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Original Paper

A Mathematical Model of the Dynamics of Crypto Currency Mining Addiction

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Abstract - In order to understand the dynamics of cryptocurrency mining addiction and possibly eliminate the rate at which people become addicted, a six-compartmental model that includes the susceptible human population, the newbies, the addiction class, counselling, and recovery class was formulated. The local equilibrium points were properly analyzed, and it was shown that the equilibrium points are unstable whenever the fundamental addiction number is greater than one (R_0>1) and locally asymptotically stable whenever it is less than one (R_0<1). The result of the basic addiction number R_o which determines whether addiction will die off or persist was carefully calculated using the method of next generation matrix and it was revealed that people will become more addicted to crypto currency mining whenever R_o >1and if R_o < 1, the society will become gradually free from such addiction. Sensitivity analysis was performed on basic reproduction number; numerical simulation was carried out using MAPLE 18 software to analyze the transmission/spread of the addiction, and the finding shows that in order to have a society with lesser number of addicted individuals, there should be adequate counseling and awareness of the dangers associated to crypto-currency mining addiction.

Keywords - C*ryptocurrency, Mining, Addiction, Mathematical modeling, Sensitivity index.*

1. Introduction

Crypto currency mining is a technique used to record and validate transactions by Blockchain networks such as Bitcoin (Catalini & Gans, 2016; Nakamoto, 2008). The term mining also refers to the creation of new coins that enter circulation during this process (Nakamoto, 2008). Mining has expanded rapidly, drawing the attention of participants worldwide (Catalini & Gans, 2016). Miners solve intricate puzzles using specialized hardware and software to mine bitcoins, generating hash values that satisfy the cryptocurrency's difficulty requirements (Antonopoulos, 2017). The incentive of newly produced bitcoins for the first miner to discover a workable method encouraged ongoing participation. (Antonopoulos, 2017). This incentive scheme gives miners the power to log transactions on the blockchain and helps them protect the network (Narayanan et al., 2016).

Notwithstanding the technical complexity of the mining process, it entails assembling transaction information, including wallet addresses and amounts, into blocks. These blocks are subsequently subjected to a cryptographic hash function, which generates a distinct 64-character hex. Although it depends on the network, mining a block takes about ten minutes on average. The periodic halving event, which lowers the block reward by half roughly every four years or after every 210,000 blocks, is a significant component of Bitcoin mining.

(Makarov & Schoar, 2022). Miners' profitability is impacted by this mechanism, which slows the rate at which new bitcoins enter circulation. April 2024 saw the most recent halving, which reduced the reward to 3.125 BTC each block. It is estimated that the reward will further decrease to about 1.5625 BTC by 2028 and approximately 0.78125 BTC by 2032 due to these scheduled halving events (Antonopoulos, 2017). By dividing the current block reward by the average block time, one may determine the issuance rate of Bitcoin. With a payout of 3.125 BTC and an average block time of 9.412 minutes on November 6, 2024, for instance, the issuance rate was roughly 3.01 minutes per bitcoin created. This rate varies according to shifts in mining difficulty and network hash rate. As rewards diminish, miners tend to allocate increasing computational resources to maintain profitability (Narayanan et al., 2016). In addition to mining's technical and financial ramifications, there are worries that it may encourage addictive habits. The signs of cryptocurrency mining addiction are similar to those of other behavioral dependencies, according to research, and they have a detrimental effect on social relationships, mental health, and financial stability (Gullo *et al*., 2022; Kuss & Lopez-Fernandez, 2016). The inherent volatility and potential for high rewards contribute to an environment prone to compulsive involvement.

Researchers from all over the world are becoming more interested in this addiction because of its detrimental effects on family life, work productivity, and academic performance, as well as the wider societal repercussions (Kuss Daria and Griffiths Mark, 2011). In order to address bitcoin mining addiction, we must comprehend its causes and effects. Effective therapies and preventative strategies for excessive mining include therapy, laws, and educational initiatives that increase public knowledge of the dangers of excessive mining, just like for other behavioral disorders (Grant J.E, Potenza M.N, Weinstein A, Gorelick D.A. 2010). There is evidence that behavioral interventions such as turning off notifications, setting time limits for mining, uninstalling mining software, unplugging devices from networks, and limiting the use of gadgets in private areas can lessen the intensity of addiction (Lu P. *et al.,* 2025). Numerous studies have used mathematical modeling to comprehend the dynamics of different addictive behaviors. For example, models of infectious diseases have been modified to examine dependencies, including excessive use of social media, smoking, drinking, and online gaming.

Sánchez Fabio et al., (2007) created a model examining the dynamics of alcohol addiction, while Azwan et al. (2024) used comparable frameworks to investigate the addiction to online gaming. The majority of studies in the fields of sociology, psychology, computer science, economics, and public health have concentrated on the technological, financial, and environmental elements of cryptocurrency mining, despite growing awareness of the addiction tendencies linked to this activity. Analytical methods that explain how mining addiction spreads within people are noticeably lacking, particularly in environments where economic vulnerability and internet exposure are increasing.

In order to close this gap, this study investigates the transmission dynamics of cryptocurrency mining addiction using a mathematical model. In addition to analyzing how people move between behavioral states, the model will pinpoint important thresholds and equilibrium conditions that dictate whether addiction endures or disappears in a community. This study will support the development of efficient interventions and regulations by educators, legislators, and health professionals to lower the dangers of mining addiction.

2. Model Description

This section describes and examines the transmission dynamics of mining cryptocurrency involving six populations. Under the following presumptions, we examine a deterministic mathematical model for the development of the dynamics of cryptocurrency mining addiction: Six subpopulations, each representing a crypto mining state, are created by the model from the entire population. This encompasses the population of resistance (denoted by V_c). These individuals have built a wall of defense against cryptocurrency mining because, for a variety of reasons, they do not support the concept in its entirety. Those that do not engage in crypto currency mining, most likely due to a lack of interaction with compulsive miners, are considered susceptible crypto currency miners (denoted by S_c). Exposed people (Denoted by L_c), often known as "newbies" in the crypto currency world, are those who are just starting out in crypto currency mining but do not become addicted. Those who spend the majority of their valuable working time mining crypto currency are known as addicted crypto currency miners (denoted by A_c). Individuals who seek assistance and counseling in order to shift their perspective away from crypto currency mining and its addiction are referred to as the counseling subpopulation (denoted by C_c). Those who recovered from the CCMA but still have the potential to become vulnerable are referred to as recovered persons (denoted by R_c).

The total population at time t, denoted by $N(t)$ can thus be expressed numerically as

$$N(t) = V_c(t) + S_c(t) + L_c(t) + A_c(t) + C_c(t) + R_c(t). \tag{1}$$

Following from the schematic diagram, we can see that susceptible individuals to crypto currency mining are recruited into the population at a rate Λ, and these individuals start venturing into crypto currency mining by interaction rate β with addicted individuals, with a force of transmission $\frac{\beta A_c}{N}$ and move to the exposed compartment. Also there are some persons whom because of inability to access the internet or challenges of acquiring electronic device has built resistance of a sort to crypto currency mining addiction and so move to the resistance compartment at the rate a_1 and also with change in circumstance move back to susceptible compartment at the rate a_2. The exposed individuals become addicted and join the addicted compartment at rate ε and the remaining proportion of this exposed individuals seek counseling at a rate $(1-\kappa)\varphi$. the addicted individuals either through enlightenment or self-realization and/or treatment the addicted individuals also move to the counseling compartment. After counseling, the individual moves to the recovered compartment and the recovered individuals become again susceptible to the CCMA at a rate that is the same as ω. the whole population, have an average death rate of μ. The parameters are described in Table 1. The flow diagram of the model is shown in Figure 1.

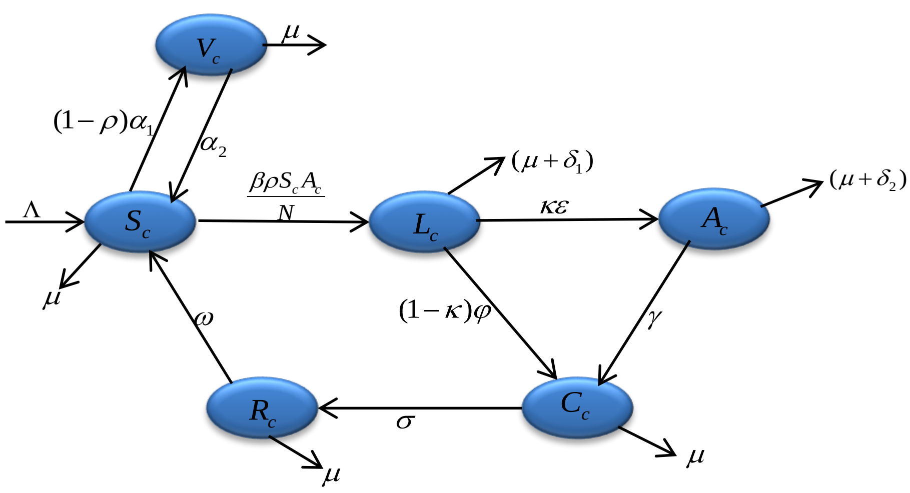

Fig. 1 Schematic diagram of the model without control

The equations for the crypto currency mining addiction model are presented in Equations (1) to (6).

$$
\left.\begin{aligned}
\frac{dV_c}{dt} &= (1-\rho)\alpha_1 S_c - \alpha_2 V_c - \mu V_c \\
\frac{dS_c}{dt} &= \Lambda - \frac{\beta\rho S_c A_c}{N} + \alpha_2 V_c + \omega R_c - (1-\rho)\alpha_1 S_c - \mu S_c \\
\frac{dL_c}{dt} &= \frac{\beta\rho S_c A_c}{N} - (1-\kappa)\varphi L_c - \kappa\varepsilon L_c - (\mu+\delta_1) L_c \\
\frac{dA_c}{dt} &= \kappa\varepsilon L_c - \gamma A_c - (\mu+\delta_2) A_c \\
\frac{dC_c}{dt} &= (1-\kappa)\varphi L_c + \gamma A_c - \sigma C_c - \mu C_c \\
\frac{dR_c}{dt} &= \sigma C_c - \omega R_c - \mu R_c
\end{aligned}\right\} \tag{2}
$$

With the primary conditions as follows,

$$
V_c\,(0), S_c\,(0), L_c\,(0), A_c\,(0), C_c\,(0), R_c\,(0) \geq 0 \tag{3}
$$

Table 1. Definition of parameters and variables for the crypto currency mining model

Parameters / Variables	Description
Λ	Recruitment term of the susceptible individuals
α_1	Rate at which the susceptible build immunity against mining addiction
α_2	Rate at which crypto currency miners become susceptible again
ρ	Proportion of susceptible individuals that leave the susceptible class of crypto currency mining
φ	Rate at which newbies or those exposed go for counseling
β	interaction rate between crypto currency miners and susceptible individuals
γ	Rate at which addicted individuals go for counseling
μ	Per capita death rate of crypto currency mining
σ	Rate at which individuals' consoles move to the recovery class of crypto currency mining.
δ_1	Death as a result of the mining activity of newbies
δ_2	Death as a result of the mining activity of addicted individuals
ω	Rate at which recovered individuals move back to the susceptible class
S_C	Susceptible crypto currency mining population
V_C	Resistance crypto currency mining population
L_C	Newbies of crypto currency miners
A_C	Addictive crypto currency miners
C_C	Counseling class of crypto currency miners
R_C	The recovered class of the currency mining population
N	Total population of crypto currency miners

3. Method of Model Analysis

This part builds the equilibrium point, analyzes the model's stability, and demonstrates that the model equation's solution is bounded:

3.1. Fundamental Characteristics of the Model

3.1.1. Positivity and Solution Boundedness

Determining the conditions under which the system should have a positive solution is crucial. The model would have biological importance if all solutions with positive initial circumstances remained positive over time.

Theorem 1

If the initial condition of the model is within,

$\Phi = \{(V_c, S_c, L_c, A_c, C_c, R_c) \in \Re_+^6 : 0 \le N(t) \le \frac{\Lambda}{\mu}$ then all solutions of the system equations of the model enter and remain in Φ

Proof

Given the set $\left(V_c(t), S_c(t), L_c(t), A_c(t), C_c(t), R_c(t)\right)$ with any solution of the system (3),

$N = V_c + S_c + L_c + A_c + C_c + R_c$, then we have,

$$\frac{dN}{dt} \le \Lambda - \delta_1 Lc - \delta_2 A_c - \mu N \tag{4}$$

If there is no death due to the activities of newbies and the addicted crypto mining individuals, Equation (8) becomes,

$$\frac{dN}{dt} + \mu N \le \Lambda$$

By the method of integrating factor, we have,

$$Ne^{\mu t} \le \frac{\Lambda}{\mu} e^{\mu t} + C$$

$$N \le \frac{\Lambda}{\mu} + Ce^{-\mu t}$$

Then as $t \to \infty \quad N(t) \to \frac{\Lambda}{\mu}$. Hence, the model positive invariant region is given by;

$$\Phi = \{(V_c, S_c, L_c, A_c, C_c, R_c) \in \Re_+^6 : 0 \le N(t) \le \frac{\Lambda}{\mu}$$

Theorem 2

The system of solution *(3.1-3.6)* with the initial state *(3.7)* remains positive and uniformly bounded inside the region.

$$\Phi = \{(V_c, S_c, L_c, A_c, C_c, R_c) \in \Re^6_+ : 0 \le V_c + S_c + L_c + A_c + C_c + R_c \le \frac{\Lambda}{\mu}\}$$

Proof

From Equation (1), $\frac{dS_c}{dt} = \Lambda + \alpha_2 V_c + \omega R_c - \frac{\beta\rho S_c A_c}{N} - \mu S_c$

$$\frac{dS_c}{dt} \le \Lambda - \mu S_c \tag{5}$$

Then we have

$$\frac{dS_c}{\Lambda - \mu S_c} \le dt$$

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

As $t \to \infty$ we obtain $0 \le S_c(t) \le \frac{\Lambda}{\mu}$. Hence, all feasible solutions for system (3) lie in the region ϕ. Thus, the model is well posed.

3.2. Crypto Mining Addiction-Free Equilibrium

The crypto currency addiction in the Free State (E_0) for the system is given by,

$$E_0 = \left(V_c^0, S_c^0, L_c^0, A_c^0, C_c^0, R_c^0\right)$$

$$= \left(\frac{\Lambda\alpha_1(\alpha_2+\mu)(1-\rho)}{\left(\mu(\alpha_2+\mu)+\alpha_1\alpha_2(1-\rho)\right)(\alpha_2+\mu)}, \frac{\Lambda(\alpha_2+\mu)}{\mu(\alpha_2+\mu)+\alpha_1\alpha_2(1-\rho)}, 0, 0, 0, 0\right)$$

3.3. Basic Reproduction Number (Ro) of the Model

In a fully sensitive population, the basic reproduction number (R_0) calculates the average number of new people who develop an addiction to crypto mining as a result of being influenced by one addict over their period of addiction (Diekmann and Heesterbeek 2002). The fundamental reproduction number (R_0) is determined using the next generation method as

$R_0 = \rho(FV^{-1})$ Where ρ is the spectral radius,

Given the matrices f and v below;

$$F_i = \begin{bmatrix} \frac{\beta\rho S_c A_c}{N} \\ 0 \end{bmatrix} \text{ And } V_i = \begin{bmatrix} (1-\kappa)\varphi L_c + \kappa\varepsilon L_c + (\mu+\delta_1)L_c \\ ((\mu+\delta_2)+\gamma)A_c - \kappa\varepsilon L_c \end{bmatrix}$$

At an addiction-free equilibrium,

$$F=\begin{bmatrix}0 & \dfrac{\beta\rho S_c}{N}\\ 0 & 0\end{bmatrix},\ V=\begin{bmatrix}(1-\kappa)\varphi+\kappa\varepsilon+(\mu+\delta_1) & 0\\ -\kappa\varepsilon & (\mu+\delta_2)+\gamma\end{bmatrix}$$

At free equilibrium,

$$F=\begin{bmatrix}0 & \dfrac{\beta\rho\mu(\alpha_2+\mu)}{\mu(\alpha_2+\mu)+\alpha_1\alpha_2(1-\rho)}\\ 0 & 0\end{bmatrix}$$

Thus, the basic reproduction number (R_0) of the dynamics of crypto currency mining $R_0=\rho(FV^{-1})$ is given below;

$$R_0=\frac{\beta\rho\mu(\alpha_2+\mu)\kappa\varepsilon}{\mu(\alpha_2+\mu)+\alpha_2\alpha_1(1-\rho)(1-\kappa)\phi+\kappa\varepsilon(\mu+\delta_1)(\mu+\gamma+\delta_2)} \tag{6}$$

Where,

$$\left.\begin{aligned}&C_1=\beta\rho\mu(\alpha_2+\mu), C_2=\mu(\alpha_2+\mu)+\alpha_1\alpha_2(1-\rho), C_3=(1-\kappa)\varphi+\kappa\varepsilon+(\mu+\delta_1)\\ &C_4=\mu+\gamma+\delta_2\end{aligned}\right\}$$

3.4. Local Stability of Addiction-Free Equilibrium

3.4.1. Theorem 1

The addiction-free equilibrium of the model equation is locally stable if $R_0 < 1$ and unstable if $R_0 > 1$.

3.4.2. Proof

To determine the local stability, the Jacobian matrix is computed and evaluated at the addiction-free equilibrium $E_0=\left(0,\dfrac{\Lambda}{\mu},0,0,0,0\right)$.

$$J(E_0)=\begin{bmatrix}-q_1 & q_2 & 0 & 0 & 0 & 0\\ \alpha_2 & -q_3 & 0 & q_4 & 0 & 0\\ 0 & 0 & -q_5 & q_4 & 0 & 0\\ 0 & 0 & \kappa\varepsilon & -q_6 & 0 & 0\\ 0 & 0 & q_7 & \gamma & -q_8 & 0\\ 0 & 0 & 0 & 0 & \sigma & -q_9\end{bmatrix} \tag{7}$$

Where,

$$\left.\begin{aligned}&q_1=\alpha_2+\mu, q_2=(1-\rho)\alpha_1, q_3=\mu+(1-\rho)\alpha_1, q_4=\frac{\beta\rho\mu(\alpha_2+\mu)}{\mu(\alpha_2+\mu)+\alpha_1\alpha_2(1-\rho)}\\ &q_5=1-\kappa)\varphi+\kappa\varepsilon+(\mu+\delta_1, q_6=\mu+\gamma+\delta_2, q_7=(1-\kappa)\varphi, q_8=\sigma+\mu, q_9=\omega+\mu\end{aligned}\right\} \tag{8}$$

The characteristic polynomial of Equation (7) gives where, $A_0 = 1$,

$$A_1 = (\kappa\varepsilon\alpha_2 q_2 q_4 - \kappa\varepsilon q_1 q_3 q_4 - \kappa\varepsilon q_1 q_4 q_8 - \kappa\varepsilon q_1 q_4 q_9 - \kappa\varepsilon q_3 q_4 q_8 - k\varepsilon q_3 q_4 q_9$$
$$-k\varepsilon q_8 q_4 q_9 - \alpha_2 q_2 q_5 q_6$$
$$-\alpha_2 q_2 q_5 q_8 - \alpha_2 q_2 q_5 q_9 - \alpha_2 q_2 q_6 q_8 - \alpha_2 q_2 q_6 q_9 - \alpha_2 q_2 q_8 q_9$$
$$+q_1 q_3 q_5 q_6 + q_1 q_3 q_5 q_8 + q_1 q_3 q_5 q_9 + q_1 q_3 q_6 q_8 + q_1 q_3 q_6 q_9 + q_1 q_3 q_8 q_9$$
$$+q_1 q_5 q_6 q_8 + q_1 q_5 q_6 q_9 + q_1 q_5 q_8 q_9 + q_1 q_6 q_8 q_9$$
$$+q_3 q_5 q_6 q_8 + q_3 q_5 q_6 q_9 + q_3 q_5 q_8 q_9 + q_3 q_6 q_8 q_9 + q_5 q_6 q_8 q_9)$$

$$A_2 = (\kappa\varepsilon\alpha_2 q_2 q_4 - \kappa\varepsilon q_1 q_3 q_4 - k\varepsilon q_1 q_4 q_8 - k\varepsilon q_1 q_4 q_9 - k\varepsilon q_3 q_4 q_8 + k\varepsilon q_3 q_4 q_9$$
$$-k\varepsilon q_4 q_8 q_9 - \alpha_2 q_2 q_5 q_6 - \alpha_2 q_2 q_5 q_8 - \alpha_2 q_2 q_5 q_9$$
$$-\alpha_2 q_2 q_6 q_8 - \alpha_2 q_2 q_6 q_9 - \alpha_2 q_2 q_8 q_9$$
$$+q_1 q_3 q_5 q_6 + q_1 q_3 q_5 q_8 + q_1 q_3 q_5 q_9 + q_1 q_3 q_6 q_8 + q_1 q_3 q_6 q_9$$
$$+q_1 q_3 q_8 q_9 + q_1 q_5 q_6 q_8 + q_1 q_5 q_6 q_9 + q_1 q_5 q_8 q_9 + q_1 q_6 q_8 q_9 + q_3 q_5 q_6 q_8$$
$$+q_3 q_5 q_6 q_9 + q_3 q_5 q_8 q_9 + q_3 q_6 q_8 q_9 + q_5 q_6 q_8 q_9$$

$$A_3 = (K\varepsilon\alpha_2 q_2 q_4 - \kappa\varepsilon q_1 q_3 q_4 - k\varepsilon q_1 q_4 q_8 - k\varepsilon q_1 q_4 q_9 - k\varepsilon q_3 q_4 q_8 - k\varepsilon q_3 q_4 q_9$$
$$-k\varepsilon q_4 q_8 q_9 - \alpha_2 q_2 q_5 q_6 - \alpha_2 q_2 q_5 q_8 - \alpha_2 q_2 q_5 q_9 - \alpha_2 q_2 q_6 q_8$$
$$-\alpha_2 q_2 q_8 q_9 + q_1 q_3 q_5 q_6 + q_1 q_3 q_5 q_8 + q_1 q_3 q_5 q_9 + q_1 q_3 q_6 q_8 + q_1 q_3 q_6 q_9$$
$$+q_1 q_3 q_8 q_9 + q_1 q_5 q_6 q_8 + q_1 q_5 q_6 q_9 + q_1 q_5 q_8 q_9 + q_1 q_6 q_8 q_9$$
$$+q_3 q_5 q_6 q_8 + q_3 q_5 q_6 q_9 + q_3 q_5 q_8 q_9 + q_3 q_6 q_8 q_9 + q_5 q_6 q_8 q_9)$$

$$A_4 = (K\varepsilon\alpha_2 q_2 q_4 - \kappa\varepsilon q_1 q_3 q_4 - k\varepsilon q_1 q_4 q_8 - k\varepsilon q_1 q_4 q_9$$
$$-k\varepsilon q_3 q_4 q_8 - k\varepsilon q_3 q_4 q_9 - k\varepsilon q_4 q_8 q_9 - \alpha_2 q_2 q_5 q_6 - \alpha_2 q_2 q_5 q_8$$
$$-\alpha_2 q_2 q_6 q_9 - \alpha_2 q_2 q_8 q_8 + q_1 q_3 q_5 q_6 + q_1 q_3 q_5 q_8 + q_1 q_3 q_5 q_9$$
$$+q_1 q_3 q_6 q_8 + q_1 q_3 q_6 q_9 + q_1 q_3 q_8 q_9 + q_1 q_5 q_6 q_8 + q_1 q_5 q_8 q_9 + q_1 q_6 q_8 q_9$$
$$+q_3 q_5 q_6 q_8 + q_3 q_5 q_6 q_9 + q_3 q_5 q_8 q_9 + q_3 q_6 q_8 q_9 + q_5 q_6 q_8 q_9)$$

$$A_5 = (K\varepsilon\alpha_2 q_2 q_4 q_8 - \kappa\varepsilon q_1 q_3 q_4 q_9 - k\varepsilon q_1 q_3 q_4 q_8 - k\varepsilon q_1 q_3 q_4 q_9 - k\varepsilon q_1 q_8 q_4 q_9 - k\varepsilon q_3 q_4 q_8 q_9$$
$$-\alpha_2 q_2 q_5 q_6 q_8 - \alpha_2 q_2 q_5 q_6 q_9 - \alpha_2 q_2 q_5 q_8 q_9 - \alpha_2 q_2 q_6 q_8 q_9$$
$$+q_1 q_3 q_5 q_6 q_8 + q_1 q_3 q_5 q_6 q_9 + q_1 q_3 q_5 q_8 q_9$$
$$+q_1 q_3 q_6 q_8 q_9 + q_1 q_5 q_6 q_8 q_9 + q_3 q_5 q_6 q_8 q_9)$$

$$A_6 = q_9 q_8 (k\varepsilon\alpha_2 q_2 q_4 - k\varepsilon q_1 q_3 q_4 - \alpha_2 q_2 q_5 q_6 + q_1 q_3 q_5 q_6)$$

Applying the Routh-Hurwitz criterion, which states that all roots of the polynomial have negative real parts if and only if the coefficients A_i (i=0, 1, 2, 3) are positive and matrices $H_i > 0$, for (i = 0, 1, 2, 3, 4). Therefore, from Equation (7), we have,

$$H = \begin{pmatrix} A_1 & A_0 & 0 & 0 & 0 & 0 \\ A_3 & A_2 & A_1 & A_0 & 0 & 0 \\ A_5 & A_4 & A_3 & A_2 & A_1 & A_0 \\ 0 & A_6 & A_5 & A_4 & A_3 & A_2 \\ 0 & 0 & 0 & A_6 & A_5 & A_4 \\ 0 & 0 & 0 & 0 & 0 & A_6 \end{pmatrix} \quad (9)$$

H is called a Hurwitz matrix, and the principal minors are

$$H_1 = A_1 > 0$$

$$H_2 = \begin{vmatrix} A_1 & A_0 \\ A_3 & A_2 \end{vmatrix} = A_1A_2 - A_0A_3 > 0$$

$$\Rightarrow A_1A_2 > A_0A_3$$

$$H_3 = \begin{vmatrix} A_1 & A_0 & 0 \\ A_3 & A_2 & A_1 \\ A_5 & A_4 & A_3 \end{vmatrix} > 0$$

$$H_3 = A_1 \begin{vmatrix} A_2 & A_1 \\ A_4 & A_3 \end{vmatrix} - A_0 \left\|\begin{matrix} A_1 & 0 \\ A_5 & A_3 \end{matrix}\right\| + 0 \begin{vmatrix} A_1 & A_0 \\ A_3 & A_2 \end{vmatrix}$$

$$A_1A_2A_3 - A_1^2A_4 + A_0A_1A_3$$

$A_1A_2A_3 - A_1^2A_4 + A_1A_3 > 0$ If and only if

$$A_1A_2A_3 > (A_1^2A_4 + A_1A_3)$$

$$H_4 = \begin{vmatrix} A_1 & A_0 & 0 & 0 \\ A_3 & A_2 & A_1 & A_0 \\ A_5 & A_4 & A_3 & A_2 \\ 0 & 0 & A_5 & A_4 \end{vmatrix} > 0$$

$$= A_1 \begin{vmatrix} A_2 & A_1 & A_0 \\ A_4 & A_3 & A_2 \\ 0 & A_5 & A_4 \end{vmatrix} - A_0 \begin{vmatrix} A_1 & 0 & 0 \\ A_5 & A_3 & A_2 \\ 0 & A_5 & A_4 \end{vmatrix}$$

$$= A_1A_2 \begin{vmatrix} A_3 & A_2 \\ A_5 & A_4 \end{vmatrix} - A_1^2 \left\|\begin{matrix} A_2 & A_0 \\ 0 & A_4 \end{matrix}\right\| + A_1A_0 \begin{vmatrix} A_2 & A_1 \\ A_4 & A_3 \end{vmatrix} - A_0A_1 \begin{vmatrix} A_3 & A_2 \\ A_5 & A_4 \end{vmatrix}$$

$H_4 > 0$ If and only if

$$A_1A_2A_3A_4 + A_1 A_2A_3 + A_1A_2A_5 > (A_1A_2^2A_5 + A_1^2 \mathrm{A}_2\mathrm{A}_4 + \mathrm{A}_1^2\mathrm{A}_4 + A_1A_3A_4)$$

$$= A_1\begin{vmatrix} A_2 & A_1 & A_0 & 0 \\ A_4 & A_3 & A_2 & A_1 \\ 0 & A_5 & A_4 & A_3 \\ 0 & 0 & A_0 & A_5 \end{vmatrix} - A_0\begin{vmatrix} A_1 & 0 & 0 & 0 \\ A_5 & A_3 & A_2 & A_1 \\ 0 & A_5 & A_4 & A_3 \\ 0 & 0 & 0 & A_5 \end{vmatrix}$$

$$A_1A_2\begin{vmatrix} A_3 & A_2 & A_1 \\ A_5 & A_4 & A_3 \\ 0 & 0 & A_5 \end{vmatrix} - A^2{}_1\begin{vmatrix} A_2 & A_0 & 0 \\ 0 & A_4 & A_3 \\ 0 & 0 & A_5 \end{vmatrix} + A_1A_0\begin{vmatrix} A_2 & A_1 & 0 \\ A_4 & A_3 & A_1 \\ 0 & 0 & A_5 \end{vmatrix} - A_0A_1\begin{vmatrix} A_3 & A_2 & A_1 \\ A_5 & A_4 & A_3 \\ 0 & 0 & A_5 \end{vmatrix}$$

$H_5 > 0$ If and only if

$$A_1A_3A_5{}^2 + 2A_1A_4A_5{}^2 + A_1A_2A_3A_4A_5 > (A_3{}^2A_4A_5 + A_1{}^2A_2A_5{}^2 + A_1{}^2A_4{}^2A_5 + A_5{}^3)$$

$$H_6 = \begin{vmatrix} A_1 & A_0 & 0 & 0 & 0 & 0 \\ A_3 & A_2 & A_1 & A_0 & 0 & 0 \\ A_5 & A_4 & A_3 & A_2 & A_1 & A_0 \\ 0 & A_6 & A_5 & A_4 & A_3 & A_2 \\ 0 & 0 & 0 & A_6 & A_5 & A_4 \\ 0 & 0 & 0 & 0 & 0 & A_6 \end{vmatrix} > 0$$

$H_6 > 0$ If and only if

$$2A_1{}^2A_2A_5A_6{}^2 + A_1{}^2A_3A_4A_6{}^2 + 2A_1A_4A_5{}^2 + A_2A_3A_5{}^2 + A_3{}^3A_6{}^2 + A_1A_2A_3A_4A_5 > (A_1{}^2A_4{}^2A_5$$
$$+ A_1A_2{}^2A_5{}^2 + A_1A_2A_3{}^2A_6{}^2 + 3A_1A_3A_5A_6{}^2 + A_3{}^2A_4A_5 + A_5{}^3 + A_1{}^3A_6{}^3)$$

Therefore, all the eigenvalues of the Jacobian matrix $J(\mathrm{E}_0)$ have negative real parts when $R_0 < 1$ the disease-free equilibrium point is locally asymptotically stable.

3.5. Sensitivity Analysis

The threshold quantity's (R_0) behavior in relation to its parameters is examined using the sensitivity analysis. Thus, it enables us to find the characteristics that have a considerable impact on (R_0). Intervention strategies should focus on these in order to determine the best way to control this addiction. Below, we will calculate the reproduction number's normalized forward sensitivity index in relation to both natural recovery and the included vector reduction.

3.5.1. Definition

Supposing a variable 'P' which is differentiable, depends on a parameter 'w', then, the normalized forward sensitivity index of 'p' with respect to 'w' is denoted by Xp, which is defined as,

$$Xp = \frac{p}{w}\frac{\partial w}{\partial p}$$

As we have explicitly shown R_0, we derive an analytical expression for the sensitivity of R_0 as,

$$X_w^{R_0} = \frac{dR_0}{dw} \times \frac{w}{R_0}$$

For each parameter involved R_0, the results of the sensitivity indices R_0 are as shown in the table below.

Table 2. Numerical values of the sensitivity Analysis of the parameters

Parameter	Descriptions	Sensitivity Values
R_0	Reproduction number	0.0001772048912
β	interaction rate between crypto currency miners and susceptible individuals	1
ρ	Proportion of susceptible individuals that leave the susceptible class	1
μ	Per capita death rate	0.5696873613
κ	Proportion	1
ε	Progression rate into addiction	0.9915895713
α_2	Rate at which immune individuals lose immunity and become susceptible again	-0.3051204118
γ	Rate at which addicted individuals go for counselling	0.56813
δ_1	Death as a result of the mining activity of newbies	-0.02102607233
δ_2	Death as a result of the mining activity of addicted individuals	-0.02298850575
φ	Rate at which newbies or those exposed go for consoling	-0.8654331370
α_1	Rate at which the susceptible build immunity against mining addiction	-0.4271685760

4. Numerical Simulation

The numerical behavior of the model equation is studied using MAPLE 18 software with parameter values presented in the table below;

Table 3. Description of Parameters with Values

Parameter	Description	Values
Λ	Recruitment term of the susceptible individuals	0.5
α_1	Rate at which the susceptible build immunity against mining addiction	0.1
α_2	Rate at which immune individuals lose immunity and become susceptible again	0.02
ρ	Proportion of susceptible individuals that leave the susceptible class	0.1
φ	Rate at which newbies or those exposed go for consoling	0.0027
β	interaction rate between crypto currency miners and susceptible individuals	0.32
γ	Rate at which addictive individuals go for conseling	0.8
μ	Natural death rate	0.05-0.25
σ	Rate at which individuals who are consoling move to the recovery class	0.7
δ_1	Death as a result of the mining activity of newbies	0.01
δ_2	Death as a result of the mining activity of addicted individuals	0.02
ω	Rate at which recovered individuals move back to the susceptible class	0.35
κ	Proportion	0.02

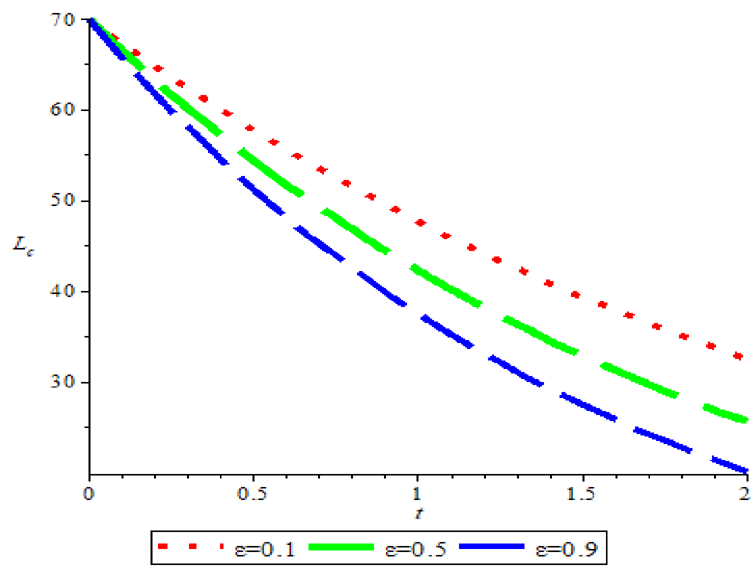

Fig. 2 Graph showing the impact of addiction on the newbie class

This Figure 2 shows the trend of addiction among novices over time. It shows that when more people are exposed to crypto currency mining, the number of new participants progressively increases before stabilizing or declining in response to intervention measures.

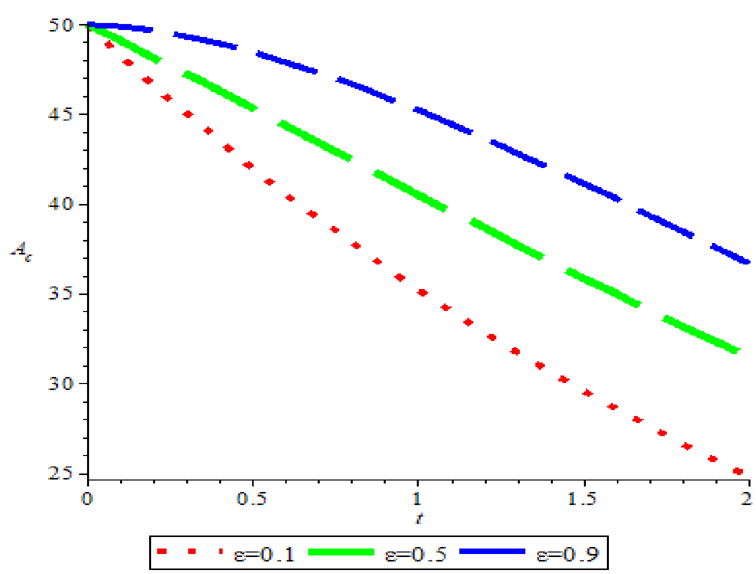

Fig. 3 Shows the impact of progression rate from newbies on the addiction class

This Figure 3 highlights the transition from the newbie class to addiction. It reveals that as engagement intensifies, individuals quickly progress from casual mining to addictive behaviors, emphasizing the need for early intervention.

The impact of counseling on lowering the number of people in the novice category is illustrated in this Figure 4. The decrease in the number of newbies suggests that successful counseling can reroute people before they get completely addicted.

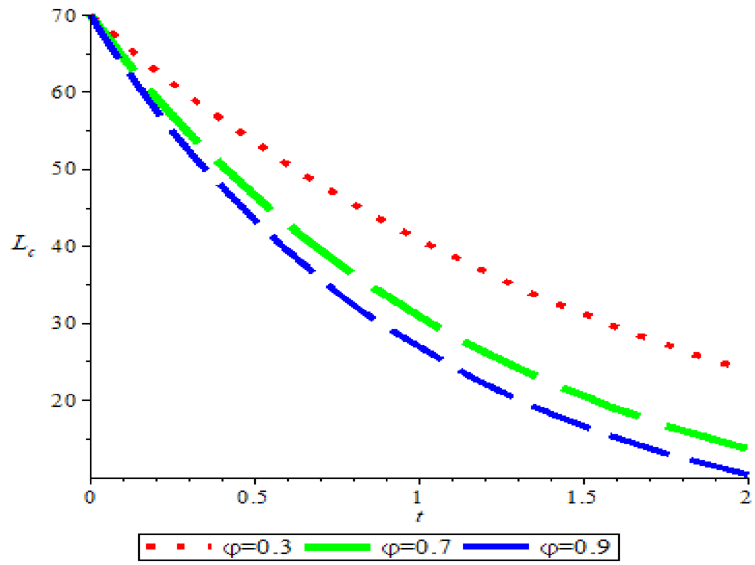

Fig. 4 Shows the effect of counseling on the newbies class

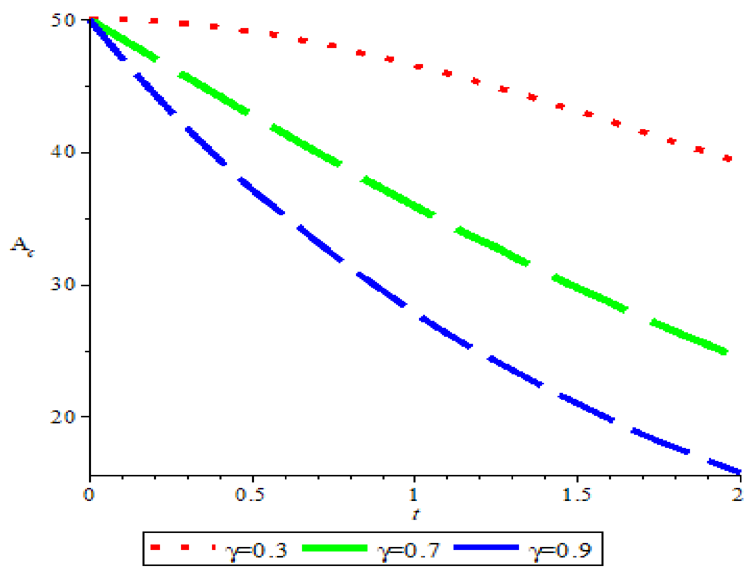

Fig. 5 Shows the impact of counseling on crypto currency mining addiction

The overall effect of counseling on lowering addiction to crypto currency mining is depicted in this Figure 5. Addiction rates are steadily declining as more people seek therapy and treatment.

This Figure 6 statistic demonstrates how well counseling works to encourage recovery. It shows that the number of people who have recovered increases dramatically with the number of counseling interventions, indicating that structured treatment programs are essential to understanding the mechanics of mining addiction.

The effect of recovery on the vulnerable population is depicted in this Figure 7. It highlights the cyclical nature of addiction and the significance of ongoing prevention initiatives by demonstrating that more people who recover from addiction return to the susceptible class.

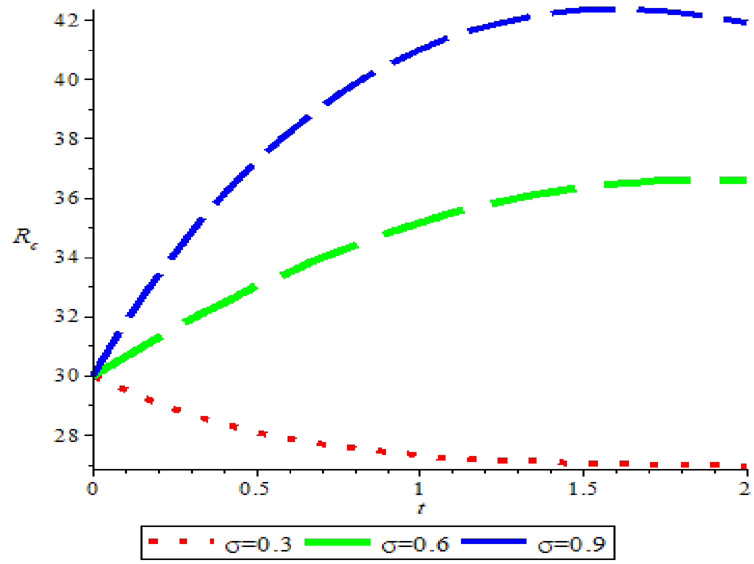

Fig. 6 Shows the effectiveness of counseling on recovering from crypto currency mining addiction

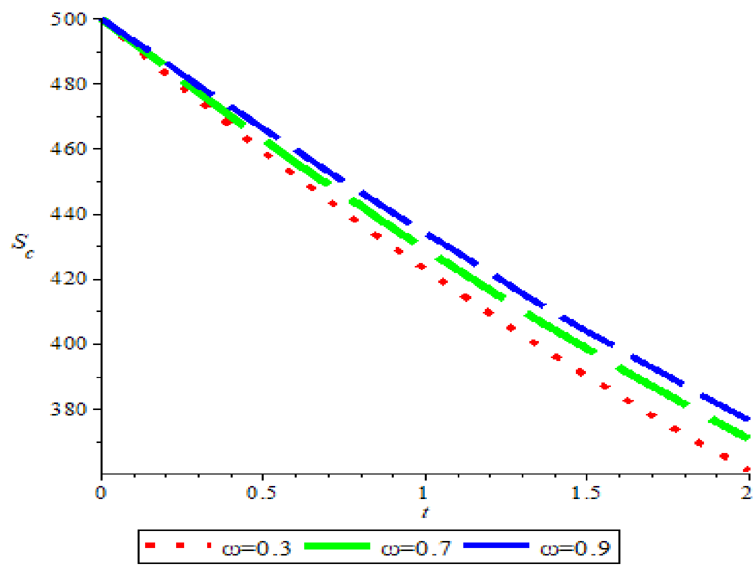

Fig. 7 Shows the effectiveness of recovery on the susceptible population

5. Conclusion

The mechanics of crypto currency mining addiction were examined in this study. A thorough derivation and analysis of the model's basic reproduction number, existence, and stability of the Crypto Currency Mining Addiction Free Equilibrium point (CCMAFE) were conducted. The study demonstrates that the (CCMAFE) is locally asymptotically stable if the reproduction number is smaller than one. This suggests that the addiction to mining crypto currency dies out since only people who are sensitive and resistant to it remain, while the other populations drop to zero. All population groups are present in the model, albeit if the reproduction number is higher than one, indicating that the system is unstable. The Addiction-Free Equilibrium (AFE) occurs when $R_0 < 1$. Thus, crypto currency mining addiction does not persist in the long run. Stability analysis using the Routh-Hurwitz criterion confirms that the AFE is locally asymptotically stable when $R_0 < 1$. Using Maple18, numerical simulations were run to examine how the system behaved with various parameter settings.

The findings showed how several factors affect trends in addiction. The number of vulnerable people declines (as illustrated in Figure 2) as more people become rookies through encounters with addicts, whereas the addiction class rises (as illustrated in Figure 3). Figure 5 shows that the number of addiction classes decreases dramatically when more people seek counseling. Additionally, the data demonstrates that the more people who seek treatment, the higher the recovery rate from addiction to crypto currency mining, which in turn increases the population at risk (Figures 6 and 7).

These results highlight the value of intervention techniques like therapy and public education initiatives in halting the rise of addiction to crypto currency mining.

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