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SEIRS MATHEMATICAL MODEL FOR ANALYZING THE SPREAD AND PERSISTENCE OF GADGET ADDICTION IN ELEMENTARY SCHOOL CHILDREN

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ABSTRACT

Gadget addiction among elementary school-aged children has become a serious concern, especially with the increasing screen time that potentially disrupts learning focus, social interaction, and emotional development. Despite various efforts to control gadget usage, many schools and parents struggle to monitor and predict addiction trends effectively. This gap highlights the need for a structured approach to analyze and predict the spread of gadget addiction. Therefore, this study aims to model the dynamics of gadget addiction using the SEIRS (Susceptible-Exposed-Infected-Recovered-Susceptible) mathematical model. Data were collected through questionnaires to categorize individuals into susceptible (S), exposed (E), addicted (I), and recovered (R) groups. The model was numerically solved using the 5th-order Runge-Kutta method in MATLAB. Simulation results show a decrease in the susceptible group over time, an initial increase and eventual decline in exposed and addicted individuals, and a steady increase in the recovered group, with possible relapse into susceptibility. The analysis reveals that gadget addiction is likely to persist when the basic reproduction number exceeds a critical threshold, signifying the potential for long-term behavioral entrenchment. Sensitivity analysis indicates that the dynamics of gadget addiction are strongly influenced by the rate of peer interaction and the speed at which exposure leads to addiction, whereas higher recovery rates play a significant role in reducing its prevalence. The numerical analysis contributes by offering a reliable and accurate method for simulating real-world addiction patterns. This model provides a quantitative basis for designing more effective intervention strategies. However, this study is limited by the absence of real-time observational data and relies on parameter estimation from survey-based responses.

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1. INTRODUCTION

Technology is unavoidable, and everyone must adapt to it [1]. In today's digital era, gadgets have become inseparable from daily life; both children and adults rely on them for various activities, further intensified by the COVID-19 pandemic, which has made human life increasingly dependent on digital devices [2]-[4]. Gadgets are a communication tool that cannot be separated from human life [5]. The high level of digital media usage, especially the internet and gadgets in Indonesia, is evident in data from APJII (Indonesian Internet Service Providers Association), which recorded 215.6 million internet users in 2022–2023, out of a total population of 275.7 million [6]. Children around the world are increasingly engaging with immersive technologies, and over time, innovative applications have been shown to effectively support the development of daily living skills in children, including those with disabilities [7]. Children's use of gadgets today leads to various perceptions, both positive and negative. The vast range of content accessible to children inevitably influences them in different ways. Whether the impact is beneficial or harmful largely depends on the level of parental supervision during gadget use. Often, parents who are preoccupied with work tend to allow their children to use gadgets independently without much oversight [8].

Advances in technology have unavoidably transformed daily lifestyles, especially among children. This transformation is reflected in shifting behaviors, including increased engagement with digital devices, altered dietary patterns, and reduced physical activity [9]. While digital tools offer certain educational benefits, such as facilitating language acquisition and enhancing classroom engagement, their excessive or unregulated use can also lead to negative consequences, making problematic gadget use a growing concern [10]. Excessive gadget use can lead to anxiety, depression, sleep disorders, social isolation, poor academic performance, and problematic behavior [11]. This access to digital technology, specifically "screen time," is not limited to school but is now widely available in homes [12] . Excessive screen time has become a common behavior among children and adolescents around the world [13]. A study revealed that 50.01% of elementary school students are highly active in gadget use, with most using them for non-educational purposes such as watching YouTube, playing games, using Instagram, chatting in WhatsApp groups, creating or watching TikTok videos, and uploading photos to Facebook [14]. The excessive use of gadgets among children has raised significant concerns regarding their cognitive, behavioral, and academic development. Madigan et al. conducted a longitudinal cohort study, which found that preschoolers exposed to screen media for more than two hours per day experienced delays in achieving developmental milestones, particularly in language and communication [15]. Adelantado-Renau et al., through a large meta-analysis, consistently reported negative associations between screen media use and academic performance, especially in mathematics and reading [16]. Most recently, Nagata et al. analyzed data from over 9,500 U.S. adolescents aged 9–10 years and followed them for two years; they found that higher total screen time was prospectively associated with depressive, attention-deficit/hyperactivity, conduct, and somatic symptoms, with the strongest effects linked to video chat, texting, videos, and video games [17]. These converging findings underscore the long-term risks of excessive screen exposure in children, reinforcing the need for rigorous mathematical models such as SEIRS to better understand and intervene in gadget addiction dynamics among young learners. The development of elementary school students today is inevitably influenced by a mathematical model.

Mathematical modeling has long been used as a tool to represent and solve real-world problems through formal mathematical structures. One of the earliest and most well-known models is the SIR (Susceptible–Infectious–Recovered) model introduced by Kermack and McKendrick in 1927, which has been widely applied in epidemiology [18]. Over time, various extensions of this model have been developed to address more complex dynamics, such as MSEIR (Immunity–Susceptible–Exposed–Infected–Recovered), MSEIRS (Immunity–Susceptible–Exposed–Infected–Recovered–Susceptible), SEIR (Susceptible–Exposed–Infected–Recovered), SEIRS (Susceptible–Exposed–Infected–Recovered–Susceptible), SIR (Susceptible–Infected–Recovered), SIRS (Susceptible–Infected–Recovered–Susceptible), SEI (Susceptible–Exposed–Infected), SEIS (Susceptible–Exposed–Infected–Susceptible), SI (Susceptible–Infected), and SIS (Susceptible–Infected–Susceptible) [19]. These models have been used to analyze the spread of infectious diseases and other phenomena, including pneumonia in toddlers [20], the dynamics of COVID-19 transmission with vaccination factors [21], [22] and the spread of the Hepatitis B disease in Ambon City using the SEIR mathematical model [23].

In the field of behavioral modeling, Fatahillah applied the SEIRS model to online game addiction among high school students. This model categorized individuals into four compartments: Susceptible (S), Exposed (E), Addicted (I), and Recovered (R), and accounted for the possibility of relapse, i.e., individuals in the R compartment becoming susceptible again [24]. This behavioral extension of the SEIRS framework reflects the non-linear, cyclical nature of addiction and recovery in non-biological contexts.

Despite the growing body of research, existing models still show limitations when applied to gadget addiction among elementary school-aged children, particularly in adapting parameters that reflect behavioral, psychological, and social factors typical at this developmental stage. Previous works have focused on older age groups (e.g., teenagers) or generalized addiction without sufficient attention to age-specific behavioral dynamics, such as early exposure, parental influence, and impulsivity. The SEIRS model was chosen in this study because it captures the dynamic and cyclical nature of behavioral phenomena such as gadget addiction. Unlike simpler models such as SI or SIR, which assume permanent infection or recovery, the SEIRS framework includes a return-to-susceptibility phase, allowing individuals who have recovered to become vulnerable again. This feature mirrors the real-world pattern of relapse observed in children who may temporarily abstain from gadget use but eventually resume excessive usage due to environmental or psychological triggers. Thus, the SEIRS model is well-suited to represent both the spread and persistence of gadget addiction over time.

Moreover, previous models have not emphasized high-accuracy numerical methods for simulating long-term behavioral dynamics. While methods such as Euler and Heun are commonly used for solving differential equations [25],[26], they often suffer from larger error bounds. In contrast, the Runge-Kutta method, particularly its fifth-order version, offers improved precision and convergence [27].

Therefore, this study aims to construct and develop a mathematical model for gadget addiction among elementary school children using the fifth-order Runge-Kutta method, known for its high-order local truncation accuracy in approximating solutions to systems of differential equations.

2. RESEARCH METHODS

2.1 Research Scope and Data Sources

This study focuses on elementary school students based on their demographic composition, which primarily consists of students from upper-middle socioeconomic backgrounds, where the use of digital devices has been integrated into daily activities for both academic and non-academic purposes. This environment presents a higher potential for gadget addiction, making these schools suitable for investigating the phenomenon using a mathematical SEIRS model. The study employed a purposive sampling technique, targeting elementary school students in grades 4 to 6 who were identified as regular gadget users. Respondents were selected through coordination with school representatives, and data were collected online via Google Form. Participation was voluntary, and informed consent was obtained from the students' parents or guardians. A total of 100 students met the inclusion criteria and completed the questionnaire. Several compartmental models, such as SIR, SIS, and SEIR, have been widely used to model the spread of diseases and behavioral phenomena. However, these models have limitations in representing the recurrent nature of behavioral addictions. For instance, the SIR model assumes permanent recovery without the possibility of relapse, while the SIS model does not account for latency or exposure stages. Although the SEIR model adds an exposed compartment, it still lacks the transition back to susceptibility after recovery. The SEIRS model, on the other hand, introduces a critical feature: individuals who have recovered (R) can return to a susceptible state (S), allowing for the possibility of relapse. This characteristic is essential for modeling gadget addiction, as individuals, particularly children, may repeatedly return to gadget use after periods of abstinence, driven by environmental triggers, peer influence, or lack of parental control.

This study utilizes a questionnaire as the primary instrument for data collection. The questionnaire was administered online using Google Forms, which were distributed to students through school networks with the assistance of teachers. Prior informed consent was obtained from parents, and students completed the form under teacher supervision in school. The questionnaire was adapted from Suratna [28] with several modifications to suit the context of the research. It was designed to measure behavioral patterns of gadget use among elementary school children in accordance with the SEIRS (Susceptible–Exposed–Infected–Recovered–Susceptible) framework. It comprises 22 statement items measured using a Likert scale and is categorized into four dimensions corresponding to the SEIRS model: Susceptible (5 items), Exposed (6 items), Infected (6 items), and Recovered (5 items). Each dimension reflects a distinct behavioral phase in the gadget addiction process. The Susceptible items measure environmental influences and initial exposure to gadgets without active use. The Exposed items capture low-frequency or contextual gadget use, often under parental supervision. The Infected items assess compulsive use behaviors, such as prioritizing gadgets over offline activities and displaying withdrawal symptoms. Lastly, the Recovered items evaluate behavioral improvements, reduced gadget dependence, and the re-establishment of healthier routines.

Prior to deployment, the instrument underwent validity testing using SPSS software. The validity of the items was assessed through the Pearson Product-Moment correlation method. The results of the analysis indicate that all questionnaire items yielded correlation coefficients (r-calculated) exceeding the critical value of the r-table (0.195), based on a sample size of 100 respondents at a 5% significance level ($\alpha = 0.05$). Subsequently, the validated data are analyzed using the SEIRS mathematical model to explore the dynamics of gadget addiction and to identify potential strategies for effective intervention.

2.2 Data Analysis Technique

In this study, data analysis is conducted numerically through several systematic stages to model gadget addiction using the SEIRS framework.

First, questionnaire data, comprising responses based on a Likert scale, are tabulated and categorized into four SEIRS compartments: Susceptible, Exposed, Infected, and Recovered. The responses are converted into numerical scores (e.g., 1 for "Strongly Disagree" to 5 for "Strongly Agree") and then aggregated to determine the proportion of individuals in each compartment. These proportions serve as the initial population values S(0), E(0), I(0), and R(0) in the SEIRS model.

Second, relevant model parameters (such as transmission rate β, transition rate σ, infection rate γ, and recovery rate δ) are estimated using descriptive statistics from the questionnaire data or are taken from the literature if empirical derivation is not feasible. These values are then set as input parameters in the model.

Third, the SEIRS model equations, formulated as a system of differential equations, are implemented using MATLAB. A numerical method, such as the Runge-Kutta 5th order method, is employed to solve the model over a defined time interval.

During the simulation, several metrics are recorded:

1. Error values between iterations (e.g., using absolute error or root mean square error),
2. Total number of iterations, and
3. Graphical visualization showing dynamic changes in the SEIRS compartments.

The effectiveness of the method is evaluated based on the error metric: the smaller the numerical error at each step, the more accurate and reliable the simulation results are. A higher error implies lower effectiveness and may indicate the need for method refinement or parameter adjustment. This detailed approach ensures that other researchers can replicate the process by following each step from questionnaire coding, parameter determination, model implementation, to result interpretation.

2.3 Theory of the 5th-order Runge-Kutta Method

The Runge-Kutta Method was introduced by C. Runge and M. W. Kutta in 1900. The Runge-Kutta method is a single-step technique that involves multiple stages, where the number of stages determines the method's order. It can be used to solve various types of differential equations, including explicit, implicit, partial, and delay differential equations [29]. Various forms of the Runge-Kutta method exist, distinguished by the order n employed in the computation. The fifth-order Runge-Kutta method is a numerical approach used to solve ordinary differential equations (ODEs). It represents an advancement over lower-order Runge-Kutta methods, such as the second-order method (Euler's method) and the fourth-order method (the classical Runge-Kutta method [30] . The standard formula of the fifth-order Runge-Kutta method is as follows.

$$k_1 = hf(t_i, x_i), \tag{1}$$

$$k_2 = hf\left(t_i + \frac{h}{2}, x_i + \frac{k_1}{2}\right), \tag{2}$$

$$k_3 = hf\left(t_i + \frac{h}{4}, x_i + \frac{3k_1 + k_1}{16}\right), \tag{3}$$

$$k_4 = hf\left(t_i + \frac{h}{2}, x_i + \frac{k_3}{2}\right), \tag{4}$$

$$k_5 = hf\left(t_i + \frac{3h}{4}, x_i + \frac{-3k_2 + 6k_3 + 9k_4}{2}\right), \tag{5}$$

$$k_6 = hf\left(t_i + h, x_i + \frac{k_1 + 4k_2 + 6k_3 - 12k_4 + 8k_5}{7}\right), \tag{6}$$

$$x_{i+1} = x_i + \frac{1}{90}(7k_1 + 32k_3 + 12k_4 + 32k_5 + 7k_6). \tag{7}$$

2.4 Research Procedure

The procedures carried out in this study are illustrated in the flowchart in Figure 1.

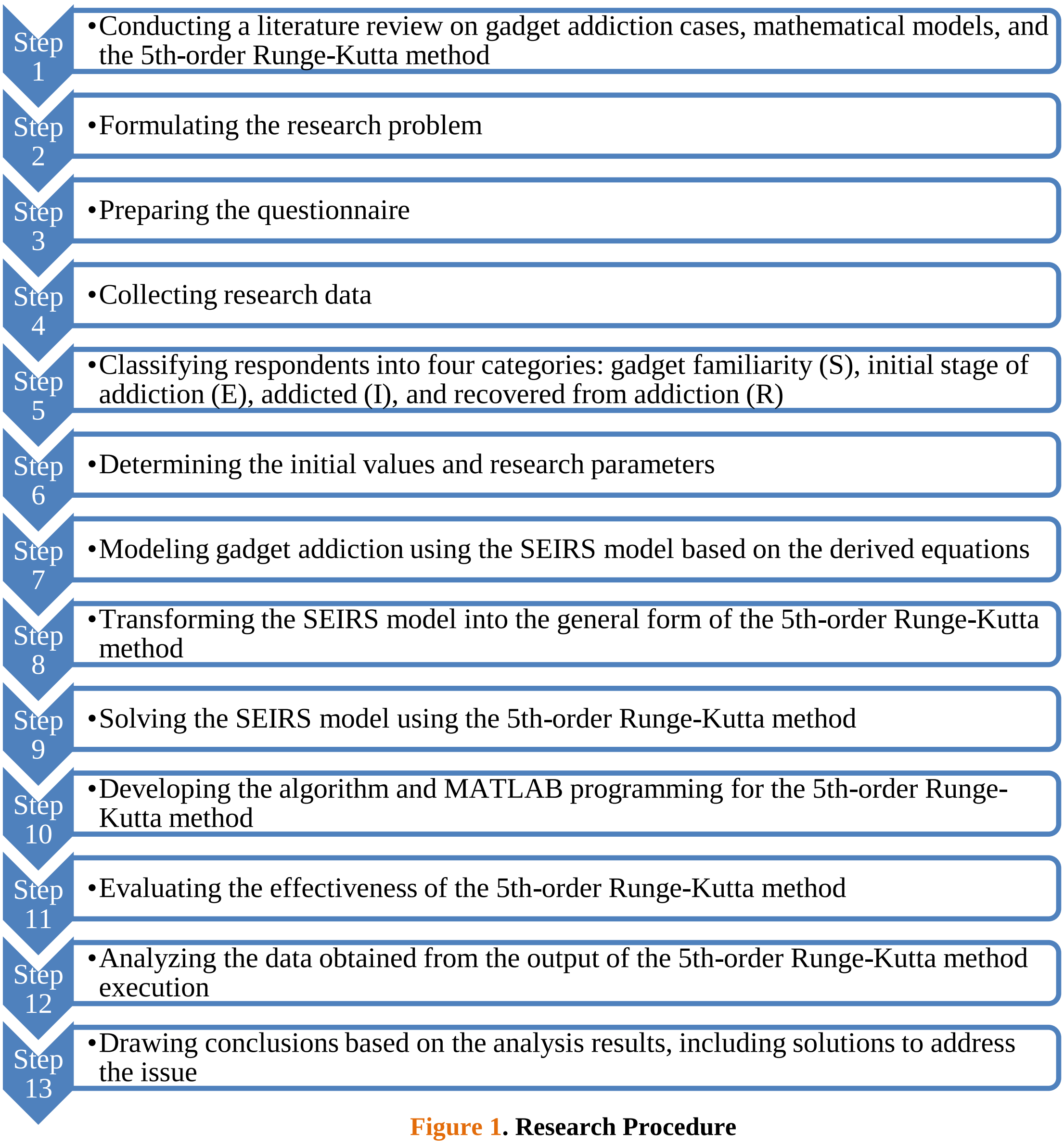

Figure 1. Research Procedure

3. RESULTS AND DISCUSSION

3.1 SEIRS Modeling for Gadget Addiction

This study develops the SEIRS model to analyze gadget addiction among elementary school children. The model assumes a closed population without demographic changes (births, deaths, or migrations) during the observation period, and homogeneous mixing, where each individual has an equal chance of interaction with others. Individuals progress through four stages: Susceptible, Exposed, Infected, and Recovered, with the possibility of relapse, transitioning back from Recovered to Susceptible. These assumptions are considered reasonable for the study population, as the data were collected from a fixed group of students within school environments where shared behaviors and peer influences are prevalent. The recurrence of gadget use after temporary cessation aligns with the SEIRS structure, justifying its use in modeling behavioral addiction dynamics.

In this behavioral context, the Susceptible group consists of children who are vulnerable to gadget use due to environmental exposure, such as family or peer influence, but who have not yet engaged in significant usage. The Exposed group refers to children who have begun using gadgets occasionally, usually under controlled circumstances like educational needs or parental guidance, but who do not yet exhibit signs of addiction. The Infected group includes children who demonstrate compulsive gadget use and symptoms of behavioral addiction, such as irritability when restricted, excessive screen time, or neglect of offline activities. The Recovered group represents children who have reduced or stopped their gadget use, either due to interventions, increased self-awareness, or stricter parental control—but who remain susceptible to relapse. This transition from Recovered back to Susceptible highlights the non-permanent nature of recovery in behavioral addictions like gadget dependence, reinforcing the suitability of the SEIRS framework for this study.

The model categorizes the population into four groups: Susceptible (S), Exposed (E), Infected (I), and Recovered (R). The main assumption of this model is that individuals who recover from gadget addiction can become susceptible again due to repeated exposure. The initial values were obtained through a research study conducted by distributing questionnaires to students in grades 4 to 6 at SD Swasta Shafiyyatul Amaliyyah Medan and SD Swasta Harapan Deli Serdang, with a total of 100 respondents. Based on the collected data, the initial conditions at time $t = 0$ were determined as follows: 96 students were categorized as susceptible ($S(0) = 96$), 3 students were in the exposed category ($E(0) = 3$), 1 student was identified as addicted ($I(0) = 1$), and no students had recovered ($R(0) = 0$). These values serve as the initial values for the numerical simulation using the SEIRS model.

The differential equations obtained in this model are:

$$\frac{dS}{dt} = -0{,}00104SI + 0{,}033R \qquad S(0) = 96$$

$$\frac{dE}{dt} = 0{,}00104SI - 0{,}02222E \qquad E(0) = 3$$

$$\frac{dI}{dt} = 0{,}01111E - 0{,}03333I \qquad I(0) = 1$$

$$\frac{dR}{dt} = 0{,}03333I + 0{,}01111E - 0{,}033R \qquad R(0) = 0$$

Based on initial values, key parameter values such as transition rates between categories and recovery rates were determined. Table 1 presents the initial values and parameters utilized in the SEIRS model to analyze gadget addiction cases. As shown in the table, the rate of new gadget users and the rate of users leaving gadgets are both assumed to be zero. This indicates that, in the initial simulation, there is no external addition or reduction in the population of gadget users, allowing the analysis to focus solely on the internal transitions between compartments within the SEIRS model.

Table 1. Initial Values and SEIRS Model Parameters

Parameter Definition	Value	Source
Rate of new gadget users	0	Estimated
Rate of users leaving gadgets	0	Estimated
Transition rate from S to E	0.00104	$\beta = \frac{3}{96 \times 30} = 0{,}00104$
Transition rate from E to I	0.01111	$\alpha = \frac{1}{3 \times 30} = 0{,}01111$
Recovery rate	0.03333	$\lambda = \frac{1}{30} = 0{,}033$
Transition rate from R to S	0.033	$\varepsilon = \frac{1}{1 \times 30} = 0{,}03333$
Transition rate from E to R	0.01111	$\theta = \frac{1}{3 \times 30} = 0{,}01111$

The transition rate from the Susceptible group to the Exposed group (β) is set at 0.00104, reflecting the initial likelihood of individuals being exposed to gadgets. The rate of transition from Exposed to Infected (ε) is 0.01111, suggesting that a small proportion of those exposed begin to show signs of addiction. The recovery rate (γ) is 0.03333, while the rate at which recovered individuals become susceptible again (ω) is 0.033, indicating the possibility of relapse.

Additionally, the model considers that some individuals in the Exposed group may recover without becoming addicted, as reflected in the parameter ρ with a value of 0.01111. These parameters form the foundation for simulating the SEIRS model using MATLAB and play a crucial role in determining the dynamics of transition between groups within the observed population.

3.2 Mathematical Analysis

3.2.1 Equilibrium Analysis

To better understand the behavior of the proposed SEIRS model in the context of gadget addiction among elementary school children, we first determine the system's equilibrium points. The model comprises four compartments: susceptible (S), exposed (E), addicted/infected (I), and recovered (R). The governing system of differential equations is as follows:

$$\frac{dS}{dt} = -\beta SI + \omega R$$
$$\frac{dE}{dt} = \beta SI - (\varepsilon + \rho)E$$
$$\frac{dI}{dt} = \varepsilon E - \gamma I$$
$$\frac{dR}{dt} = \gamma I + \rho E - \omega R$$

The model assumes no new students enter or leave the population during the study period. This is justified by the short timeframe of data collection (one academic semester) during which student turnover is minimal, allowing the model to focus on behavioral transitions within a stable group. The addiction-free equilibrium (AFE) is obtained by setting E = I = R = 0, resulting in S = N = 100. Thus, the AFE is $E_0 = (100, 0, 0, 0)$.

The endemic equilibrium (EE) assumes I > 0 and yields steady-state values:

$$E = \frac{\gamma}{\varepsilon} I \approx 3I$$
$$R = \frac{\gamma I + \rho E}{\omega} \approx 2.02I$$
$$S = \frac{(\varepsilon + \rho)\gamma}{\beta\varepsilon} \approx 64.06$$

To determine the approximate value of I, we use the total population constraint S + E + I + R = 100. Substituting the expressions for S, E = 3I, and R = 2.02I into the equation, we get:

$$64.06 + 3I + I + 2.02I = 100 \rightarrow 6.02I = 35.94 \ \rightarrow I \approx 5.97.$$

Hence, the endemic equilibrium can be expressed as $E_1 = (64.06, 17.91, 5.97, 12.06)$, indicating that around 6% of the population is predicted to be in the addicted (I) state at equilibrium under the given parameter assumptions.

3.2.2 Local Stability Analysis

The stability of the addiction-free equilibrium is analyzed using the Jacobian matrix linearized around the point E_0. The Jacobian matrix of the system is computed and evaluated at S = 100, E = I = R = 0, resulting in:

$$J_{AFE} = \begin{bmatrix} 0 & 0 & -0.104 & 0.033 \\ 0 & -0.02222 & 0.104 & 0 \\ 0 & 0.01111 & -0.03333 & 0 \\ 0 & 0.01111 & 0.03333 & -0.033 \end{bmatrix}.$$

The eigenvalues of this matrix are computed as:

$$\lambda_1 \approx 0.0000, \qquad \lambda_2 \approx -0.0330, \qquad \lambda_3 \approx -0.0622, \qquad \lambda_4 \approx +0.0067$$

The presence of a positive eigenvalue ($\lambda_4 \approx +0.0067$) indicates that the addiction-free equilibrium is locally unstable. This implies that, in the presence of even a small number of addicted individuals, the system may evolve toward persistent gadget addiction in the population.

3.2.3 Basic Reproduction Number R_0 and Its Interpretation

The basic reproduction number R_0 is a critical threshold parameter that indicates the expected number of secondary addiction cases generated by one addicted child in a fully susceptible population. The basic reproduction number R_0 is derived using the next-generation matrix method by defining the vector of infected compartments $x = [E, I]^T$. The new infection matrix F and transition matrix V are constructed and evaluated at the addiction-free equilibrium. The resulting next-generation matrix $K = FV^{-1}$ yields the spectral radius R_0, which represents the expected number of new addiction cases generated by one addicted individual in a fully susceptible population.

Let the infected compartments be $x = [E, I]^T$. Then the rate of new infections and transitions is given by:

$$F = \begin{bmatrix} \beta S_0 I \\ 0 \end{bmatrix},$$

$$V = \begin{bmatrix} (\alpha + \rho)E \\ -\alpha E + \gamma I \end{bmatrix}.$$

It is derived using the next-generation matrix approach:

$$R_0 = \frac{\beta \varepsilon S_0}{(\varepsilon + \rho)\gamma}$$

The Jacobian matrices of F and V, evaluated at the disease-free equilibrium (S_0, E = 0, I = 0), are:

$$F = \begin{bmatrix} 0 & \beta S_0 \\ 0 & 0 \end{bmatrix}$$

$$V = \begin{bmatrix} \alpha + \rho & 0 \\ -\alpha & \gamma \end{bmatrix}$$

The next-generation matrix is $K = FV^{-1}$. First, compute V^{-1}:

$$V^{-1} = \frac{1}{(\alpha + \rho)\gamma} \begin{bmatrix} \gamma & 0 \\ \alpha & \alpha + \rho \end{bmatrix}.$$

Then, the next-generation matrix $K = FV^{-1}$ becomes:

$$K = \begin{bmatrix} \frac{\beta S_0 \alpha}{(\alpha + \rho)\gamma} & \frac{\beta S_0}{\alpha + \rho} \\ 0 & 0 \end{bmatrix}.$$

The spectral radius (dominant eigenvalue) of matrix K gives the basic reproduction number R_0:

$$R^0 = \frac{\beta \alpha S^0}{(\alpha + \rho)\gamma}.$$

If we define $\varepsilon = \alpha$, then this reduces to:

$$R^0 = \frac{\beta \varepsilon S^0}{(\varepsilon + \rho)\gamma}.$$

Substituting the parameter values and initial condition $S_0 = 96$, we obtain:

$$R_0 \approx \frac{0.00104 \times 0.01111 \times 96}{0.02222 \times 0.03333} \approx 1.5.$$

Since $R_0 > 1$, the model predicts that gadget addiction will persist and potentially spread within the population unless effective control measures are introduced.

3.2.4 Global Stability Analysis

From a global perspective, the addiction-free equilibrium is not globally stable when $R_0 > 1$. Although a full Lyapunov function or LaSalle's invariance proof is beyond the scope of this study, numerical simulations confirm that trajectories diverge from the AFE and converge toward the endemic equilibrium. This suggests that the EE acts as a global attractor, reinforcing the persistence of addiction dynamics in the long term under current parameter values. To analyze the global stability of the disease-free equilibrium (DFE), we construct a Lyapunov function $V = E + I$, where $E(t)$ and $I(t)$ represent the exposed and infected subpopulations, respectively. The function is positive definite and continuously differentiable. Its time derivative is given by:

$$\frac{dV}{dt} = I(\beta S - \gamma)$$

Since the total population N is constant and $S \leq N$, we obtain $\frac{dV}{dt} \leq I\gamma(R_0 - 1)$, where $R_0 = \frac{\beta N}{\gamma}$. Therefore, if $R_0 < 1$, then $\frac{dV}{dt} < 0$ for all $I > 0$, and the DFE is globally asymptotically stable. This result confirms that the addiction-free state will be reached asymptotically if the basic reproduction number remains below one.

3.2.5 Sensitivity Analysis of Key Parameters

To identify the parameters most influential on the system's behavior, particularly on R_0, a sensitivity analysis was performed. The normalized forward sensitivity index for a parameter p is given by:

$$\Upsilon_p^{R_0} = \frac{\partial R_0}{\partial p} \cdot \frac{p}{R_0}$$

The computed indices are:

1. $\Upsilon_\beta^{R_0} = +1$: R_0 increases proportionally with the contact rate.
2. $\Upsilon_\gamma^{R_0} = -1$: R_0 decreases proportionally with the recovery rate.
3. $\Upsilon_\varepsilon^{R_0} > 0$: Increased progression from exposure to addiction increases R_0.
4. $\Upsilon_\omega^{R_0} = 0$: The relapse rate does not directly affect R_0, though it influences long-term dynamics.

Sensitivity analysis was conducted to examine how changes in each parameter affect the basic reproduction number R_0, a key threshold indicator in epidemiological and behavioral models. The normalized forward sensitivity indices computed for R_0 are as follows: $\Upsilon_\beta^{R_0} = +1$, indicating that R_0 increases proportionally with the contact rate; $\Upsilon_\gamma^{R_0} = -1$, showing that higher recovery rates reduce R_0; $\mathrm{Y}^{\alpha R_0} > 0$, meaning that faster progression from exposure to addiction increases R_0; and $\Upsilon_\omega^{R_0} = 0$, suggesting that the relapse rate does not directly affect R_0, although it significantly influences the long-term dynamics of the system. These results highlight the critical role of intervention strategies aimed at reducing transmission and progression rates while increasing recovery effectiveness to control gadget addiction among schoolchildren. This analysis highlights that reducing the contact rate (β) and increasing recovery rate (γ) are the most effective strategies for minimizing gadget addiction in the population.

3.2.6 Intervention Scenario Simulation

To evaluate potential intervention strategies, scenario simulations were conducted by adjusting key parameters identified in the sensitivity analysis. First, the transmission rate (β) was reduced by 25% to simulate effective parental control, digital literacy education, or screen time restrictions. This adjustment significantly reduced the peak number of infected individuals and shortened the overall duration of the addiction cycle.

In a second scenario, the recovery rate (γ) was increased by 30%, representing intensified behavioral interventions such as counseling, mentoring programs, or parental involvement. The simulation results showed a faster transition of individuals from the Infected (I) to the Recovered (R) compartment and a delayed return to the Susceptible state.

Lastly, the effect of increasing the relapse rate (ω) by 20% was explored to model the impact of poor post-recovery support. This resulted in a higher number of individuals returning to addiction, sustaining the overall number of infected cases over time. These simulations highlight how changes in behavioral, educational, and policy-based parameters can quantitatively influence the trajectory of gadget addiction in children.

3.3 Simulation Results and Analysis

The SEIRS model was numerically solved using the 5th-Order Runge-Kutta Method in MATLAB. A step size of $h = 0.01$ was used, providing highly accurate results. The numerical solution was obtained in the form of graphs showing changes in the number of individuals in each category over the simulation period.

3.3.1 Population Dynamics

Each compartment of the SEIRS model is analyzed based on its numerical trends over time, as visualized in the subsequent graphs.

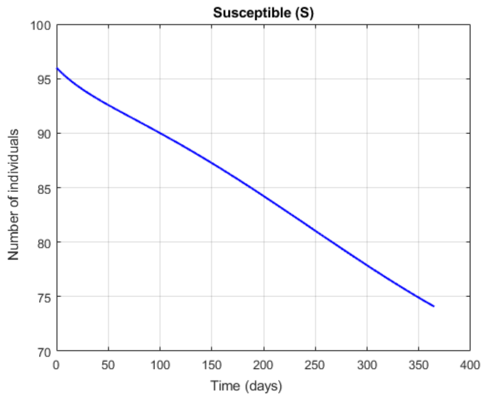

Figure 2. 5th-Order Runge-Kutta Graph for Susceptible (S)

The trend of the Susceptible (S) population, which exhibits a consistent decline over the 365-day simulation period, is illustrated in Fig. 2. At the beginning of the observation, the number of susceptible individuals is approximately 96. This figure gradually decreases to around 74 by day 365. The downward trajectory suggests a continual shift of individuals from the susceptible category to the exposed group, in accordance with the transition dynamics of the SEIRS model. This decrease highlights the growing number of individuals becoming exposed to gadget use and potentially progressing toward addiction. The observed trend emphasizes the importance of early preventive measures aimed at sustaining a high proportion of unaffected individuals, particularly through educational campaigns and awareness initiatives that foster responsible and balanced gadget use behaviors.

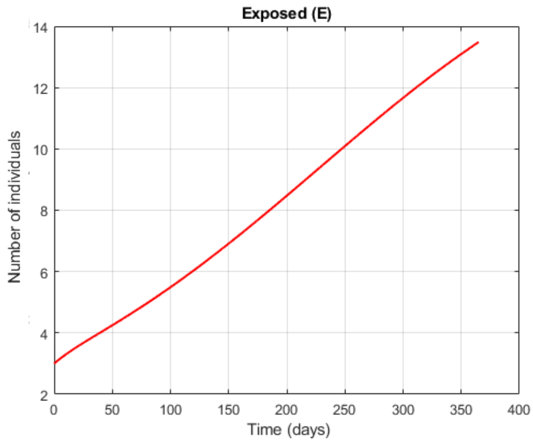

Figure 3. 5th-Order Runge-Kutta Graph for Exposed (E)

The dynamics of the Exposed (E) population are depicted in Fig. 3, revealing a steady and linear increase in the number of individuals who have been exposed to gadget use but have not yet shown signs of addiction. Throughout the 365-day simulation, the exposed population increases from approximately 3 to over 13 individuals. This consistent upward trend reflects a continuous shift from the susceptible category to the exposed group, indicating heightened interaction with gadgets within the population. Within the SEIRS model framework, the exposed phase represents a pivotal transition point, where individuals may either advance to the infected stage or return to a non-risk status based on environmental factors and preventive actions. These findings underscore the urgency of implementing focused educational and behavioral strategies during this critical period to prevent the development of full-scale addiction.

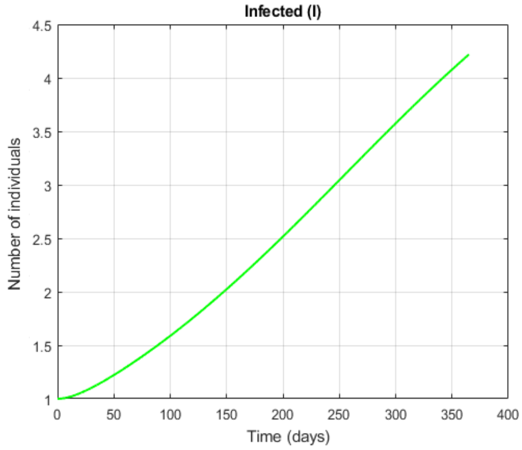

Figure 4. 5th-Order Runge-Kutta Graph for Infected (I)

The dynamics of the Infected (I) compartment are illustrated in Fig. 4, showing a gradual yet accelerating increase in the number of individuals identified as addicted to gadgets. At the start of the simulation (day 0), the infected population begins at approximately 1 individual and grows to over 4 individuals by day 365. Although the numerical increase appears modest, the consistent upward trajectory indicates a compounding effect over time, aligning with the transmission characteristics embedded in the SEIRS model. This trend highlights the necessity of proactive interventions aimed at curbing the progression from exposure to full addiction. Key measures may include monitoring gadget usage patterns, implementing digital literacy programs, and conducting early screening to detect behavioral indicators of addiction, thereby reducing the potential for continued growth within this compartment.

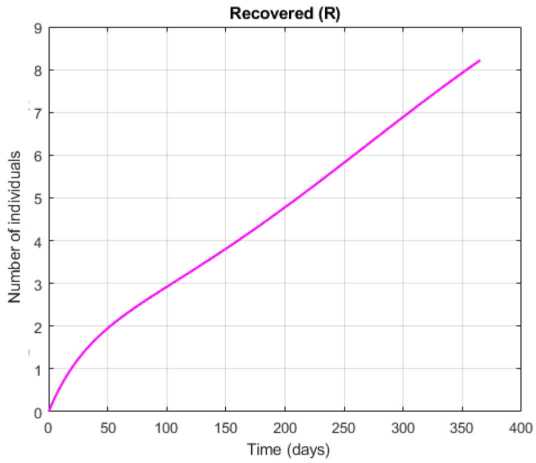

Figure 5. 5th-Order Runge-Kutta Graph for Recovered (R)

The trajectory of the Recovered (R) compartment is presented in Fig. 5, which displays a clear upward trend in the number of individuals who have successfully overcome gadget addiction. The increase in recovery is initially rapid, followed by a gradual deceleration, with the recovered population rising from 0 to approximately 8 individuals over the 365-day simulation period. The concave-down curvature of the graph reflects a decreasing rate of recovery over time, potentially signaling the increasing difficulty in maintaining the effectiveness of interventions as the simulation progresses. This trend emphasizes that while recovery from gadget addiction is attainable, it necessitates consistent and structured support. For elementary school-aged children, such support must involve collaborative strategies among parents, educators, and mental health professionals to foster sustainable behavioral improvements and minimize the likelihood of relapse.

3.3.2 Error Analysis

This study employs the relative approximation error to assess numerical accuracy. The relative approximation error obtained through the application of the fifth-order Runge-Kutta method to the SEIRS model is presented in the subsequent section.

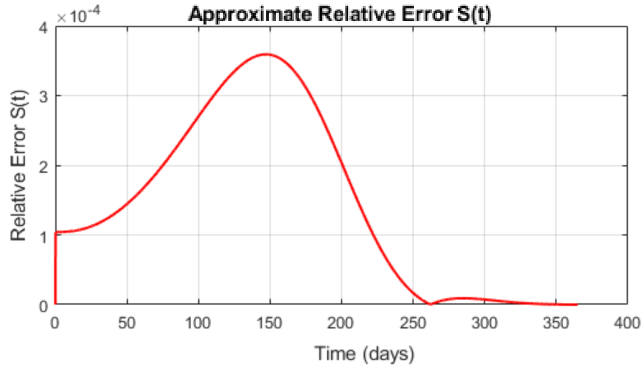

Figure 6. Approximate Relative Error for Susceptible (S)

The progression of the approximate relative error $S(t)$ over a 365-day period is presented in Fig. 6, illustrating the temporal evolution of numerical error in the applied computational method. The relative error remains within a tiny magnitude, on the order of 10^{-4}, yet demonstrates a gradual and consistent increase as time advances. At the initial time point, the error is approximately 1×10^{-4}, and by day 365, it approaches 0.0006×10^{-4}. This trend suggests a mild exponential or quadratic growth in error accumulation. Such a pattern is characteristic of numerical methods where truncation errors and round-off errors accumulate over successive time steps. In this context, the error behavior may be attributed to the use of the fifth-order Runge-Kutta method, which, while generally exhibiting high accuracy, is still subject to local and global discretization errors, particularly when larger time step sizes are employed or when the underlying model exhibits nonlinear or sensitive dynamics. Furthermore, inaccuracies in the initial conditions or parameter estimates may amplify the error propagation over time. Despite the relatively small magnitude of the error, its upward trajectory indicates the need for careful consideration, especially for long-term simulations. To enhance accuracy and ensure numerical stability, it is recommended to assess the influence of the time step size, conduct a convergence analysis, and, where possible, validate the numerical solution against exact or benchmark solutions.

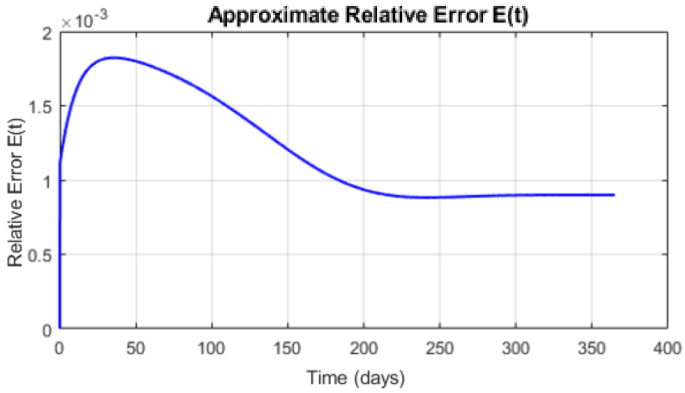

Figure 7. Approximate Relative Error for Exposed (E)

The progression of the approximate relative error $E(t)$ over a time span of 365 days is depicted in Fig.7, providing insight into the numerical stability and accuracy of the computational method employed in the underlying model. At the initial time point, the error is approximately 1×10^{-3}, and by day 365, it approaches 0.8996×10^{-3}. This downward trend may suggest that the model enters a more stable or quasi-steady regime, in which the computational method, potentially the fifth-order Runge-Kutta method, achieves improved accuracy due to reduced variability in the system's state variables. The presence of such a peak-and-decline pattern is indicative of an adaptive numerical response to initial instability, followed by convergence toward a more consistent solution behavior.

Although the magnitude of the relative error remains within an acceptable range throughout the simulation (on the order of 10^{-3}), the observed dynamics underscore the importance of error monitoring across all time intervals. This behavior also highlights the need to assess the influence of step size selection and the suitability of the numerical method for long-term simulations. To enhance confidence in the computational results, it is recommended to perform sensitivity analyses, refine the temporal discretization if necessary, and compare the numerical solution against analytical benchmarks or higher-precision methods when available.

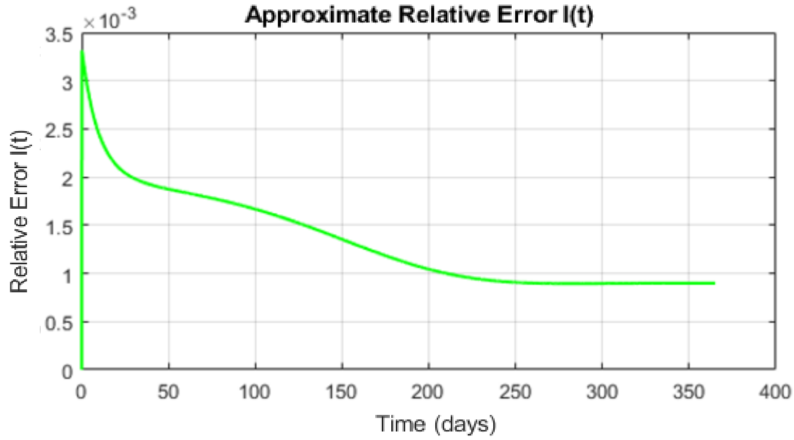

Figure 8. Approximate Relative Error for Infected (I)

The behavior of the approximate relative error $I(t)$ over a 365-day period is illustrated in Fig. 8. At the beginning of the simulation, the relative error is relatively high, reaching approximately 3.3×10^{-3}. However, a rapid decrease is observed in the early stages, indicating that the numerical method experiences a significant reduction in error during the initial phase. After this sharp decline, the error continues to decrease gradually and steadily, reaching a value of around 0.899×10^{-3} by day 365.

This trend suggests that the model transitions from an unstable or highly sensitive state at the beginning to a more stable regime over time. The numerical method, likely the fifth-order Runge-Kutta, appears to handle the system's dynamics more effectively as the simulation progresses, resulting in a continuous decline in relative error. Such a pattern is indicative of convergence behavior, where the numerical solution becomes increasingly accurate as the influence of initial conditions diminishes.

Although the error remains within an acceptable range throughout the entire simulation period, this analysis highlights the importance of considering early-stage errors, especially in models with rapid initial changes. To enhance the reliability of the results, it is recommended to evaluate the impact of step size and to perform further testing against reference solutions or analytical benchmarks.

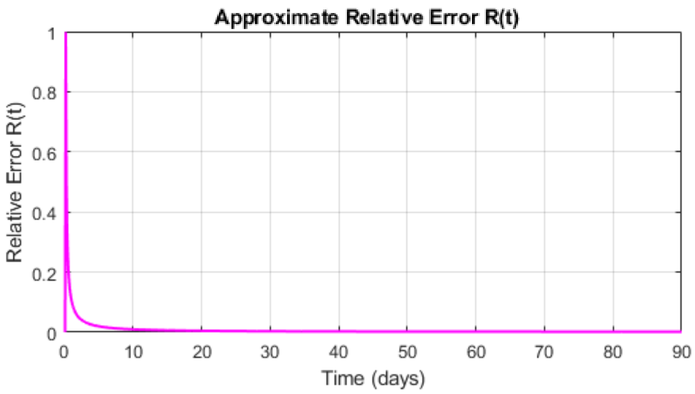

Figure 9. Approximate Relative Error for Recovered (R)

The approximate relative error $R(t)$ over a 365-day simulation period is displayed in Fig. 9. At the onset, the relative error is significantly high, approaching a value close to 1.0. However, the error exhibits a sharp decline within the first few days, rapidly decreasing to near-zero values. After approximately day 10, the error stabilizes at a value that is practically negligible and remains consistent throughout the remainder of the simulation.

This sharp decline, followed by stabilization, indicates that the numerical method employed (likely the fifth-order Runge-Kutta) quickly captures the system dynamics and achieves numerical stability. The initial high error may be attributed to transient effects or sensitivity to initial conditions, which diminish rapidly. The long-term behavior suggests strong convergence properties, with minimal numerical deviation over time.

Such a pattern reflects high computational efficiency and accuracy, implying that the model is capable of producing reliable results after an initial adjustment period. This also underlines the robustness of the method in maintaining low relative error values over extended simulation durations.

Details of the approximate relative error of the SEIR model compartments: Susceptible, Exposed, Infected, and Recovered, over a simulation period of three months, are presented in Table 2.

Table 2. Approximate Relative Error Results

t (months)	Susceptible	Exposed	Infected	Recovered
1	0.00012	0.00182	0.00198	0.00329
2	0.00016	0.00177	0.00184	0.00209
3	0.00024	0.00162	0.00172	0.00179
4	0,00032	0,00143	0,00155	0,00161
5	0,00036	0,00121	0,00135	0,00141
6	0,00029	0,00102	0,00115	0,00121
7	0,00015	0,00091	0,00100	0,00105
8	0,000039	0,00088	0,00091	0,00095
9	0,000005	0,00089	0,000896	0,00091
10	0,000007	0,000897	0,000895	0,000899
11	0,000002	0,000899	0,000898	0,000898
12	0,00000006	0,0008996	0,000899	0,000899

Overall, the analysis of the relative error graphs for each compartment: $S(t)$, $E(t)$, $I(t)$, and $R(t)$ demonstrates that the numerical method used in the simulation maintains a high level of accuracy throughout the simulation period. For the Susceptible (S) compartment, the relative error increases and peaks around day 150 before significantly decreasing toward zero, indicating that while early-stage dynamics were intense, the system stabilized over time, allowing for more accurate approximations. In the Exposed (E) compartment, the error initially spikes, reaching a maximum of approximately 1.9×10^{-3}, before gradually stabilizing, reflecting early modeling challenges in capturing the dynamics of exposed individuals that lessen as the population changes slowly. For the Infected (I) group, the error begins at a relatively high value due to the rapid infection rate but shows a consistent downward trend, suggesting the method's adaptability to the system's evolving behavior. In the Recovered (R) compartment, the error is initially very high, mainly due to the initially small number of recovered individuals, but quickly drops and remains very low for the remainder of the simulation, indicating high accuracy in modeling recovery dynamics after the critical early phase.

In summary, the fifth-order Runge-Kutta method performs well in approximating the numerical solution of the SEIRS model for gadget addiction. The decreasing error in each compartment indicates strong convergence and stability over a long simulation period. Therefore, this method is considered effective for analyzing the dynamics of gadget addiction, producing numerical solutions that closely follow the actual system behavior, with error values approaching zero over time.

3.4 Model Behavior and Literature Comparison

The simulated behavior of the SEIRS model showed persistent cycles of gadget addiction, where individuals who had recovered eventually returned to the susceptible state. This cyclical pattern is consistent with findings by Madigan et al. [1], who reported that excessive early screen exposure is associated with long-term developmental issues in children, including reduced attention and delayed social-emotional development. These outcomes align with the SEIRS model's prediction of long-lasting and recurrent gadget dependency.

Additionally, the model's relapse loop reflects behavioral patterns highlighted by Montag and Walla [31] , who described digital overuse as a repetitive engagement–withdrawal cycle. These comparisons suggest that although the model is theoretical, it reflects behavioral realities documented in empirical studies, thereby supporting its relevance and applicability.

4. CONCLUSION

Based on the results and analysis presented in this study, several key conclusions can be drawn, as summarized below:

1. The SEIRS model effectively captured the dynamic transitions among the Susceptible (S), Exposed (E), Addicted (I), and Recovered (R) compartments in modeling gadget addiction among elementary school children.
2. The number of susceptible individuals showed a gradual decrease over time, while exposed and addicted populations initially increased before declining, and the recovered group consistently increased.
3. These trends indicate a natural behavioral cycle of exposure, addiction, and recovery, with the possibility of relapse to susceptibility.
4. The use of the 5th-order Runge-Kutta method in MATLAB yielded highly accurate numerical results, as shown by consistently small and decreasing relative errors over time.
5. This numerical approach is proven effective for simulating and analyzing the spread of gadget addiction and may inform intervention strategies.
6. However, the study has limitations, such as the lack of real-world longitudinal validation.
7. Future research should include empirical validation and integrate broader contextual variables to improve the model’s accuracy and applicability.

Author Contributions

Dedy Juliandri Panjaitan: Conceptualization, methodology, software, supervision, writing–original draft, validation. Annisa Fadhillah Putri Siregar: Data curation, investigation, formal analysis, visualization, writing–review & editing. Andy Sapta: Methodology, software, validation, writing–review & editing. Rima Aprilia: Resources, project administration, data curation, writing–review & editing. All authors collaboratively reviewed, revised, and approved the final version of the manuscript.

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Declarations

The authors declare that they have no conflict of interest.

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