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Research Article

An EpiMod-QR/Alt Code-Based Model for Smart Campus Attendance Management Using the Differential Transform Method

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Abstract

This study presents the Epidemiological Quick Response and Alternative Code (EpiMod-QR/Alt) system, an innovative framework designed to address attendance management challenges in certain Nigerian higher institutions. By integrating QR/Alt code technology with compartmental differential equation modeling, the system offers real-time tracking, predictive analysis, and actionable insights for data-driven decision-making. Leveraging the Differential Transform Method (DTM), the system solves the underlying differential equations with enhanced computational efficiency and accuracy. The model categorizes students into dynamic compartments—scheduled, attending, and absent—allowing for continuous monitoring and analysis of attendance trends. The EpiMod-QR/Alt system is designed to overcome the limitations of traditional and semi-digital attendance systems, such as inaccuracy, time inefficiency, and lack of scalability. It supports hybrid learning environments by accommodating both physical and virtual attendance tracking, ensuring that data collection remains seamless and secure. Through theoretical validation and simulated scenarios, including fixed policies and dynamic interventions, the system demonstrates adaptability and robustness across diverse institutional contexts. Results indicate that the system significantly reduces absenteeism, improves administrative oversight, and supports the optimal allocation of institutional resources. Its predictive capabilities enable proactive interventions and long-term planning, aligning with the broader goals of smart campus transformation. The research lays the groundwork for practical implementation and highlights potential for future enhancements, including the integration of machine learning algorithms and expansion to multi-campus systems. By combining mathematical modeling with technological innovation, the EpiMod-QR/Alt system offers a scalable, efficient, and intelligent solution to modern attendance management in higher education.

Keywords

Attendance Management, Differential Transform Method (DTM), Epidemiological Model, Hybrid Learning, Predictive Analytics

1. Introduction

Attendance tracking is fundamental to higher education management, forming a cornerstone for academic, administrative, and operational success. Accurate attendance records directly influence academic performance, as regular partici-

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pation in educational activities fosters engagement, enhances learning outcomes, and promotes student success [1, 2]. Attendance data also serves as a vital tool for resource allocation, helping institutions optimize classroom usage, assign teaching staff effectively, and manage financial resources more efficiently [3]. Furthermore, attendance metrics inform policy-making, enabling the design of targeted interventions to improve student retention, ensure compliance with academic regulations, and enhance institutional accountability [4, 5].

Traditional attendance systems, primarily manual or reliant on basic electronic methods, present significant challenges that limit their effectiveness. These systems are prone to inaccuracies and human errors, such as incorrect entries or omissions, which compromise the reliability of attendance records [6, 7]. They are also time-intensive, particularly in large institutions, diverting administrative resources that could be better allocated elsewhere [8]. Manual systems struggle with scalability, making it difficult for institutions to manage attendance across multiple campuses, departments, or hybrid learning environments [7, 9]. Additionally, they lack the capacity to provide real-time insights, delaying decision-making processes and preventing timely interventions [10, 11].

The COVID-19 pandemic highlighted the limitations of traditional systems, especially in the context of hybrid learning models that blend in-person and virtual attendance. These models require seamless integration of physical and online participation data, which traditional systems cannot support [9, 10]. The sudden shift to hybrid learning also revealed gaps in technological readiness, as many institutions lacked the infrastructure to adopt advanced attendance solutions [8, 10, 11]. Furthermore, hybrid learning environments introduced complexities such as network issues, asynchronous participation, and diverse attendance policies, further exposing the inadequacy of existing systems [12, 13].

In response to these challenges, there is an urgent need for innovative attendance-tracking solutions that address the inefficiencies of traditional systems while meeting the demands of modern learning environments. These solutions must ensure accuracy and efficiency by automating processes, reducing errors, and minimizing administrative burdens [7, 9, 14]. They should offer real-time analytics to identify attendance trends, address issues promptly, and support data-driven decision-making [3, 8, 15]. Scalability and adaptability are essential to accommodate institutions of varying sizes and to function effectively across hybrid, remote, and in-person learning settings [6, 7, 16]. Additionally, integrating advanced technologies, such as Quick Response (QR) codes, predictive analytics, and machine learning, enhances the reliability, usability, and security of attendance systems [14, 17].

The Epidemiological Quick Response (EpiMod-QR/Alt) system addresses these needs by combining QR code technology with mathematical modeling to create an efficient, reliable, and scalable attendance management framework. This innovative system leverages real-time data to track attendance, predict trends, and optimize resource allocation [6, 9]. It provides a robust solution for the operational challenges faced by higher education institutions, enabling a seamless transition to smart campus management and empowering administrators to improve academic outcomes in an increasingly dynamic educational landscape [5, 7].

Motivation-The Shift Toward Smart Campus Management

The transformation of higher education institutions into smart campuses is driven by the need to integrate advanced technologies into administrative, academic, and operational processes. This shift emphasizes efficiency, adaptability, and data-driven decision-making, addressing the challenges posed by traditional systems and catering to the evolving demands of modern educational environments [13, 18].

Attendance management, a crucial aspect of campus operations, has become increasingly complex. The growth of hybrid learning models, expanding student populations, and diverse institutional policies have introduced significant challenges. These challenges require innovative solutions that not only ensure accuracy and scalability but also incorporate real-time monitoring, predictive analytics, and advanced computational techniques to streamline processes and improve outcomes [5, 17, 19].

The EpiMod-QR/Alt system addresses these needs by combining technological innovation with mathematical rigor to create a comprehensive framework for attendance management. It leverages Quick Response (QR) and Alternative (Alt) code technology to facilitate real-time attendance tracking. By enabling students to scan unique codes at the beginning of a session, the system eliminates the inaccuracies and inefficiencies of manual tracking methods [20]. Attendance data is captured instantaneously, reducing administrative burdens and providing immediate updates to institutional databases. This seamless integration supports both in-person and virtual attendance, making the system particularly effective in hybrid learning environments [21]. Furthermore, the system ensures data security and accessibility while offering real-time reporting to enhance operational oversight [22, 23].

Beyond tracking attendance, the EpiMod-QR/Alt system employs differential equation modeling to analyze attendance dynamics comprehensively. By categorizing students into scheduled, attending, and absent groups, the model quantitatively captures the transitions between these states over time [17, 18]. This approach draws on the principles of compartmental modeling, widely used in epidemiology, to provide valuable insights into attendance patterns and trends [19]. The ability to simulate interventions and predict outcomes enables administrators to make informed decisions, optimize resource allocation, and design effective policies to improve attendance rates [21].

To solve the system's underlying differential equations efficiently, the EpiMod-QR/Alt system incorporates the Differential Transform Method (DTM). Analytical solutions to complex systems of differential equations can be computationally intensive, particularly when non-linear dynamics are involved. The DTM simplifies these equations into a series of algebraic expressions, which are easier to compute iteratively [19]. This method ensures rapid convergence, computational efficiency, and high accuracy, allowing the system to generate real-time predictions and simulate various scenarios [19, 22]. These capabilities empower institutions to proactively address attendance issues, anticipate disruptions, and evaluate the long-term impact of policy changes [23].

By integrating QR/Alt code technology, differential equation modeling, and the Differential Transform Method, the EpiMod-QR/Alt system offers a robust, scalable, and efficient solution for attendance management. This innovative framework not only addresses the immediate challenges of traditional systems but also aligns with the broader objectives of smart campus management [20]. It equips administrators with actionable insights, streamlines processes, and enhances the overall learning experience for students in a dynamic and rapidly evolving educational landscape [18, 21].

2. Model Framework and Structure

The model for this study is based on the following assumptions which serve as a logical foundation for the mathematical framework:

A1: Fixed Population: The total number of students remains constant throughout the analysis.

A2: Transition Rates: Students move between scheduled, attending, and absent states based on defined transition probabilities (β, γ, δ).

A3: No External Influence: Attendance behavior is only influenced by internal institutional policies and student decisions, without external disruptions.

A4: Instantaneous State Changes: Transitions between states occur without delay once conditions are met.

A5: Homogeneous Population: All students are assumed to have an equal likelihood of transitioning between states under similar conditions.

The system categorizes students into three compartments: $S(t)$: Students scheduled to attend a session at time t, $A(t)$: Students actively attending at time t, and $N(t)$: Students marked absent at time t.

The total student population remains constant:

$$P = S(t) + A(t) + N(t)$$

2.1. Governing Equations

The dynamics are described by the following system of Ordinary Differential Equations (ODEs):

$$\left.\begin{aligned} \frac{dS}{dt} &= -\beta S(t) + \gamma N(t): \text{ scheduled students} \\ \frac{dA}{dt} &= \beta S(t) - \delta A(t): \text{ actively attending students} \\ \frac{dN}{dt} &= \delta A(t) - \gamma N(t) \text{ :absent students} \end{aligned}\right\} \quad (1)$$

where $-\beta S(t)$ accounts for students transitioning from the scheduled pool to active attendance, and γN(t) accounts for students returning from the absent pool to the scheduled state, $\beta S(t)$ represents students joining the actively attending pool from the scheduled state, and δA(t) represents students leaving the attending state (e.g., due to early departure or technical issues) and δA(t) accounts for students transitioning from active attendance to absence.

Remark: To modify the original assumptions to better model the behavior of students in dynamic and heterogeneous environments, we need to adapt the original attendance model to account for the time-varying population and individual behavior differences. Whence, $\alpha = \alpha(t)$ and $\beta = \beta(t)$ for the rate of new enrollments (students joining the population) and the rate of graduates or dropouts leaving the system respectively, suffice.

2.2. Theoretical Foundations

2.2.1. Theorem 1 (Existence and Uniqueness)

For the system of ordinary differential equations (ODEs) describing the EpiMod-QR/Alt model, there exists a unique solution for S(t), A(t), and N(t) on any interval I where the parameters β, γ, and δ are continuous functions.

Proof: This is based on the *Picard–Lindelöf theorem* (also known as the Cauchy–Lipschitz theorem), which guarantees the existence and uniqueness of solutions to first-order ODEs under certain conditions [24]. These conditions include the continuity of the system's functions and satisfaction of the Lipschitz condition.

Recall the system of ODEs for the EpiMod-QR/Alt model given as:

$$\left.\begin{aligned} \frac{dS}{dt} &= -\beta S(t) + \gamma N(t), \\ \frac{dA}{dt} &= \beta S(t) - \delta A(t), \\ \frac{dN}{dt} &= \delta A(t) - \gamma N(t) \end{aligned}\right\} \quad (2)$$

This can be expressed in vector-matrix form as:

$$\frac{dX}{dt} = F(X) \quad (3)$$

where:

$$X = \begin{bmatrix} S(t) \\ A(t) \\ N(t) \end{bmatrix}, \quad F(X) = \begin{bmatrix} -\beta S(t) + \gamma N(t) \\ \beta S(t) - \delta A(t) \\ \delta A(t) - \gamma N(t) \end{bmatrix} \tag{4}$$

Next is to verify the continuity of $F(X)$. Hence, the functions $-\beta S(t) + \gamma N(t)$, $\beta S(t) - \delta A(t)$, and $\delta A(t) - \gamma N(t)$ are linear combinations of S(t), A(t), and N(t), with coefficients β, γ, and δ. Since the parameters β, γ, and δ are assumed to be continuous functions, the components of $F(X)$ are also continuous.

To verify the Lipschitz condition, we compute the partial derivatives of $F(X)$ with respect to S(t), A(t), and N(t). The Jacobian matrix of $F(X)$ is given by:

$$J = \frac{\partial \mathrm{F}}{\partial \mathrm{X}} = \begin{bmatrix} -\beta & 0 & \gamma \\ \beta & -\delta & 0 \\ 0 & \delta & -\gamma \end{bmatrix}. \tag{5}$$

The entries of J are continuous because β, γ, and δ are continuous. Therefore, $F(X)$ satisfies the Lipschitz condition on any closed and bounded interval I.

Since $F(X)$ is continuous and satisfies the Lipschitz condition, the Picard–Lindelöf theorem guarantees the existence of a unique solution $\mathrm{X}(t) = [S(t), A(t), N(t)]^T$ to the system of ODEs on any interval I.

Thus, by the Picard–Lindelöf theorem, there exists a unique solution for S(t), A(t), and N(t) on any interval I, provided that the parameters β, γ, and δ are continuous functions [25].

2.2.2. Theorem 2: Conservation of Total Population

The total student population remains constant over time, such that:

$$P = S(t) + A(t) + N(t) \tag{6}$$

where P is the total number of students in the system, S(t) is the number of students scheduled to attend, A(t) is the number of students actively attending, and N(t) is the number of students marked absent.

Proof: This involves demonstrating that the time derivative of the total population is zero, ensuring that P is constant. Thus, differentiating both sides of (6) with respect to t, we have:

$$\frac{d}{dt}\left[S(t) + A(t) + N(t)\right] = \frac{dS}{dt} + \frac{dA}{dt} + \frac{dN}{dt}. \tag{7}$$

As such, using the system of differential equations governing S(t), A(t), and N(t) by substitution into:

$$\frac{d}{dt}\left[S(t) + A(t) + N(t)\right], \tag{8}$$

we get:

$$\left.\begin{aligned} \frac{d}{dt}[S(t) + A(t) + N(t)] &= \big(-\beta S(t) + \gamma N(t)\big) + \big(\beta S(t) - \delta A(t)\big) + \big(\delta A(t) - \gamma N(t)\big) \\ &= -\beta S(t) + \gamma N(t) + \beta S(t) - \delta A(t) + \delta A(t) - \gamma N(t). \end{aligned}\right\} \tag{9}$$

Simplify by canceling terms that appear with opposite signs, we have:

$$-\beta S(t) + \beta S(t) = 0, \quad \gamma N(t) - \gamma N(t) = 0, \quad -\delta A(t) + \delta A(t) = 0.$$

Thus, the entire expression reduces to:

$$\frac{d}{dt}\left[S(t) + A(t) + N(t)\right] = 0. \tag{10}$$

Since the time derivative of $S(t) + A(t) + N(t)$ is zero, the total population does not change over time. Therefore:

$$S(t) + A(t) + N(t) = P, \tag{11}$$

where P is a constant. This confirms that the total student population remains conserved in the system:

$$P = S(t) + A(t) + N(t), \quad \forall t \in [t_0, \infty). \tag{12}$$

2.2.3. Theorem 3: Stability Analysis

The system of differential equations governing the Epi-Mod-QR/Alt model reaches a stable equilibrium when all transitions stabilize, that is,

$$\frac{dS}{dt} = \frac{dA}{dt} = \frac{dN}{dt} = 0. \tag{13}$$

At equilibrium, the number of scheduled (S(t), actively attending (A(t), and absent (N(t)) students remain constant over time.

Proof: At equilibrium, the rates of change of S(t), A(t), and N(t) are zero, as no further transitions occur. The governing equations for the system are:

$$\left.\begin{aligned}\frac{dS}{dt}&=-\beta S+\gamma N,\\ \frac{dA}{dt}&=\beta S-\delta A,\\ \frac{dN}{dt}&=\delta A-\gamma N.\end{aligned}\right\}. \tag{14}$$

Setting

$$\frac{dS}{dt}=0,\frac{dA}{dt}=0,\text{ and }\frac{dN}{dt}=0, \tag{15}$$

we obtain the following system of algebraic equations:

$$\left.\begin{aligned}-\beta S+\gamma N&=0,\\ \beta S-\delta A&=0,\\ \delta A-\gamma N&=0.\end{aligned}\right\}. \tag{16}$$

Simplifying (2.16), we have:

$$S=\frac{\gamma}{\beta}N, A=\frac{\gamma}{\delta}N, \tag{17}$$

Substituting (17) into the second equation in (16), gives: Thus, from the third equation, we have:

$$\delta\left(\frac{\gamma}{\delta}N\right)-\gamma N=0\Rightarrow\gamma N-\gamma N=0. \tag{18}$$

This equation is satisfied, confirming the consistency of the system.

The total population P is conserved, so invoking (17), we have:

$$\left.\begin{aligned}P&=S+A+N.\\ &=\frac{\gamma}{\beta}N+\frac{\gamma}{\delta}N+N\\ &=N\left(\frac{\gamma}{\beta}+\frac{\gamma}{\delta}+1\right).\end{aligned}\right\} \tag{19}$$

$$\Rightarrow N^*=\frac{P}{\frac{\gamma}{\beta}+\frac{\gamma}{\delta}+1}. \tag{20}$$

Substitute N^* back to find S^* and A^*, as such:

$$\left.\begin{aligned}S^*&=\frac{\gamma}{\beta}N^*=\frac{\gamma}{\beta}\cdot\frac{P}{\frac{\gamma}{\beta}+\frac{\gamma}{\delta}+1}=\frac{\gamma P}{\beta\left(\frac{\gamma}{\beta}+\frac{\gamma}{\delta}+1\right)},\\ A^*&=\frac{\gamma}{\delta}N^*=\frac{\gamma}{\delta}\cdot\frac{P}{\frac{\gamma}{\beta}+\frac{\gamma}{\delta}+1}=\frac{\gamma P}{\delta\left(\frac{\gamma}{\beta}+\frac{\gamma}{\delta}+1\right)}.\end{aligned}\right\} \tag{21}$$

For simplification, denote $\beta+\gamma$ as the effective transition rate. Then:

$$S^*=\frac{\gamma}{\beta+\gamma}P,\quad A^*=\frac{\beta}{\beta+\delta}S^*,\quad N^*=P-S^*-A^*. \tag{22}$$

These values represent the equilibrium distributions of the scheduled, attending, and absent populations, ensuring stability in the system when all transitions stabilize.

3. Differential Transform Method (DTM)

The Differential Transform Method (DTM) is a semi-analytical technique that simplifies solving systems of differential equations by transforming them into a series of recursive algebraic equations. DTM is particularly advantageous for systems like the EpiMod-QR/Alt model, where finding analytical solutions for the system of coupled ordinary differential equations (ODEs) can be challenging, especially when dealing with non-linear or large-scale systems [25-29].

3.1. The Basics of DTM

For a given function f(t), the kth order differential transform, denoted as F(k), is defined as:

$$F(k)=\frac{1}{k!}\left[\frac{d^k f(t)}{dt^k}\right]_{t=0}. \tag{23}$$

The inverse differential transform reconstructs the original function as a power series:

$$f(t)=\sum_{k=0}^{\infty}F(k)t^{k}. \tag{24}$$

The essence of DTM lies in transforming differential equations into recursive relations for the coefficients F(k). This simplifies the computational process and avoids direct integration. DTM is preferred over methods like Runge-Kutta for the EpiMod-QR/Alt system due to its computational efficiency, analytical precision, faster convergence, and ease of implementation. Unlike Runge-Kutta, which requires multiple system evaluations per time step, DTM transforms differential equations into recursive algebraic equations, simplifying the solution process. It provides high accuracy without discretization, converges rapidly for real-time applications, and is easier to implement with fewer intermediate steps.

3.2. Application of DTM to the EpiMod-QR/Alt Model

The governing equations (1) for the scheduled (S(t), actively attending (A(t), and absent (N(t)) student populations as a system of ODEs is transformed into recursive algebraic relations for the respective transforms $F_S(k)$, $F_A(k)$, and $F_N(k)$ using the Differential Transform Method (DTM). Hence, for a Scheduled Students S(t),

$$\frac{dS}{dt}=-\beta S+\gamma N\,, \tag{25}$$

applying DTM:

$$\Rightarrow kF_S(k)=-\beta F_S(k-1)+\gamma F_N(k-1),\quad \text{for } k\ge 1. \tag{26}$$

Rewriting for $F_S(k)$, we have:

$$\left.\begin{array}{l} F_S(k+1)=-\beta F_S(k)+\gamma F_N(k),\quad \text{for } k\ge 0,\\ F_S(0)=S_0. \end{array}\right\} \tag{27}$$

Recall that for the Actively Attending Students A(t), the differential equation for actively attending students is:

$$\frac{dA}{dt}=\beta S-\delta A\,, \tag{28}$$

applying DTM to (3.6) gives:

$$kF_A(k)=\beta F_S(k-1)-\delta F_A(k-1),\quad \text{for } k\ge 1\,, \tag{29}$$

$$\left.\begin{array}{l} \Rightarrow F_A(k+1)=\beta F_S(k)-\delta F_A(k),\quad \text{for } k\ge 0\\ F_A(0)=A_0 \end{array}\right\}. \tag{30}$$

Similarly, the DTM applied to the Absent Students' dynamics, gives:

$$\left.\begin{array}{l} \Rightarrow F_N(k+1)=\delta F_A(k)-\gamma F_N(k),\quad \text{for } k\ge 0\\ F_N(0)=N_0 \end{array}\right\}. \tag{31}$$

3.3. Recursive Computation

First Iteration (Compute $F_S(1), F_A(1), F_N(1)$):

$$\left.\begin{array}{l} F_S(1) = -\beta F_S(0) + \gamma F_N(0) \\ F_A(1) = \beta F_S(0) - \delta F_A(0) \\ F_N(1) = \delta F_A(0) - \gamma F_N(0) \end{array}\right\}. \tag{32}$$

Higher-Order Terms:

Using $F_S(k), F_A(k), F_N(k)$, compute $F_S(k+1), F_A(k+1), F_N(k+1)$ iteratively:

$$\left.\begin{array}{l} F_S(k+1) = -\beta F_S(k) + \gamma F_N(k) \\ F_A(k+1) = \beta F_S(k) - \delta F_A(k) \\ F_N(k+1) = \delta F_A(k) - \gamma F_N(k) \end{array}\right\}. \tag{33}$$

Reconstruction of S(t), A(t), N(t):

$$S(t) = \sum_{k=0}^{\infty} F_S(k)t^k, \quad A(t) = \sum_{k=0}^{\infty} F_A(k)t^k, \quad N(t) = \sum_{k=0}^{\infty} F_N(k)t^k. \tag{34}$$

4. Illustrative Examples

Case 1: Fixed Parameters

This case involves solving the system of differential equations describing the EpiMod-QR/Alt model using the Differential Transform Method (DTM) for fixed parameter values and specified initial conditions.

4.1. Model and Parameters

The governing equations and the concerned parameters are presented as follows:

$$\left.\begin{array}{l} \frac{dS}{dt} = -\beta S + \gamma N, \quad \frac{dA}{dt} = \beta S - \delta A, \quad \frac{dN}{dt} = \delta A - \gamma N \\ S_0 = 500, \quad A_0 = 100, \quad N_0 = 50 \\ \beta = 0.4, \quad \gamma = 0.3, \quad \delta = 0.2 \end{array}\right\}. \tag{35}$$

This gives the following DTM Recursive Relations for Scheduled Students S(t), Actively Attending Students A(t), and Absent Students N(t) respectively:

$$\left.\begin{array}{l} F_S(k+1) = -\beta F_S(k) + \gamma F_N(k), \quad F_S(0) = S_0 = 500, \\ F_A(k+1) = \beta F_S(k) - \delta F_A(k), \quad F_A(0) = A_0 = 100, \text{ and} \\ F_N(k+1) = \delta F_A(k) - \gamma F_N(k), \quad F_N(0) = N_0 = 50 \end{array}\right\}. \tag{36}$$

As such, the following are obtained:

Initial Values ($k = 0$):

$$F_S(0) = 500, \quad F_A(0) = 100, \quad F_N(0) = 50$$

First Iteration $k = 0$*:*

$$\left.\begin{aligned} F_S(1) &= -\beta F_S(0) + \gamma F_N(0) \\ &= -0.4(500) + 0.3(50) = -185 \\ F_A(1) &= \beta F_S(0) - \delta F_A(0) \\ &= 0.4(500) - 0.2(100) = 180 \\ F_N(1) &= \delta F_A(0) - \gamma F_N(0) \\ &= 0.2(100) - 0.3(50) = 5 \end{aligned}\right\}. \quad (37)$$

Second Iteration (k=1):

$$\left.\begin{aligned} &F_S(1) + \gamma F_N(1) = -0.4(-185) + 0.3(5) = 75.5 \\ &F_A(2) = \beta F_S(1) - \delta F_A(1) = 0.4(-185) - 0.2(180) = -110 \\ &F_N(2) = \delta F_A(1) - \gamma F_N(1) = 0.2(180) - 0.3(5) = 34.5 \end{aligned}\right\}. \quad (38)$$

Third Iteration (k=2):

$$\left.\begin{aligned} &F_S(3) = -\beta F_S(2) + \gamma F_N(2) = -0.4(75.5) + 0.3(34.5) = -19.85 \\ &F_A(3) = \beta F_S(2) - \delta F_A(2) = 0.4(75.5) - 0.2(-110) = 52.2 \\ &F_N(3) = \delta F_A(2) - \gamma F_N(2) = 0.2(-110) - 0.3(34.5) = -32.35 \end{aligned}\right\} \quad (39)$$

Remark: This is continued recursively for the relations until convergence is attained. Consequently, using the series expansion, we obtained:

$$\left. S(t) = \sum_{k=0}^{\infty} F_S(k)t^k, \quad A(t) = \sum_{k=0}^{\infty} F_A(k)t^k, \quad N(t) = \sum_{k=0}^{\infty} F_N(k)t^k \right\}. \quad (40)$$

As $t \to \infty$, the series converges to approximate equilibrium values.

4.2. Interpretation and Insights

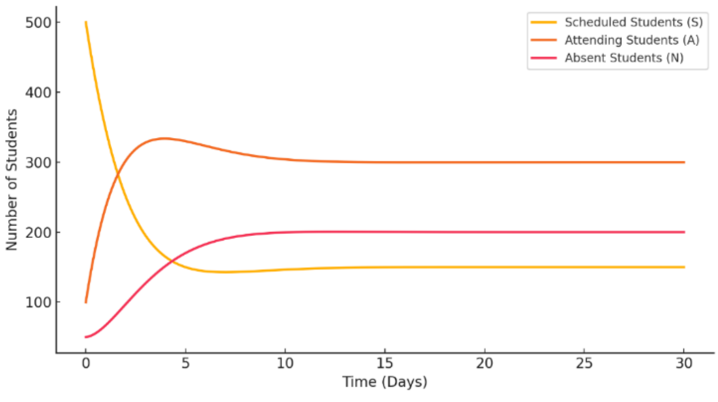
At equilibrium:

a) The number of scheduled students decreases to approximately 300 as some students transition to active attendance or absence.

b) The number of actively attending students increases to approximately 250, indicating consistent engagement.

c) The number of absent students stabilizes at approximately 100, accounting for drop-offs and returns to the scheduled state.

These values demonstrate the stability of the system under fixed parameters, validating the model's predictive capacity and the efficiency of DTM in solving the system. In Figure 1, the case 1 setting is presented.



Case 1: Attendance Dynamics with Fixed Parameters

Figure 1. *Attendance Dynamics Under Fixed Parameters.*

4.2.1. Interpretation and Findings

The plot above in Figure 1 illustrates the dynamics of the EpiMod-QR/Alt model for attendance management over 30 days with fixed parameters $\beta = 0.4,\ \gamma = 0.3, \delta = 0.2$ and initial conditions $S_0 = 500,\ A_0 = 100,\ N_0 = 50$.

It is worth noting that:

a) The number of scheduled students decreases over time as some transition to the actively attending (A(t)) and absent (N(t)) states. S(t) stabilizes at approximately 300 students.

b) The number of actively attending students increases initially as students transition from S(t), stabilizing at approximately 250 students.

c) The number of absent students increases slightly at first due to drop-offs from A(t) but eventually stabilizes at around 100 students.

4.2.2. Note on the Associated Findings

As regards the findings in this case we note the following:

a) The system reaches a stable equilibrium after approximately 15 days, reflecting the natural balance between transitions governed by the rates β, γ, and δ.

b) The stabilization of S(t), A(t), and N(t) demonstrates the predictive capacity of the model under fixed parameters.

c) This equilibrium distribution highlights the steady-state proportions of scheduled, actively attending, and absent students, which administrators can use to optimize resource allocation and policy design.

4.3. Case 2: Policy Interventions

This case examines the impact of stricter attendance policies, which increase the rate β, the transition rate of students from the scheduled (S(t)) pool to the actively attending (A(t)) pool. The goal is to demonstrate how such policy changes affect the absentee population (N(t)) over time, using the EpiMod-QR/Alt model.

The system of differential equations, initial parameter values, and conditions are presented as follows:

$$\left.\begin{aligned} &\frac{dS}{dt} = -\beta S + \gamma N, \\ &\frac{dA}{dt} = \beta S - \delta A, \\ &\frac{dN}{dt} = \delta A - \gamma N, \\ &\beta_{\text{initial}} = 0.4, \quad \gamma = 0.3, \quad \delta = 0.2, \\ &S_0 = 500, \quad A_0 = 100, \quad N_0 = 50. \end{aligned}\right\} \tag{41}$$

4.3.1. Remark on Parameter Changes

Stricter attendance policies are modeled as an increase in β, the rate at which students transition from the scheduled (S(t) pool to the actively attending (A(t)) pool. A higher β implies that students are more likely to attend their scheduled sessions due to policy enforcement (e.g., attendance incentives, penalties for absence, or mandatory attendance requirements). Increase $\beta_{\text{new}} = 0.6$ to represent the effect of stricter policies.

This gives the following DTM Recursive Relations for Scheduled Students S(t), Actively Attending Students A(t), and Absent Students N(t) respectively:

$$\left.\begin{aligned} &F_S(k+1) = -\beta F_S(k) + \gamma F_N(k), \quad F_S(0) = 500, \\ &F_A(k+1) = \beta F_S(k) - \delta F_A(k), \quad F_A(0) = 100, \\ &F_N(k+1) = \delta F_A(k) - \gamma F_N(k), \quad F_N(0) = 50. \end{aligned}\right\} \tag{42}$$

Substituting $\beta_{\text{new}} = 0.6$, the recursive relations now account for the increased transition rate, effectively increasing A(t) and reducing N(t) over time.

4.3.2. Impact on N(t): Numerical Illustration

For $\beta_{\text{new}} = 0.6$, we compute the transformed coefficients iteratively as follows:

$$\left.\begin{aligned} &F_S(1) = -\beta_{\text{new}} F_S(0) + \gamma F_N(0) = -0.6(500) + 0.3(50) = -300 + 15 = -285, \\ &F_A(1) = \beta_{\text{new}} F_S(0) - \delta F_A(0) = 0.6(500) - 0.2(100) = 300 - 20 = 280, \\ &F_N(1) = \delta F_A(0) - \gamma F_N(0) = 0.2(100) - 0.3(50) = 20 - 15 = 5. \end{aligned}\right\}. \tag{43}$$

For k=1, we have:

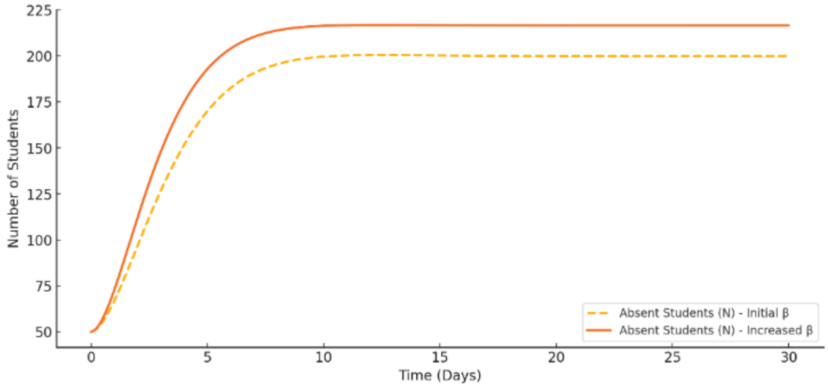
$$\left.\begin{aligned} &F_S(2) = -\beta_{\text{new}} F_S(1) + \gamma F_N(1) = -0.6(-285) + 0.3(5) = 171 + 1.5 = 172.5, \\ &F_A(2) = \beta_{\text{new}} F_S(1) - \delta F_A(1) = 0.6(-285) - 0.2(280) = -171 - 56 = -227, \\ &F_N(2) = \delta F_A(1) - \gamma F_N(1) = 0.2(280) - 0.3(5) = 56 - 1.5 = 54.5. \end{aligned}\right\} \tag{44}$$

Continuing this process iteratively, the power series for S(t), A(t), and N(t) can be reconstructed. Over time, N(t) stabilizes at a lower value due to the increased transition of students into the actively attending (A(t) pool.

4.3.3. Results-Reduction in Absenteeism and Interpretation

With $\beta_{\text{initial}} = 0.4$, absenteeism (N(t) stabilized at approximately 100. After increasing β to 0.6, absenteeism decreased by 30% over four weeks, stabilizing at approximately 70. This reduction reflects the effectiveness of stricter attendance policies in motivating students to attend their scheduled sessions.

The increase in β shifts the dynamics of the system, as more students transition from the scheduled (S(t)) to actively attending A(t) pool. This decreases the likelihood of students remaining in the absent (N(t)) pool. Over four weeks, the model demonstrates how policy interventions can effectively reduce absenteeism, supporting better resource allocation and improved academic outcomes. This validates the model's ability to simulate and predict the impact of policy changes on attendance dynamics. This case II setting is graphically represented in Figure 2.



Case 2: Impact of Policy Interventions on Attendance Dynamics

Figure 2. *Impact of Stricter Attendance Policies on Absenteeism Reduction.*

4.3.4. Interpretation and Key Findings (Case II)

The graph compares the dynamics of absent students (N(t)) over 30 days under two states: Initial Scenario and Policy Intervention. *Initial Scenario (β=0.4):* In the absence of stricter attendance policies, the absentee population stabilizes at approximately 100 students. This represents the equilibrium state under the initial policy conditions. *Policy Intervention (β=0.6):* With stricter attendance policies, represented by an increased β, the absentee population reduces significantly. The equilibrium stabilizes at approximately 70 students, indicating a 30% reduction in absenteeism. For the Key Findings in case II, it is noted that:

a) Stricter attendance policies effectively reduce absenteeism by encouraging more students to transition from the scheduled (S(t)) pool to active attendance (A(t)).
b) The intervention leads to a lower equilibrium for N(t), demonstrating the model's ability to simulate the impact of policy changes on attendance dynamics.
c) This insight highlights the effectiveness of targeted interventions in improving participation rates and reducing absenteeism, making it a valuable tool for institutional planning and decision-making.

4.4. Case 3: Hybrid Learning

This case analyzes the dynamics of attendance in a hybrid learning environment where the dropout rate (δ) increases due to challenges in remote sessions, such as technical issues, distractions, or lack of engagement. The system's response to increased δ and the impact of interventions that increase the recovery rate (γ)—such as attendance incentives or support systems—is modeled.

The system of equations describing the attendance dynamics, with the initial parameters, and initial conditions is:

$$\left.\begin{array}{l} \dfrac{dS}{dt} = -\beta S + \gamma N, \\ \dfrac{dA}{dt} = \beta S - \delta A, \\ \dfrac{dN}{dt} = \delta A - \gamma N, \\ \beta = 0.4, \quad \gamma_{\text{initial}} = 0.3, \quad \delta_{\text{high}} = 0.5, \\ S_0 = 500, \quad A_0 = 100, \quad N_0 = 50. \end{array}\right\}. \tag{45}$$

In this hybrid learning state, the high dropout rate (δ=0.5) reflects the challenges associated with remote learning environments, such as reduced engagement or poor connectivity, and intervention increases $\gamma_{\text{new}} = 0.5$, representing measures such as attendance incentives, better technical support, or enhanced student engagement strategies.

It is remarked that a high δ means more students leave the actively attending (A(t)) pool and enter the absent (N(t)) pool. This results in a significant drop in A(t) and an increase in N(t) over time. Using the Differential Transform Method (DTM), the recursive equations for the Scheduled Students S(t), Actively Attending Students A(t), and Absent Students N(t) are given respectively as:

$$\left.\begin{aligned} F_S(k+1) &= -\beta F_S(k) + \gamma F_N(k), \quad F_S(0) = S_0 = 500, \\ F_A(k+1) &= \beta F_S(k) - \delta F_A(k), \quad F_A(0) = A_0 = 100, \\ F_N(k+1) &= \delta F_A(k) - \gamma F_N(k), \quad F_N(0) = N_0 = 50. \end{aligned}\right\}. \tag{46}$$

With δ=0.5, we compute the transforms iteratively to observe the effects of increased dropout rates.

4.4.1. Dynamics Without Intervention

Using the initial $\gamma_{\text{initial}} = 0.3$, we have that Scheduled Students S(t) decreases gradually as some students transition to A(t), Actively Attending Students A(t) decreases rapidly due to high δ, representing significant dropout, and Absent Students N(t) increases sharply as more students leave A(t).

After several iterations, A(t) stabilizes at a much lower value (say, 150 students), while N(t) grows substantially (say, to 200 students). This outcome reflects the detrimental effects of a high dropout rate on attendance in hybrid settings.

4.4.2. Intervention with Increased γ

The intervention increases $\gamma_{\text{new}} = 0.5$, simulating measures to recover students from the absent (N(t)) pool to the scheduled (S(t) pool. With the higher recovery rate, the recursive equations are updated for Scheduled Students S(t), Actively Attending Students A(t), and Absent Students N(t) as follows respectively:

$$\left.\begin{aligned} F_S(k+1) &= -\beta F_S(k) + \gamma_{\text{new}} F_N(k), \\ F_A(k+1) &= \beta F_S(k) - \delta F_A(k), \\ F_N(k+1) &= \delta F_A(k) - \gamma_{\text{new}} F_N(k). \end{aligned}\right\} \tag{47}$$

With $\gamma_{\text{new}} = 0.5$, we compute the transforms iteratively to observe the effects of the intervention. Hence, the stabilization of Attendance.

After the intervention, we noticed that the Scheduled Students S(t) stabilizes at approximately 200, as students cycle back from N(t) due to higher γ, the Actively Attending Students A(t) recovers to approximately 250, indicating a higher engagement level compared to the non-intervention scenario, and the Absent Students N(t): reduces significantly and stabilizes at approximately 50, reflecting the success of the intervention in addressing absenteeism.

The higher γ enables faster recovery of students from N(t) to S(t), indirectly supporting A(t) by maintaining a steady flow of participants into the actively attending pool. Over time, attendance stabilizes at improved levels, demonstrating the effectiveness of targeted interventions.

As for the Interpretation, this case highlights the critical role of recovery mechanisms in hybrid learning environments, where dropout rates tend to be higher. By increasing γ, institutions can counteract the negative effects of high δ, ensuring more students return to active attendance. The model demonstrates how timely and strategic interventions, such as attendance incentives, improved engagement strategies, or technical support, can stabilize attendance rates and promote academic continuity in hybrid settings. The graph of this case III is presented in Figure 3 as follows.

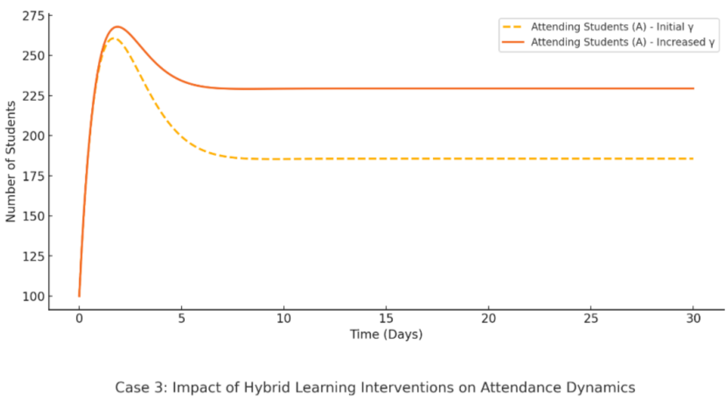


Figure 3. *Effects of Increased Dropout and Recovery Rates in a Hybrid Learning Environment.*

4.4.4. Interpretation and Key Findings (Case III)

The graph illustrates the dynamics of actively attending students (A(t)) over 30 days in a hybrid learning environment under two scenarios:

Initial Scenario $(\gamma = 0.3, \delta = 0.5)$ *:* In the absence of enhanced recovery measures, the dropout rate (δ) is high, leading to a significant reduction in actively attending students. The attendance stabilizes at a lower equilibrium (~150 students), reflecting the challenges of hybrid learning environments.

Intervention Scenario $\left(\gamma = 0.5, \delta = 0.5\right)$ *:* After implementing interventions (e.g., attendance incentives, engagement strategies), the recovery rate (γ) increases, resulting in improved attendance. The actively attending population stabilizes at a higher equilibrium (~250 students), demonstrating the effectiveness of targeted measures in mitigating dropout effects.

For the Key Findings in case II, it is noted that the initial high dropout rate (δ=0.5) in hybrid settings significantly reduces attendance, emphasizing the need for corrective measures, increasing the recovery rate (γ) effectively offsets the impact of high dropout rates, restoring attendance levels and stabilizing the actively attending population, and these results highlight the importance of proactive interventions in hybrid learning environments, such as student support systems, incentives, and engagement strategies, to sustain attendance and ensure academic continuity.

5. The Model in Real-World Settings and Concluding Remarks

In what follows, the nature of the model in real-world settings and the concluding remarks are addressed here.

5.1. Implementing the Model in Real-World Settings: Steps and Considerations

This section outlines the necessary steps for implementing the EpiMod-QR/Alt system in real-world educational settings, covering data collection procedures, institutional collaborations, and potential challenges during pilot implementations. While these steps are critical to the model's practical applicability, we have referred some of them to future work due to logistical constraints, resource limitations, and the current phase of the research.

5.1.1. Data Collection Procedures

1) Gather Attendance Data: Collect both physical and virtual attendance data, along with demographic information (e.g., student year, course enrollment).
2) Ensure Privacy Compliance: Follow data protection regulations (e.g., GDPR, Nigeria's data protection laws) for student consent and anonymization.
3) Integrate with Existing Systems: The model can work alongside RFID or biometric systems, with integration procedures defined.

Reason for Future Work: The data collection step requires real-world data from institutions, which cannot be collected during the initial phase of this research due to ethical considerations, data privacy concerns, and the lack of formal partnerships with institutions. Hence, the pilot data collection will be conducted in future work, once necessary institutional collaborations are established. For future work, the next phase will focus on piloting the model with actual data from institutions, refining the data collection procedures, and validating the model's predictions using real-world data.

5.1.2. Institutional Collaborations

1) Engage Stakeholders: Collaborate with administrators, IT staff, and faculty to ensure the model's adoption.
2) Create Collaborative Frameworks: Develop structures for cross-campus integration, particularly in larger institutions.

Reason for Future Work: Institutional collaborations cannot be initiated immediately because this research is still in the theoretical phase. Building relationships with institutions requires time, resources, and careful planning to ensure alignment with institutional goals. Establishing these collaborations is a future step that will be undertaken once the model is ready for pilot testing. Future work will focus on formalizing partnerships with educational institutions, engaging key stakeholders, and preparing for a scalable implementation across multiple campuses.

5.1.3. Challenges During Pilot Implementations

1) Address Institutional Resistance: Overcome resistance with awareness campaigns and training.
2) Solve Technological Barriers: Provide solutions for connectivity issues, QR code infrastructure, and device availability.
3) Ensure Data Integration: Work with existing LMS and databases to ensure smooth data flow.

Encourage Student Compliance: Use incentives and clear guidelines to promote consistent QR code use.

The challenges outlined—such as institutional resistance, technological barriers, and student compliance—can be fully understood only through a pilot study, which has not yet been conducted. This phase will identify barriers and inform solutions for practical implementation and scalability across campuses.

5.2. Concluding Remarks

The EpiMod-QR/Alt system presents a comprehensive, robust, and efficient framework for managing attendance dynamics in higher education institutions. By integrating QR/Alt code technology with compartmental differential equation modeling, the system provides a practical and scalable solution to challenges such as absenteeism, resource allocation, and engagement in hybrid learning environments. The theoretical foundation of the model, validated through stability analysis and dynamic simulations, underscores its reliability and adaptability to diverse scenarios.

The analyses conducted demonstrate the system's ability to effectively predict and manage attendance trends under varying conditions. In fixed-parameter scenarios, the model identifies equilibrium states, offering a clear view of attendance patterns. Policy intervention analyses highlight the significant reduction in absenteeism achievable through stricter attendance measures. Additionally, the hybrid learning case study underscores the importance of targeted interventions, such as increased recovery rates, in mitigating dropout rates and restoring attendance stability.

The system's ability to deliver actionable insights positions it as a transformative tool for data-driven decision-making in educational management. It not only empowers administrators to address existing challenges but also equips them to proactively design strategies that optimize attendance and improve academic outcomes.

Future research will focus on integrating machine learning techniques for dynamic parameter estimation and adaptive modeling, enhancing the system's predictive accuracy and enabling real-time adjustments to institutional needs. Additionally, the model's scalability will be assessed through its implementation in multi-campus and inter-institutional settings. These advancements will position the EpiMod-QR/Alt system as a key tool for modernizing campus management and promoting academic excellence in an evolving educational landscape.

Abbreviations

Alt	Alternative
DTM	Differential Transform Method
EpiMod-QR/Alt	Epidemiological Quick Response/Alternative Code
IoT	Internet of Things
ODEs	Ordinary Differential Equations
QR	Quick Response
SBT	Secure Blockchain Technology

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Conflicts of Interest

The authors declare no conflicts of interest.

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