Indonesian Journal of Early Childhood Educational Research
ISSN : 2963-6760 (Online)
ISSN : 2962-1364 (Print)

Dynamics of Smartphone Addiction Among Young Children in Padang, Indonesia

Amalina Amalina[1], N.A. Samat[2*], Jhoni Warmansyah[3]
[1,2]Universiti Pendidikan Sultan Idris, Malaysia
[3]Universitas Islam Negeri Mahmud Yunus Batusangkar, Indonesia

***Corresponding Author**: N.A. Samat **E-mail**: norazah@fsmt.upsi.edu.my

Received: February 18, 2025	Revised: April 22, 2025	Accepted: May 25, 2025	Online: June 30, 2025

ABSTRACT
The increasing use of smartphones among early childhood populations has raised concerns regarding its impact on children's development and behavior. Therefore, this study analyzes the dynamics of smartphone addiction among young children in Padang City, Indonesia, using the CSAR (Children–Susceptible–Addicted–Recovered) model. Population data and smartphone usage statistics from 2021 to 2024 were incorporated into the modeling process, while parameter estimation was conducted using a genetic algorithm with six mutation-rate variations. The best estimation result produced an error rate of 3.3646%, indicating a strong agreement between the model and empirical data. The basic reproduction number (R_0) of 0.6156 places the system in the moderate category. This suggests that although the spread of smartphone addiction among young children in Padang City is currently under control and not self-sustaining, continuous monitoring and strengthened preventive measures remain necessary to anticipate potential increases in future cases. Sensitivity analysis reveals that the transmission of addictive behavior through social interaction is the most influential factor affecting changes in R_0. These findings highlight the importance of managing peer-group interactions, such as limiting shared digital activities and strengthening collaborative non-digital play, as effective preventive strategies. Numerical simulations further support these results by demonstrating the system's tendency toward an addiction-free equilibrium. Overall, this study provides a solid theoretical and empirical foundation for policy formulation and future research on early childhood digital behavior.

Keywords: *Smartphone Addiction, Children, Estimation Parameter, Genetic Algorithm*

Journal Homepage https://ejournaluinmybsk.ecampus.id/index.php/ijecer/index

How to cite: Amalina, A., Samat, N. A., & Warmansyah, J. (2025). Dynamics of Smartphone Addiction Among Young Children in Padang, Indonesia. *Indonesian Journal of Early Childhood Educational Research (IJECER), 4(2),* 306-316. https://doi.org/10.31958/ijecer.v4i1.16106
Published by: Universitas Islam Negeri Mahmud Yunus Batusangkar, Indonesia

INTRODUCTION

Smartphone addiction among young children has become an increasingly alarming issue over the past decade, particularly in rapidly developing urban areas such as Padang, Indonesia. With growing access to digital devices, children are increasingly exposed to entertainment applications, interactive games, and videos designed with features that reinforce dependency. Although smartphones provide cognitive stimulation and educational benefits, numerous studies have shown that uncontrolled use can negatively affect emotional regulation, impulse control, sleep quality, and social interaction among young children (Amalina & Samat, 2023; Hidayanto et al., 2021; Pasca et al., 2023). Early childhood is a highly sensitive developmental stage in which children form habitual patterns based on the behaviors they observe directly in their surroundings, making them vulnerable to imitating excessive digital use from peers or adults around them (K. H. Jeong, S. Kim, J.H. Ryu, & S.Lee, 2024; B. Kim et al., 2021).

Recent studies further show that reward mechanisms embedded in digital applications reinforce repetitive smartphone use, such as notifications, visually stimulating displays, and game-level systems that encourage continuous engagement (Chen & Lee, 2019; Oulasvirta & Rattenbury, 2012). Prolonged screen exposure has also been linked to reduced face-to-face interaction and impairments in language and empathy development, especially in early childhood (Pempek et al., 2014). Thus, smartphone addiction can be understood not merely as an individual behavioral issue but also as a social phenomenon driven by imitation processes and environmental influences.

To understand the spread of this behavioral pattern more scientifically, researchers have increasingly relied on mathematical modeling as an analytical approach. Compartmental models allow addictive behaviors to be examined structurally by representing transition rates between behavioral states in a population (Bacaër, 2011). Adopting this methodological perspective, the present study builds upon the conceptual framework originally introduced by Amalina and Samat (2025), who classified children's digital behavior into four compartments: Children (C), Susceptible (S), Addicted (A), and Recovered (R). This structure aligns with contemporary perspectives that view digital habits in young children as socially transmitted behaviors influenced by observation, self-regulation, and peer interaction patterns (Gavcar et al., 2024; Over & Carpenter, 2012; Sarkar et al., 2025).

By refining the CSAR model, through comprehensive parameter estimation, numerical simulations, and sensitivity analysis, this study provides a deeper understanding of how smartphone addiction develops, spreads, and diminishes within early childhood populations in Padang. The model not only explains the quantitative dynamics of addictive behavior but also reveals the social factors that contribute to smartphone use patterns. By emphasizing the role of digital exposure and peer interaction, this study highlights the need for targeted interventions to prevent the development of risky behavioral habits during a critical developmental period.

RESEARCH METHODOLOGY

This study employs a quantitative research design grounded in mathematical modeling to analyze the dynamics of smartphone addiction among early childhood populations in Padang, Indonesia. The research builds upon the foundational CSAR (Children–Susceptible–Addicted–Recovered) model previously conceptualized by Amalina and Samat (2025), who first introduced the compartmental structure for describing transitions in children's digital behavior. The present study extends their framework by integrating empirical population data and performing full analytical procedures. The model categorizes children into four compartments, those not yet exposed to smartphones (C), susceptible users (S), addicted individuals (A), and recovered individuals (R) with transitions governed by five key parameters: recruitment rate (π), exposure rate (α), addiction rate (β), recovery rate (b), and exit rate (μ). The compartmental model of the CSAR is shown in Figure 1 (Amalina & Samat, 2025).

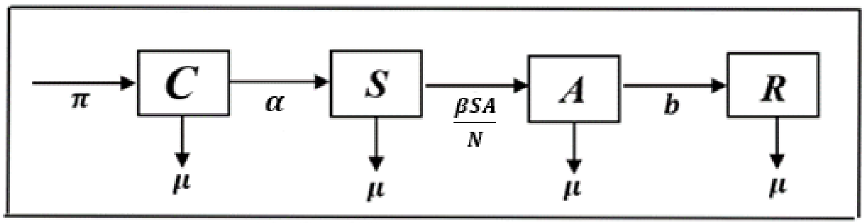

Figure 1. Smartphone Addiction Model

Data on the population of children under six years old and smartphone usage in Padang from 2021 to 2024 were collected from official BPS reports and used as the empirical basis for parameter calibration. To estimate the unknown parameters α, β, and b, this study employs a genetic algorithm (GA), an optimization technique capable of searching complex solution spaces. The parameter estimation procedure in this study follows the general stages of genetic algorithms as described by Mitchell (1999). The process begins with the random initialization of a population of chromosomes, where each chromosome represents a unique combination of parameter values for the compartmental model. These chromosomes are then evaluated using a fitness function, calculated through the mean squared error (MSE) between the model's simulated outcomes and the observed data. Chromosomes with lower MSE values are considered more optimal and are selected to form the basis of the next generation. Through crossover and mutation, mechanisms that exchange and alter parameter segments, new offspring solutions are generated to preserve diversity and prevent premature convergence.

This iterative cycle of evaluation, selection, crossover, and mutation continues across multiple generations until a stopping criterion is met, such as a predefined number of iterations or achievement of a sufficiently low error value. The final output of the optimization process is the best-performing parameter set, which minimizes the discrepancy between model predictions and empirical data. This optimized set is subsequently used for simulation and analysis, ensuring that the compartmental model closely reflects the real-world patterns of smartphone addiction among young children and enhances the model's reliability for further interpretation and policy recommendations. Six mutation rate variations (0.05 to 0.5) were tested, with 100 iterations per variation, and the parameter set yielding the lowest error rate was selected as the optimal solution.

After parameter estimation, the basic reproduction number (R_0) was derived and analyzed to assess the potential for smartphone addiction to persist or decline within the population. Numerical simulations were conducted using the estimated parameter values to visualize the temporal behavior of each compartment under different initial conditions.

Furthermore, a sensitivity analysis was performed to identify which model parameters exert the strongest influence on R_0, using sensitivity index formulations established in the mathematical epidemiology literature. The normalized sensitivity index of the variable V with respect to the parameter p is defined as:(Chitnis et al., 2008)

$$C_p^V = \frac{\partial V}{\partial p} \times \frac{p}{V}$$

$\boldsymbol{V}$ represents the variable analyzed with respect to the parameter $\boldsymbol{p}$

Through this methodological approach, the study provides a comprehensive quantitative assessment of addiction dynamics and the factors driving behavioral transitions among early childhood populations in Padang.

RESULTS AND DISCUSSION

The data regarding the number of early childhood children under the age of 6 years in Padang, denoted by N, and smartphone usage among this age group, denoted by S, during the period from 2021 to 2024 is presented in Table 1.

Table 1. Data on Early Childhood Children and Smartphone Usage

Year	N	S
2021	105774	42712
2022	105514	40665
2023	112000	49974
2024	113252	51734

Source: BPS (2021, 2022, 2023, 2024)

Table 1 shows a consistent increase in both the number of early childhood children (N) and smartphone users (S) in Padang from 2021 to 2024, indicating a growing trend of smartphone exposure among children under the age of 6 years. This increasing pattern supports the urgency of modeling smartphone addiction dynamics within this age group. Therefore, Table 2 presents the parameter values used in the CSAR model based on this trend and other relevant data sources.

Table 2. The CSAR Model Parameter

Notation	Description	Value	Unit
$\boldsymbol{\pi}$	Recruitment rate (entry of new children into the population)	$N \times \frac{1}{6}$	Person x year^{-1}
$\boldsymbol{\mu}$	Exit Rate (natural exit from population)	$\frac{1}{6}$	Person x year^{-1}
$\boldsymbol{\alpha}$	Transition rate from compartment C to S (Exposure Rate)	Estimated	year^{-1}
$\boldsymbol{\beta}$	Transition rate from compartment S to A (Addiction Rate)	Estimated	year^{-1}
b	Recovered Rate	Estimated	year^{-1}

The CSAR model employs five parameters (π, μ, α, β, and b), three of which, α, β, and b, were estimated. In this model, the child population is assumed to be closed, encompassing early childhood from infancy until the age of six. Children are considered to enter the system at birth and exit upon reaching six years of age. Accordingly, the average duration of stay within the system is six years. Under this assumption, the exit rate (μ), representing the proportion of children leaving the system annually due to aging out of early childhood, is defined as $\mu = 1/6$ per year. This implies that approximately 16.7% of the child population exits the system each year. To maintain a constant population size, the inflow rate is not directly equated with μ; instead, it is adjusted to the actual population size. Therefore, the inflow rate is defined as $N \times \mu$, ensuring that the number of children entering the system each year is always proportional to the number exiting. This adjustment stabilizes the early childhood population within the model, consistent with the assumption of a closed system.

Parameter estimation in this study was conducted using a genetic algorithm approach, which searches for optimal solutions through iterative mutation of individuals within the solution space. Six mutation rate ($mutrate$) settings were examined, namely: 0.05, 0.1, 0.2, 0.3, 0.4, and 0.5 (Windarto et al., 2014). For each $mutrate$ value, 100 trials were conducted, and the parameter values with the smallest error were selected. The resulting parameter estimates for each mutation rate configuration are summarized in Table 3.

Table 3. Estimation Parameter of the CSAR Model

$mutrate$	C	S	A	R	α	β	b	Error (%)
0.05	30544	42712	20739	11249	0.4716	0.8731	1	3.3676
0.1	30500	42712	20739	11028	0.4559	0.8075	1	3.3651
0.2	30500	42712	20739	11225	0.5094	1	1	3.3711
0.3	30500	42712	20739	11289	0.4884	0.9321	1	3.3671
0.4	**30500**	**42712**	**21207**	**11258**	**0.5003**	**0.9576**	**1**	**3.3646**
0.5	30500	42712	20739	11028	0.4861	0.9220	1	3.3655

Based on Table 3, the minimum estimation error (3.3646%) is achieved at a mutation rate of 0.4, indicating this configuration as the optimal setting for parameter identification. The resulting parameter estimates are therefore adopted as the best representation of the early childhood smartphone addiction dynamics in Indonesia. The corresponding initial conditions are specified accordingly. Notably, the recovery parameter b attains its upper admissible bound. Such boundary solutions commonly arise in optimization-based parameter estimation when supported by the empirical structure of the data and remain admissible within the CSAR model, yielding stable system dynamics.

The occurrence of $b = 1$ can be explained analytically. The annual time-scale of the dataset reflects a declining trend in the addicted compartment, thereby requiring a relatively large recovery rate to reproduce the observed dynamics. Moreover, the demographic parameters μ and π, both fixed at 1/6, contribute minimally to the system balance, effectively shifting the dominant control of the basic reproduction number R_0 to the recovery parameter

b. In addition, genetic algorithms tend to converge toward boundary values of the parameter space when such configurations minimize the objective function. Consequently, the estimated value $b = 1$ emerges as a structurally consistent and data-driven outcome of the optimization process. The estimated parameters were subsequently validated within the CSAR dynamical system.

Substituting the estimated parameters into the expression for the basic reproduction number yields $R_0 = 0.6156$. Since $R_0 < 1$, the addiction-free equilibrium is asymptotically stable, indicating that smartphone addiction cannot persist endemically within the modeled population. Each addicted child generates, on average, fewer than one secondary addicted case before recovery, leading to a gradual decay of addiction prevalence. This analytical result is supported by numerical simulations (Figure 2), which show monotonic convergence of the addicted compartment (A) toward zero, accompanied by transient adjustments in the susceptible (S), contact/exposed (C), and recovered (R) compartments.

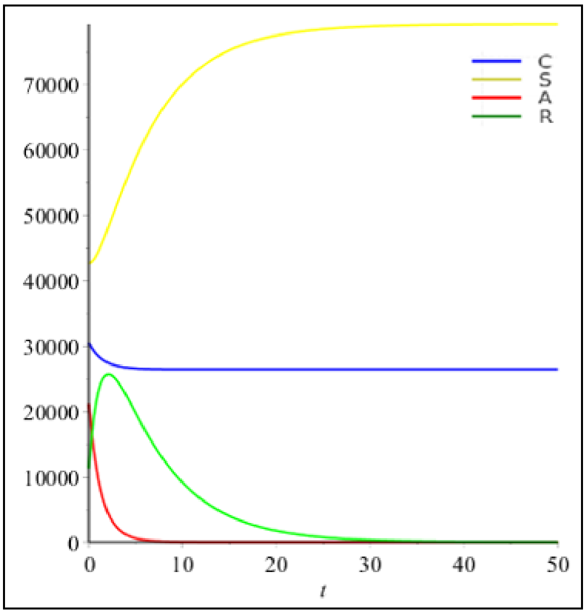

Figure 2. Numerical Simulation of Smartphone Addiction in Padang, Indonesia

Furthermore, the low R_0 value can be associated with several factors, such as the exit rate (μ). The exit rate parameter (μ) is set at 1/6, reflecting the assumption that young children will exit the system upon reaching the age of six. This aligns with the study's age constraints, where after this age, children's smartphone usage patterns are likely to change significantly due to environmental, educational, social, or regulatory influences. In this context, the relatively small R_0 value may be affected by the magnitude of the μ parameter, as a higher μ value results in individuals leaving the system more quickly, thereby reducing the chances of spreading smartphone addiction habits within the population. Therefore, it is essential to examine the sensitivity analysis of each parameter influencing R_0.

A sensitivity analysis will be conducted to identify the parameters that influence the stability of both cases in this study, namely the variable R_0. In this analysis, the parameters examined are α, β, and b, which are directly involved in the formulation of R_0. The concept and formulation of the sensitivity index using sensitivity index formulations established in the mathematical epidemiology literature (Chitnis et al., 2008). The sensitivity index for the parameter α is calculated as follows:

$$C_{\alpha}^{R_0} = \frac{\partial R_0}{\partial \alpha} \times \frac{\alpha}{R_0}$$

$$C_{\alpha}^{R_0} = \frac{\beta - \alpha\beta}{(b+\mu)(\alpha+\mu^2)} \times \frac{\alpha}{\frac{\alpha\beta}{(\alpha+\mu)(b+\mu)}}$$

$$C_{\alpha}^{R_0} = \frac{\mu}{\alpha+\mu}$$

The exact process is also applied to the other parameters. After substituting the parameter values into the R_0 equation, the sensitivity analysis results for the parameters α, β, and b are obtained sequentially as 0.2499;1;-0.857. The sensitivity analysis results indicate that the parameter with the most significant impact on R_0 is the addiction rate (β), with a sensitivity value of 1. This means that a 1% increase in β will increase R_0 by 1%. Conversely, the addiction recovery rate (b) has a negative influence, with a sensitivity value of -0.85714, indicating that the higher the recovery rate, the lower the R_0, making addiction less likely to spread. Additionally, the probability of individuals transitioning to an exposure state (α) has a sensitivity value of 0.249914, suggesting that changes in this parameter still contribute to an increase in R_0, albeit not as strongly as β. Furthermore, among all the parameters analyzed, the addiction rate β is identified as the most influential factor affecting the R_0 value. Therefore, efforts to control exposure and interactions between susceptible individuals and those already addicted are crucial to effectively suppress the spread of smartphone addiction among young children in Padang City, Indonesia. This finding underscores the importance of managing peer-group interactions, such as reducing shared digital activities, limiting exposure to highly addicted peers, and promoting collaborative non-digital play as effective strategies to curb the spread of addictive behavior.

Theoretically, the value $R_0 = 1$ is a critical point in epidemiological modeling. This point serves as a threshold that determines the direction of the spread of a phenomenon, in this case, smartphone addiction among early childhood. If the R_0 value is below one ($R_0 < 1$), the spread of addiction generally tends to decline gradually until it eventually becomes controlled and stops spreading further. This condition indicates that each addicted individual transmits the addiction to fewer than one other person on average, thereby preventing the phenomenon from escalating into a larger problem. Conversely, if the R_0 value exceeds one ($R_0 > 1$), the spread of addiction increases exponentially and has the potential to become a widespread epidemic, where each addicted individual can influence more than one other person.

However, even when $R_0 < 1$, in the context of smartphone addiction, the potential for widespread transmission still exists if systematic prevention efforts are not implemented.

Therefore, the classification of the R_0 value is modified by applying a midpoint-based approach. In this approach, the R_0 range from 0 to 1 is divided into several logical sub-intervals, each representing a different level of transmission risk. This subdivision aims to provide a more detailed and systematic understanding of the dynamics of smartphone addiction spread, enabling more targeted and effective intervention and control strategies based on the level of risk indicated by the R_0 value in each sub-interval. Based on this principle, the range of R_0 value is divided into the following logical sub-intervals, as shown in Table 4.

Table 4. New Classification and Interpretation of R_0 for Smartphone Addiction

Category	R_0 Interval	Interpretation
Controlled Situation	$0 < R_0 \leq 0.5$	Very limited spread with low risk, indicating that prevention strategies are highly effective. Regular monitoring is recommended to maintain control.
Moderate or Alert Situation	$0.5 < R_0 < 1$	Relatively low spread, but increased vigilance is required to anticipate any potential rise. Preventive strategies should be maintained or strengthened.
High Risk or Critical Threshold Situation	$R_0 = 1$	A stable situation, but highly sensitive to small changes in control measures. Evaluation and preparation of additional strategies are necessary.
Uncontrolled Situation	$R_0 > 1$	The spread is likely to increase rapidly. Intensive intervention and emergency prevention strategies are urgently required.

Based on the data presented in Table 4, the obtained R_0 value of 0.615672 places the system in the "Moderate" or "Alert Situation" category. This indicates that although the current spread of smartphone addiction remains under control, regular monitoring and enhanced preventive measures are still necessary to anticipate a potential increase in future cases, particularly among early childhood populations in Padang City, Indonesia.

The findings of this study highlight the complex behavioral dynamics underlying smartphone addiction among early childhood populations in Padang, Indonesia. The CSAR model reveals two possible equilibrium states: an addiction-free equilibrium and an addiction-endemic equilibrium. The stability analysis indicates that when $R_0 < 1$, the addiction-free equilibrium becomes locally asymptotically stable, implying that addictive behavior will decline over time. With the estimated R_0 value of 0.6156, Padang is currently in a condition where addiction is not expected to persist, although this status remains sensitive to changes in key parameters, especially the addiction rate β. If R_0 exceeds 1, the system shifts to an endemic equilibrium, enabling the addiction to spread and stabilize at higher levels within the population.

The sensitivity analysis underscores the critical role of β in shaping addiction dynamics. This aligns with previous research on children's social behavior, particularly the work of Over (2012; 2013), which emphasizes that imitation in children is influenced by social goals, peer interactions, and the desire for group acceptance. These findings imply that exposure to peers or family members who frequently engage in smartphone use can significantly increase the risk of addiction. Similarly, Sarkar (2025) explains that the need to stay socially connected drives compulsive digital engagement, reinforcing the role of social contexts in accelerating addiction. Gavcar (2024) further shows that parental phubbing, parents ignoring children to focus on their phones, contributes to children's addiction tendencies through weakened social and emotional interactions. These insights support the interpretation that β represents not only technological exposure but also broader social and environmental learning processes that shape children's digital habits.

Simulation results also reveal the importance of initial conditions. Even when $R_0 < 1$, a large initial number of addicted individuals slows the decline of the addiction curve, emphasizing the need for early detection and early-stage preventive efforts. Conversely, when $R_0 > 1$, even a small initial number of addicted children can trigger a rapid escalation if the susceptible population is large. These patterns demonstrate that preventive efforts must target both reducing exposure and addressing early signs of risky smartphone use. Moreover, the influence of μ (exit rate) on the reduction of R_0 indicates that as children age out of the early childhood category, their behavioral patterns change significantly, reducing the likelihood of transmitting addictive behavior within the modeled population. This supports the model's structural validity and the relevance of age-specific behavioral assumptions.

The application of the model to the Padang context demonstrates its effectiveness in capturing local behavioral patterns. The R_0 value indicates a manageable situation but also highlights potential vulnerability if external factors such as increased exposure, more engaging digital content, or weakened parental monitoring alter the value of β. While this study does not yet propose specific policy interventions, the analytical results provide a strong theoretical foundation for designing preventive programs. These may include parental education about screen time regulation, early childhood digital literacy, structured smartphone usage boundaries, and community-level monitoring of children's exposure to digital devices.

Collectively, the results and analyses in this study extend the earlier conceptual work by Amalina and Samat (2025) by integrating empirical data, advanced parameter estimation, and sensitivity modeling. This provides a more refined and contextual understanding of smartphone addiction dynamics, forming an important contribution to the growing body of research on early childhood digital behavior.

CONCLUSION

This study provides a comprehensive mathematical and empirical analysis of smartphone addiction dynamics among early childhood populations in Padang, Indonesia, using an extended CSAR model originally conceptualized by Amalina and Samat (2025). Through parameter estimation using the genetic algorithm, numerical simulations, and sensitivity analysis, the model successfully captures the behavioral transitions from non-exposure to susceptibility, addiction, and recovery. The estimated parameters indicate that the addiction rate (β) plays the most dominant role in influencing the basic reproduction number (R_0), while the recovery rate (b) exerts a strong suppressive effect on addiction spread. The resulting R_0 value of 0.6156 places the system within the "Moderate" or "Alert Situation" category, indicating that although the current spread of smartphone addiction remains under control, regular monitoring and strengthened preventive efforts are necessary to anticipate potential increases in future cases, especially among early childhood populations in Padang City, Indonesia. These findings highlight the critical importance of early intervention strategies focused on managing exposure, strengthening parental supervision, and promoting healthier digital habits from an early age.

ACKNOWLEDGEMENT

The authors would like to express their gratitude to the kindergarten teachers and parents who generously devoted their time to complete the questionnaires. Appreciation is also extended to UPSI for the support and resources provided throughout the course of this study.

REFERENCES

Amalina, A., & Samat, N. A. (2023). *Risk Factors and Adverse Effects of Smartphone Addiction in Early Childhood: A Systematic Review* (pp. 3–12). https://doi.org/10.2991/978-2-38476-142-5_2

Amalina, A., & Samat, N. A. (2025). *Development of New CSAR Model For Smartphone Addiction Among Early Childhood In Padang City, Indonesia*. Universiti Pendidikan Sultan Idris.

Bacaër, N. (2011). McKendrick and Kermack on epidemic modelling (1926–1927). In *A Short History of Mathematical Population Dynamics* (pp. 89–96). Springer London. https://doi.org/10.1007/978-0-85729-115-8_16

BPS. (2021). *Profil Anak Usia Dini 2021*.

BPS. (2022). *Profil Anak Usia Dini 2022*.

BPS. (2023). *Profil Anak Usia Dini 2023*.

BPS. (2024). *Profil Anak Usia Dini 2024*.

Chen, C., & Lee, M. (2019). *Dual Mechanisms of Reinforcement Reward and Habit in Driving Smartphone Addiction The Role of Smartphone Features*. *29*(6), 1551–1570. https://doi.org/10.1108/INTR-11-2018-0489

Chitnis, N., Hyman, J. M., & Cushing, J. M. (2008). Determining Important Parameters in the Spread of Malaria Through the Sensitivity Analysis of a Mathematical Model. *Bulletin of Mathematical Biology*, *70*(5), 1272–1296. https://doi.org/10.1007/s11538-008-9299-0

Gavcar, E. G., Buber, A., & Senol, H. (2024). The association of parental phubbing behavior with digital game use in preschool children. *Bulletin of the Menninger Clinic*, *88*(4), 336–359. https://doi.org/10.1521/bumc.2024.88.4.336

Hidayanto, D. K., Rosid, R., Nur Ajijah, A. H., & Khoerunnisa, Y. (2021). Pengaruh Kecanduan Telpon Pintar (Smartphone) pada Remaja (Literature Review). *Jurnal Publisitas*, *8*(1), 73–79. https://doi.org/10.37858/publisitas.v8i1.67

Jeong, K. H., Kim, S., Ryu, J. H., & Lee, S. (2024). A Longitudinal Relationship Between Mother's Smartphone Addiction to Child's Smartphone Addiction. *International Journal of Mental Health and Addiction*, *22*(4), 1771–1782. https://doi.org/10.1007/s11469-022-00957-0

Kim, B., Han, S. R., Park, E. J., Yoo, H., Suh, S., & Shin, Y. (2021). The Relationship Between Mother's Smartphone Addiction a Children's Smartphone Usage. *Psychiatry Investigation*, *18*(2), 126–131. https://doi.org/10.30773/pi.2020.0338

Mitchell, M. (1999). An Introduction to Genetic Algorithms. In *MIT Press.*

Oulasvirta, A., & Rattenbury, T. (2012). *Habits Make Smartphone Use More Pervasive*. 105–114. https://doi.org/10.1007/s00779-011-0412-2

Over, H., & Carpenter, M. (2012). Putting the social into social learning: Explaining both selectivity and fidelity in children's copying behavior. *Journal of Comparative Psychology*, *126*(2), 182–192. https://doi.org/10.1037/a0024555

Pasca, M. M., Surani, E., & Arisanti, A. Z. (2023). Hubungan Kecanduan Bermain Gadget (Smartphone) Dengan Daya Lihat Anak Pra Sekolah. *Jurnal Kebidanan Khatulistiwa*, *9*(1), 39. https://doi.org/10.30602/jkk.v9i1.622

Pempek, T. A., Kirkorian, H. L., Anderson, D. R., Pempek, T. A., Kirkorian, H. L., & The, D. R. A. (2014). The Effects of Background Television on the Quantity and Quality of Child-Directed Speech by Parents. In *Journal of Children and Media* (Vol. 8, Issue 3, p. 3). Taylor & Francis. https://doi.org/10.1080/17482798.2014.920715

Sarkar, S. K., Roy, P., Podder, A., Ghosh, S., & Sen, A. (2025). *Smartphone Addiction, Phone Snubbing, and Effects on Interpersonal Relationships and Mental Health*. Brainware University, India. https://doi.org/10.4018/979-8-3693-8804-4.ch07

Windarto, Indratno, S. W., Nuraini, N., & Soewono, E. (2014). *A comparison of binary and continuous genetic algorithm in parameter estimation of a logistic growth model*. 139–142. https://doi.org/10.1063/1.4866550