: Nov. 14, 2025. [Online]. Available: https://cmservices.com/membership-retention-basics-what-your-association-needs-to-know/