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Development and Stability Analysis of the SEIR-Epi-Mod-QR/Alt Model for Smart Campus Management of Student Stress and Academic Misconduct

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ABSTRACT

Student stress and academic misconduct remain major concerns in higher education institutions, particularly in technology-mediated learning environments. Many existing monitoring systems focus on record-keeping and are largely reactive, offering limited predictive insight for early intervention. Based on the role of early detection and intervention, a hybrid epidemiological model SEIR–Epi-Mod–QR/Alt is developed in this paper, which describes the dynamic interaction between student stress, academic misconduct, and smart campus monitoring. This model categorizes students as susceptible, exposed, misconduct-active, and recovered, and includes QR/Alt enabled early detection and mitigation. The existence, uniqueness, positivity, boundedness, equilibrium states, and local and global stability of the model are obtained through basic mathematical analysis. The numerical simulations of over a 180- day school term reveal that the threshold for stress reproduction drops from around 1.505 to 0.755 by increasing the QR/Alt-enabled early detection and mitigation rate from 0.05 to 0.20 per day, which in turn results in lower peak levels of misconduct-active students and shorter misconduct persistence. The simulations also illustrate that higher stress relapse can result in a higher likelihood that misconduct-active students will remain misconducted over time even with good early detection. The results indicate that within the model context, early detection, counselling, and ongoing academic support may be helpful in reducing academic dishonesty related to stress among students. The research establishes a mathematical framework to assess the effectiveness of early intervention plans for student support and academic integrity on a smart campus.

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INTRODUCTION

Stress among students and academic misconductare persistent challenges in higher education, impacting academic integrity, student health, and institutional reputation (Adnan *et al.*, 2021; Aithal, Prabhu, & Aithal, 2024). Some of the common academic stressors are high workload, time pressure, poor grades, economic problems, and job insecurity. Long-term exposure to these stressors could negatively affect cognitive functioning, judgment, and burnout, and promote unethical coping mechanisms by students (Verhoef and Coetser, 2021; Zhao *et al.*, 2022).High-stakes assessment, lack of academic assistance, high performance expectations, and ineffective monitoring and discipline can create a culture of academic misconduct and dishonesty. In a setting where competition is high, and the institutional checks on academic misconduct are limited, examinationmisconduct and other forms of academic dishonesty can be encouraged (Eaton, Pethrick and Turner, 2023).

Particularly concerning are these challenges in the development of higher-education systems, where infrastructural or administrative limitations may make effective monitoring and timely intervention difficult.

New challenges have arisen with the shift to online and blended learning during and after the COVID-19 pandemic. These learning spaces are linked to concerns of student stress, academic burnout, and academic misconduct (Aldhafeeri& Alotaibi, 2022; Alam, 2023; Gross *et al.*, 2023; Singh, Steele, & Singh, 2021). Additionally, traditional monitoring methods and the shortcomings of electronic records could also be insufficient for capturing real-time behavioural shifts and providing predictive data to guide timely interventions (Nkomo, Daniel, & Butson, 2021; Adebayo &Osamoka, 2024).

Digital technologies are increasingly enabling student attendance, engagement, behavioural monitoring, and technology-supported learning in higher education. QR-based systems have been highlighted as having potential for student engagement and monitoring (AlNajdi, 2022), while computer simulations have also been shown to support mathematics learning and retention (Ogala&Okeoghene, 2024). Similarly, Nkomo et al. (2021) show how digital technologies can contribute to student engagement, while machine learning-based models provide opportunities for more adaptive and data-driven learning environments.

Mathematical modelling provides a complementary framework for examining the temporal progression of behavioural and social phenomena. Compartmental models can be adapted to represent transitions among different states, while incorporating intervention and control mechanisms (Edeki*et al.*, 2020; Edeki*et al.*, 2021; Magani*et al.*, 2022; Vialatte*et al.*, 2022; Bellaj*et al.*, 2024).Such a framework makes it possible to examine how changes in intervention strategies may influence the persistence and progression of stress-driven academic misconduct.

Despite the growing use of digital technologies and mathematical models in education, limited attention has been given to integrating early detection mechanisms into a dynamical framework for student stress and academic misconduct. Existing approaches often consider attendance, engagement, and misconduct separately, without explicitly modelling progression, recovery, and relapse. This study addresses this gap by extending the SEIR framework to a smart-campus setting with QR/Alt-enabled early detection and mitigation.Previous compartmental models have demonstrated the value of explicitly distinguishing detectable and undetectable states in the analysis of dynamical systems (Edeki*et al.,* 2021).

Against this background, the SEIR–Epi-Mod–QR/Alt model is developed as an SEIR-based dynamical framework for representing student stress and academic misconduct. The model incorporates QR/Alt-enabled early detection and mitigation as an intervention mechanism and is used to examine intervention thresholds, stress and misconduct progression, and the effects of early detection and institutional responses.

The dynamic nature of student stress and academic misconduct, together with the influence of academic pressure, peer interactions, institutional policies, and interventions, motivates a time-dependent modelling framework (Virtanen *et al.,* 2021; Zhang *et al.,* 2022). Accordingly, the proposed model provides a quantitative basis for analysing stress exposure, progression, recovery, and relapse, and for assessing early intervention strategies in higher-education settings.

MATERIALS AND METHODS

The mathematical formulation of the SEIR–Epi-Mod–QR/Alt model is given in this section. The framework, as encouraged by the previous explanation, illustrates the dynamic interaction between student stress and academic misconduct due to academic pressure, peer influence, and institutional practices. A system of ordinary differential equations reflecting the time evolution of student states describes these processes. The model, through stress development and smart campus interventions, lays the groundwork for the threshold and stability analyses that are utilized to assess early detection and intervention strategies.

Model Variables and Assumptions

Let the total student population at time *t* be denoted by

$$N(t) = S(t) + E(t) + I(t) + R(t), \qquad (1)$$

Where the population is divided into 4 mutually exclusive compartments. The compartment *S(t)* represents students who have low stress levels and behave in a compliant fashion in school. Compartment *E(t)* represents the exposed students who are under moderate stress and at risk of academic misconduct. The compartment *I(t)* refers to the students who have a high level of stress and a higher tendency towards academic dishonesty. Lastly, *R(t)* represents students who have recovered and whose stress has been stabilized through counselling, academic support, or other institutional interventions. This compartmentalization (Figure 1) reflects the progressive build-up of stress and/or escalation of misbehavior in the academic setting, while allowing for transitions toward recovery and subsequent relapse through appropriate transition pathways.

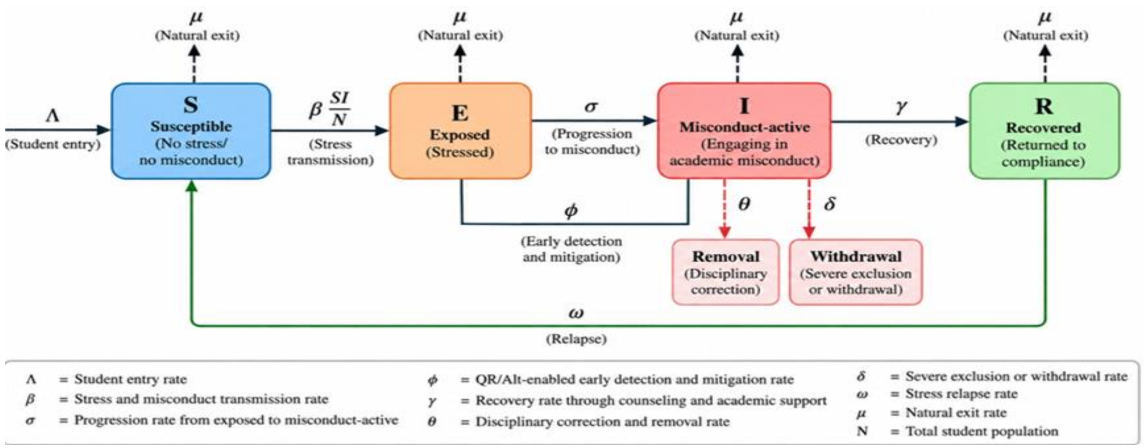

Figure 1: Schematic representation of the SEIR–Epi-Mod–QR/Alt compartmental model

Model Assumptions

The SEIR–Epi-Mod–QR/Alt model operates under the assumption that academic stress and academic misconduct develop through the process of educational interaction, peer influence, and shared learning environments. Besides, it is assumed that QR minor and alternative code-based smart campus technologies provide better opportunities for early networking and exposure to stress and risky academic behavior for prompt institutional response. The model further assumes that counseling, academic support, and necessary corrective measures facilitate recovery and reintegration into usual academic activities. For each academic term, the student population is believed to be closed, barring structured processes of entry and exit in the form of admission, graduation, or withdrawal. Finally, it is assumed that all model parameters are constant and positive, with biological and behavioral realism and mathematical consistency.

Governing Differential Model

Based on the above assumptions, the dynamics of the SEIR–Epi-Mod–QR/Alt model are governed by the following system of nonlinear ordinary differential equations:

$$\left.\begin{aligned} \frac{dS}{dt} &= \Lambda - \beta\frac{SI}{N} - \mu S + \omega R, \\ \frac{dE}{dt} &= \beta\frac{SI}{N} - (\sigma + \mu + \phi)E, \\ \frac{dI}{dt} &= \sigma E - (\gamma + \mu + \delta + \theta)I, \\ \frac{dR}{dt} &= \gamma I + \phi E - (\omega + \mu)R \end{aligned}\right\} \qquad (2)$$

In this modeling framework, the academic environment facilitates the transmission of stress between the susceptible and the exhibiting academic misconduct student. The transition of the stress from the exposure scenario to active misconduct is governed by the rate σ, with early detection based on QR/Alt intervention branching the exposed students back on the path to recovery at rate ϕ. Misconduct-active students recover through counselling and academic support at rate γ, while disciplinary correction and removal occur at rate θ, and severe exclusion or withdrawal occurs at rate δ. As a remark, the parameter θ represents disciplinary removal, while δ represents severe exclusion or withdrawal. Both parameters remove students from the active population rather than transferring them to recovery.

Parameter Description

The parameters applied in system (2), along with their respective units and realistic ranges based on empirical research and literature, are structured in Table 1. The ranges represent reasonable values selected for numerical experimentation based on the structure of the model and the study context. They are not intended as empirically estimated or calibrated parameter values.

Table 1: Model Parameters, Units, and Realistic Ranges

Parameter	Description	Unit	Simulation range	Basis for simulation range
Λ	Student entry rate (admission or registration)	day^{-1}	2.0 – 3.0	Illustrative student-entry range for the model population
β	Stress and misconduct transmission rate	day^{-1}	0.40 – 0.70	Plausible range representing varying levels of peer and academic interaction
σ	Stress progression rate from exposed to misconduct-active	day^{-1}	0.10 – 0.25	Range representing different rates of stress progression
ϕ	QR/Alt-enabled early detection and mitigation rate	day^{-1}	0.03 – 0.20	Range representing low to enhanced levels of early detection
γ	Recovery rate through counseling and academic support	day^{-1}	0.08 – 0.15	Range representing varying levels of recovery support
θ	Disciplinary correction and removal rate	day^{-1}	0.02 – 0.06	Illustrative range for institutional disciplinary response
δ	Severe exclusion or withdrawal rate	day^{-1}	0.005 – 0.02	Illustrative range for severe student exit
μ	Natural exit rate (graduation or withdrawal)	day^{-1}	0.001 – 0.002	Illustrative range for routine student exit
ω	Loss of recovery or stress relapse rate	day^{-1}	0.01 – 0.05	Range representing varying levels of relapse

With the model structure and equations in place, the next section looks into the posited system's mathematical properties. Specifically, Section 3 deals with the existence, uniqueness, positivity, boundedness, equilibrium states, and stability behavior of the SEIR–Epi-Mod–QR/Alt model,acting as the theoretical basis influencing the forthcoming numerical simulations and policy interpretation.

RESULTS AND DISCUSSION

Mathematical Analysis, Stability, and Approximate Solutions

In this section, a thorough mathematical analysis of the SEIR–Epi-Mod–QR/Alt model is provided. The well-posedness of the system is demonstrated by showing the existence, uniqueness, positivity, and boundedness of solutions. The equilibrium points are obtained, which include the stress-free equilibrium and a stress-persistent (endemic) equilibrium. The basic reproduction number R_0 provides a threshold measure for determining whether the modelled process persists or declines, and has been widely incorporated into compartmental dynamical analyses (Edeki*et al.*, 2020; Ogundile*et al.*, 2018).

The sensitivity indices of R_0 are calculated to evaluate the impact of institutional interventions. Next, a Picard–Lindelöf iteration scheme is employed to justify the numerical approximation of solutions.Numerical methods provide useful tools for obtaining approximate solutions of nonlinear dynamical systems. Recent studies have applied Picard-type iteration methods to nonlinear PDEs and differential games (Han *et al.*, 2026; El Siedy*et al.*, 2025), while spectral and stability analyses have been used in nonlinear wave models (Dauda &Ja'afaru, 2025). In this study, the Picard–Lindelöf iteration scheme is employed to obtain approximate solutions of the proposed SEIR–Epi-Mod–QR/Alt system. In what follows with regard to the mathematical analysis, the model is captured.

Let

$$X(t) = (S(t), E(t), I(t), R(t))^T,\ N(t) = S(t) + E(t) + I(t) + R(t)$$

,

And consider the system

$$\left.\begin{aligned}
\frac{dS}{dt} &= \Lambda - \beta\frac{SI}{N} - \mu S + \omega R, \\
\frac{dE}{dt} &= \beta\frac{SI}{N} - (\sigma + \mu + \phi)E, \\
\frac{dI}{dt} &= \sigma E - (\gamma + \mu + \delta + \theta)I, \\
\frac{dR}{dt} &= \gamma I + \phi E - (\omega + \mu)R,
\end{aligned}\right\} \tag{3}$$

with initial conditions S(0),E(0),I(0),R(0)≥0 and N(0)>0.

Existence and Uniqueness of Solutions

Theorem 3.1 (Existence and Uniqueness)

For every initial condition $X(0) = X_0 \in \mathbb{R}^4_{\geq 0}$ with $N(0) > 0$, system (2) admits a unique solution $X(t)$ defined for all $t \geq 0$.

Proof: Define the vector field *F(X)* as the right-hand side of system (2). The only nonlinear rational term is SI/N. In any region where $N \geq \varepsilon > 0$, the mapping

$$(S, E, I, R) \mapsto \frac{SI}{S + E + I + R} \tag{4}$$

is continuously differentiable and hence locally Lipschitz. All remaining terms are linear functions of the state variables. Therefore, F is locally Lipschitz on $\{X \geq 0 : N \geq \varepsilon\}$. Since N (0)>0, Picard–Lindelöf theory guarantees the existence and uniqueness of a local solution. Global existence follows from boundedness established in Theorem 3.2. Q.E.D.

Positivity and Boundedness of Solutions

Theorem 3.2 (Positivity and Boundedness)

Let $X(0) = (S(0), E(0), I(0), R(0)) \in \mathbb{R}^4_+$ with $N(0) > 0.$

Then the solution of the system (2) remains non-negative for all $t \ge 0$. Moreover, the total student population $N(t)$ is ultimately bounded, and the region:

$$\Omega = \left\{ (S,E,I,R) \in \mathbb{R}_+^4 : N \le \frac{\Lambda}{\mu} \right\} \tag{5}$$

Is positively invariant for initial conditions satisfying $N(0) \le \Lambda / \mu$.

Proof

Positivity: Consider the vector field on the boundary of the non-negative orthant. From system,

$$\begin{cases} \left.\dfrac{dS}{dt}\right|_{S=0} = \Lambda + \omega R \ge 0, \\ \left.\dfrac{dE}{dt}\right|_{E=0} = \beta \dfrac{SI}{N} \ge 0, \\ \left.\dfrac{dI}{dt}\right|_{I=0} = \sigma E \ge 0, \\ \left.\dfrac{dR}{dt}\right|_{R=0} = \gamma I + \phi E \ge 0. \end{cases} \tag{6}$$

Therefore, the vector field points inward or tangentially on every boundary face of $\mathbb{R}_+^4$. Hence, no component can become negative whenever the initial conditions are non-negative. Thus,

$S(t), E(t), I(t), R(t) \ge 0,\ t \ge 0.$

Consequently, the non-negative orthant $\mathbb{R}_+^4$ is positively invariant.

Boundedness: Adding the four equations of system (2) gives

$$\frac{dN}{dt} = \Lambda - \mu N - \delta I - \theta I.$$

Hence,

$$\frac{dN}{dt} = \Lambda - \mu N - (\delta + \theta) I \le \Lambda - \mu N.$$

By comparison with the scalar differential equation

$y' = \Lambda - \mu y,$

The following is obtained

$$N(t) \le N(0)e^{-\mu t} + \frac{\Lambda}{\mu}\left(1 - e^{-\mu t}\right).$$

$$\therefore\ \limsup_{t\to\infty} N(t) \le \frac{\Lambda}{\mu}.$$

In particular,

$$\begin{cases} N(0) \le \dfrac{\Lambda}{\mu}, \\ \Rightarrow\ N(t) \le \dfrac{\Lambda}{\mu},\ t \ge 0. \end{cases} \tag{7}$$

Thus, Ω is positively invariant. For arbitrary non-negative initial conditions, the preceding inequality shows that the solution is ultimately bounded and approaches the bound Λ / μ asymptotically.Therefore, all solutions with non-negative initial conditions remain non-negative and are ultimately bounded. Q.E.D.

Equilibrium Points

To obtain the equilibrium points of system (2), all the corresponding derivatives are set to zero. These steady states describe the long-term conditions of the student population and offer the basis for subsequent stability analysis. In particular, the stress-free equilibrium and the endemic equilibrium are considered. Reference is made to the following subsections for more details.

Stress-Free Equilibrium

Setting $E=I=0$ in system (2) yields the stress-free equilibrium

$$E_0 = \left(\frac{\Lambda}{\mu}, 0, 0, 0 \right). \tag{8}$$

Basic Stress Reproduction Number

Using the next-generation approach, the basic stress reproduction number is

$$R_0 = \frac{\beta\sigma}{(\sigma + \mu + \phi)(\gamma + \mu + \delta + \theta)}. \tag{9}$$

This threshold determines whether stress and misconduct die out or persist.

Local Stability of the Stress-Free Equilibrium

Theorem 3.3 (Local stability)

The stress-free equilibrium E_0 is locally asymptotically stable if $R_0 < 1$ and unstable if $R_0 > 1$.

Proof: The Jacobian matrix of system (2) at E_0 is

$$J(E_0) = \begin{pmatrix} -\mu & 0 & -\beta & \omega \\ 0 & -(\sigma + \mu + \phi) & \beta & 0 \\ 0 & \sigma & -(\gamma + \mu + \delta + \theta) & 0 \\ 0 & \phi & \gamma & -(\omega + \mu) \end{pmatrix}. \tag{10}$$

The stability of *E₀*is governed by the infected subsystem (E,I), whose characteristic polynomial has positive coefficients if and only if $R_0<1$. The Routh–Hurwitz criterion, therefore, implies local asymptotic stability when $R_0<1$. Q.E.D.

Existence of a Stress-Persistent (Endemic) Equilibrium

Theorem 3.4 (Existence of endemic equilibrium)

If $R_0>1$, system (2) admits a unique endemic equilibrium E^* with

$$S^* > 0, \quad E^* > 0, \quad I^* > 0, \quad R^* > 0.$$

Proof

At equilibrium with $I^* > 0$, system (2) implies

$$\left. E^* = \frac{\gamma + \mu + \delta + \theta}{\sigma} I^*, \quad R^* = \frac{\gamma I^* + \phi E^*}{\omega + \mu}. \right\} \tag{11}$$

Substituting into the E-equation yields

$$\beta \frac{S^*}{N^*} = \frac{(\sigma + \mu + \phi)(\gamma + \mu + \delta + \theta)}{\sigma}. \tag{12}$$

This equation admits a positive solution $S^* < N^*$ if and only if $R_0 > 1$. Uniqueness follows from the monotonicity of the incidence term. Q.E.D.

Global Stability of the Stress-Free Equilibrium

Theorem 3.5 (Global Stability)

If $R_0 < 1$, then the stress-free equilibrium E_0 is globally asymptotically stable in the positively invariant feasible region Ω.

Proof:

Let $k = \sigma + \mu + \phi,\ D = \gamma + \mu + \delta + \theta.$

Consider the Lyapunov function.

$$V(E, I) = E + \frac{k}{\sigma} I. \tag{13}$$

Clearly, $V(E,I) \ge 0$ for all $E, I \ge 0$, and $V(E,I) = 0$ if and only if $E = I = 0$.

Along the solutions of system (2),

$$\frac{dV}{dt} = \frac{dE}{dt} + \frac{k}{\sigma}\frac{dI}{dt}. \tag{14}$$

Using the E - and I -equations of system (2) gives

$$\frac{dV}{dt}=\left(\beta\frac{SI}{N}-kE\right)+\frac{k}{\sigma}\left(\sigma E-DI\right). \qquad (15)$$

Hence,

$$\frac{dV}{dt}=\beta\frac{SI}{N}-\frac{kD}{\sigma}I. \qquad (16)$$

From the definition of the basic stress reproduction number,

$$R_0=\frac{\beta\sigma}{kD}=\frac{\beta\sigma}{(\sigma+\mu+\phi)(\gamma+\mu+\delta+\theta)}, \qquad (17)$$

We obtain

$$\frac{kD}{\sigma}=\frac{\beta}{R_0}. \qquad (18)$$

Therefore,

$$\frac{dV}{dt}=\frac{kD}{\sigma}\left(R_0\frac{S}{N}-1\right)I. \qquad (19)$$

Since $0\le S/N\le 1$ in Ω, it follows that:

$$\frac{dV}{dt}\le\frac{kD}{\sigma}(R_0-1)I. \qquad (20)$$

Thus, whenever $R_0<1$,

$$\frac{dV}{dt}\le 0.$$

Moreover, $\frac{dV}{dt}=0\Rightarrow I=0$.

From the I -equation,

$$\frac{dI}{dt}=\sigma E-DI, \qquad (21)$$

and therefore, when $I=0$, invariance requires $E=0$. Consequently, the largest invariant subset of

$$\left\{(S,E,I,R)\in\Omega:\frac{dV}{dt}=0\right\} \qquad (22)$$

Is the stress-free set characterized by $E=I=0$.

At this set, the remaining equations reduce to the dynamics leading to the stress-free equilibrium E_0. Hence, by LaSalle's invariance principle, every solution originating in Ω approaches E_0 as $t\to\infty$.

So, the stress-free equilibrium E_0 is globally asymptotically stable in Ω whenever $R_0<1$. Q.E.D.

Sensitivity Analysis of the Reproduction Number

The normalized sensitivity index of *R₀* with respect to a parameter *p* is

$$\Upsilon_p^{R_0}=\frac{\partial R_0}{\partial p}\cdot\frac{p}{R_0}. \qquad (23)$$

The most relevant indices are

$$\left.\begin{aligned}&\Upsilon_\beta^{R_0}=1,\quad \Upsilon_\phi^{R_0}=-\frac{\phi}{\sigma+\mu+\phi},\\ &\Upsilon_\gamma^{R_0}=-\frac{\gamma}{\gamma+\mu+\delta+\theta},\\ &\Upsilon_\theta^{R_0}=-\frac{\theta}{\gamma+\mu+\delta+\theta}.\end{aligned}\right\} \qquad (24)$$

These results indicate that early detection and recovery mechanisms are the most effective controls for reducing stress propagation.

Picard–Lindelöf Iteration Method

System (2) can be written in integral form as

$$X(t)=X_0+\int_0^t F(X(s))ds. \qquad (25)$$

Define the Picard sequence

$$X_{n+1}(t)=X_0+\int_0^t F(X_n(s))ds,\quad n=0,1,2,\ldots \qquad (26)$$

With $X_0(t)\equiv X_0$. Since FFF is locally Lipschitz and solutions are bounded in Ω, the sequence converges uniformly on finite intervals to the unique solution of system (2). This provides a constructive approximation scheme and justifies numerical simulations (Edeki& Azu-Nwosu, 2024).

Numerical Simulations

This section presents the numerical simulation of the analytical results obtained in Sections 2 and 3. The simulations allow us to study the dynamic behavior of the SEIR–Epi-Mod–QR/Alt model at different levels of early detection with QR/Alt and to confirm how R_0 plays the threshold indication role in stress reproduction.

Simulation Setup

Numerical simulations were performed over a 180day academic period with $N(0)=455$. The initial conditions were $S(0)=400$, $E(0)=30$, $I(0)=15$, and $R(0)=10$. The baseline parameter values were $\Lambda=2.5$, $\beta=0.40$, $\sigma=0.10$, $\phi=0.05$, $\gamma=0.15$, $\theta=0.02$, $\delta=0.005$, $\mu=0.001$, and $\omega=0.01$, giving $R_0\approx 1.505>1$. For the enhanced QR/Alt intervention, ϕ was increased to 0.20, yielding $R_0\approx 0.755<1$. The relapse analysis was conducted by varying ω while keeping the other parameters fixed. The system was solved numerically over $0\le t\le 180$ days using the numerical procedure described in Section 3.9.

The Picard–Lindelöf iteration method was used to find the approximate solutions of system (2), in support of the existence, uniqueness, and boundedness results established in Section 3. The time step was determined to be small enough to provide numerical stability and accuracy.

Baseline QR/Alt Detection Setting

The baseline scenario is relatively low for QR/Alt enabled early detection: $\phi=0.05$ The value of the corresponding reproduction number is $R_0\approx 1.505>1$. The exposed and misconduct-active populations stay stable over time, as illustrated in Figure 2, suggesting that misconduct that is precipitated by stress can still be found in the student population when it is not detected early.

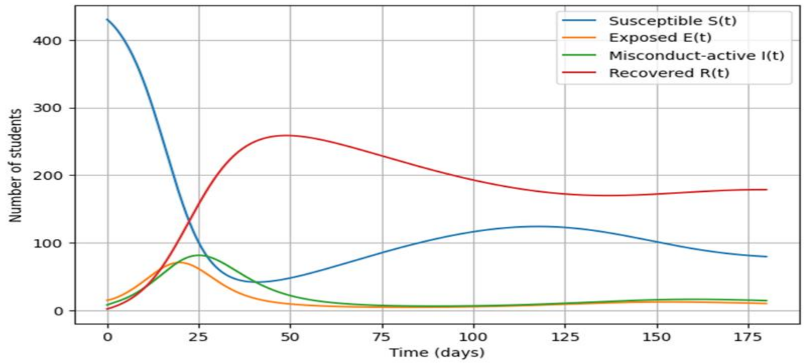

Figure 2: Time evolution of all compartments under baseline QR/Alt detection

Figure 2shows the Time evolution of the susceptible, exposed, misconduct-active, and recovered student populations under baseline QR/Alt detection.The exposed and misconduct-active populations persist over time, confirming the analytical result that the stress-free equilibrium is unstable when $R_0>1$. This illustrates how insufficient early detection allows stress-driven misconduct to remain endemic within the student population.

In the improved scenario, the rate of early detection increases to $\phi = 0.20$ and $R_0 \approx 0.755 < 1$. As seen in Figure 3, the exposed population $E(t)$ decreases more quickly, and the population of misconduct-active $I(t)$ has a lower peak and shorter persistence. This shows that a better early detection system and early intervention result in a decrease in stress-related offending behavior.

Improved QR/Alt Detection Setting

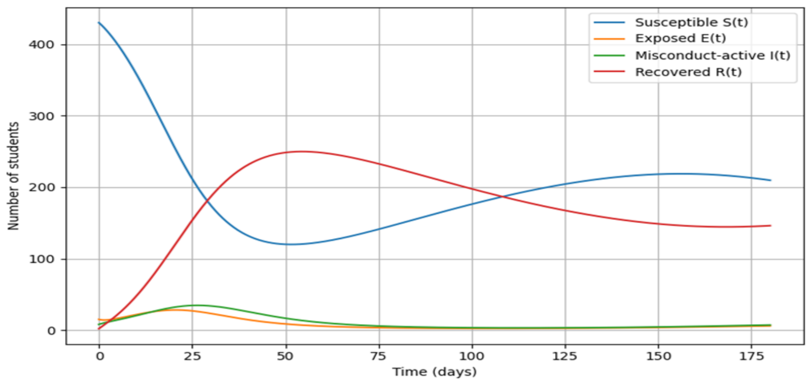

Figure 3: System dynamics under improved QR/Alt-enabled early detection

For the improved QR/Alt enabled early detection case (ϕ=0.20), Figure 3 shows a more rapid decline in exposed class *E(t)* as a result of the enhanced transition from E to R with early detection and mitigation. The misconduct-active population *I(t)* is therefore significantly lower than in the baseline scenario, with a much shorter duration of misconduct. This is a reflection of the success of early identification and timely intervention to break the cycle of increased levels of stress and stress-related misconduct prevalence.

Comparative Impact on Misconduct-Active Students

To clearly demonstrate the effect of QR/Alt-enabled detection, the misconduct-active population I(t) under both scenarios is compared directly

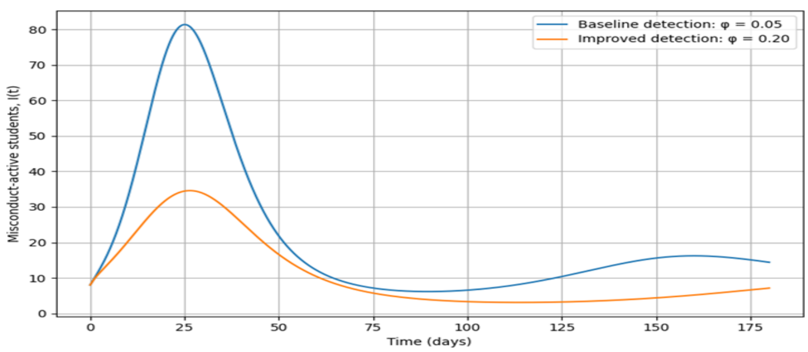

Figure 4: The misconduct-active population under baseline and improved QR/Alt detection

Figure 4 compares the misconduct-active population under baseline detection ($\phi = 0.05$) and enhanced detection ($\phi = 0.20$). The increase in the early detection rate from 0.05 to 0.20 reduces the reproduction number from approximately 1.505 to 0.755, with a corresponding reduction in the peak and persistence of the misconduct-active population.

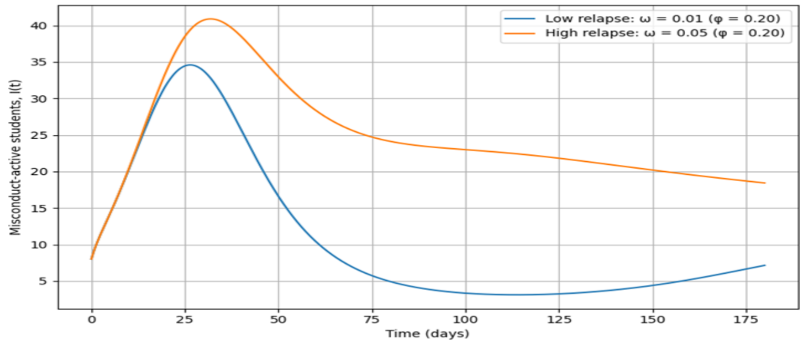

Figure 5: Effect of stress relapse on misconduct-active population under improved detection

Figure 5 illustrates the effect of increasing the relapse rate from $\omega = 0.01$ to $\omega = 0.05$ under enhanced detection. The higher relapse rate increases the persistence of the misconduct-active population, indicating the importance of sustained counseling and academic support.

Key Findings from the Simulations

The numerical simulations show that weak QR/Alt-enabled early detection permits stress and misconduct to continue within the student population, in alignment with the analytical condition $R_0 > 1$. As the early detection rate increases, the duration of stress exposure shortens, and the prevalence of misconduct-active students is substantially reduced. These results are consistent with the local and global stability analyses, which indicate convergence toward the stress-free equilibrium when effective interventions are implemented. Overall, the simulations suggest that QR/Alt-enabled early detection may support non-punitive approaches to smart campus management and enhance the potential value of integrating differential modelling with real-time monitoring systems.The simulations are deterministic and illustrative and were not calibrated against observed incidence data. The model assumes homogeneous mixing and constant parameter values. Uncertainty quantification was not undertaken, but normalized sensitivity analysis identifies parameters with the greatest influence on the reproduction number.

CONCLUSION

In this study, the SEIR–Epi-Mod–QR/Alt model was developed and analysed as a dynamical framework for examining student stress and academic misconduct in higher-education settings. The model views stress and misconduct as behavioral processes that are dependent on time and are impacted by the interaction of peers and the institutional conditions. This gives way to a thorough qualitative and quantitative exploration of the rise, spread, and control of such behaviors in the context of a university.Analysis of the theory concluded that the model was mathematically well-posed, having positive, bounded, and unique solutions. The existence of both stress-free and stress-persistent equilibrium states was illustrated, with the basic stress reproduction number R_0 governing the threshold behavior of the system. When $R_0 < 1$, the local and global stability analyses indicate convergence of the system toward the stress-free equilibrium within the feasible region, while $R_0 > 1$ permits their persistence. Simulations of numbers were in line with the analytical results and brought out the relevance of QR and alternative code-based surveillance in a practical sense. Under weak detection, stress and academic misconduct continued, but stronger monitoring led to a considerable decrease in the peak numbers ofmisconduct-active students as well as the duration of such students being active on the campus.

The analysis of the stress-reproduction number highlighted detection speed as one of the most critical things to prevent stress from increasing, highlighting the importance of quick action. The theoretical framework also has the potential for practical smart campus management guidance. As a result, universities and colleges will no longer be forced to respond to stress but will proactively prevent it by monitoring students' wellness at an early stage using QR and alternative coding, and then create a situation for their recovery and sustaining academic integrity.

In summary, the SEIR–Epi-Mod–QR/Alt model providesa structured framework for analyzing student stress and academic misconduct in universities such as in Nigeria and other higher education institutions. Future extensions of this work may include adding population heterogeneity as well as stochastic effects and real-time data from campus information systems for better applicability in evidence-based decision-making and smart-campus management.

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