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MODELING THE SPREAD OF AI-GENERATED CONTENT USING SIRS MODELS: IMPLICATIONS FOR INTELLECTUAL PROPERTY RIGHTS IN THE DIGITAL AGE

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Abstract
This paper presents a novel application of the classical SIRS (Susceptible–Infected–Recovered-Susceptible) model to study the spread of AI-generated content (AIGC) and its implications for Intellectual Property Rights (IPR). In the digital age, rapid content dissemination poses legal and ethical challenges. By modeling the dynamics of AIGC propagation, we aim to quantify its reach and propose informed interventions for digital content regulation.
Keywords: AI-generated content, Intellectual Property Rights, SIRS model, Copyright, Patent Law, Mathematical Modeling, Legal Enforcement.

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1. Introduction
Artificial Intelligence (AI) has revolutionized the production of content in all domains, from text, images, and music to code. Platforms like ChatGPT, DALLE, and Midjourney now allow individuals to create and disseminate content at a tremendous scale. This transition has opened up creative tools to more people but also poses challenging questions for today's legal environment, particularly Intellectual Property Rights (IPR).
The rapid and often unregulated dissemination of AI-generated content (AIGC) raises concerns about authorship, ownership, and fair use. In this study, we represent the dissemination of AIGC through a classical SIRS (Susceptible–Infected–Recovered–Susceptible) framework, conceptualizing digital users as a population that can be susceptible to, influenced by, or recovered from uncritical propagation of AIGC content.

2. Literature Review
The sheer pace of AI-based content growth on digital platforms poses formidable challenges in authenticating content, safeguarding intellectual property rights, and creating user awareness. To make sense of such developments, researchers have begun to extend mathematical models initially designed to model the propagation of infectious diseases to the context of digital communication. Some of these models are for modeling the propagation of rumours, misinformation, and virality of content.
Digital epidemiology and rumour diffusion theory are the central pillars of this research. Zanette [6] presented a model for rumour spreading in small-world networks early on, with the first comparisons drawn between social communication and epidemic spread. His research emphasized

the significance of network topology in determining the manner in which information propagates and goes viral.

Kiss et al. [1] built upon this method in their book Mathematics of Epidemics on Networks, detailing how modifications of the Susceptible-Infectious-Recovered (SIR) model may be used in extensive digital and social networks. Their equations form a sound theoretical foundation for modeling user activity within an evolving digital system—reflecting the phases by which AIGC progresses from initial acquaintance to mass sharing and ultimately to decline.

To explain behaviours such as awareness and forgetting, Funk et al. [2] created models that involve how awareness of an epidemic or misinformation can decrease the spread, altering the overall dynamics of an outbreak. This idea is important in this project demonstrate that users may cease to share AI-created content either because awareness of IP issues increases or policy has changed.

Yang and Jin [3] took these concepts even further by adding forgetting rates and policy decay to their models, illustrating how users can revert back to previous uninformed behaviour. These factors map over to the δ parameter in our model, which is the degradation of user watchfulness or the potency of policy actions. Aside from the technical, there has been increased talk regarding the legal and ethical ramifications of content created by AI. Smith's [7] critical analysis of ownership of IP rights over AI-generated works questions the very basis of authorship, attribution, and liability. This is a socio-legal complement to the technical modeling, highlighting the importance of increased user consciousness and regulatory frameworks. Together, these works form a rich interdisciplinary foundation-encompassing mathematics, the behavioural sciences, and law-that substantiates the construction and validation of our extended SIRS-based model for simulating the spread of AI-generated material.

3. Model Formulation

We consider a closed population N of digital users interacting with AI-generated content (AIGC). At time t, the population is divided into three compartments:

- U(t): Unaware users — individuals who have not yet encountered AIGC or are unaware of IPR issues.
- A(t): Active users — those sharing or using AIGC without understanding copyright or ethical implications.
- K(t): Knowledgeable users — those who are aware of IPR regulations and refrain from uncritical sharing.
- The total population is N = U(t) + A(t) + K(t).

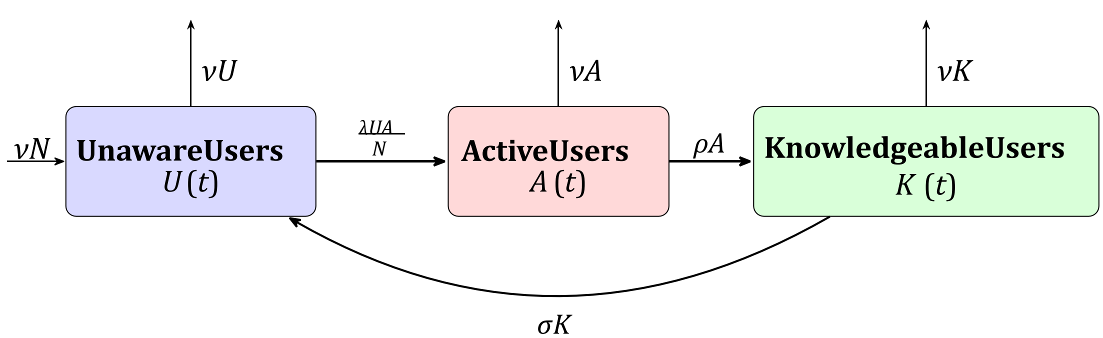

Figure 1: SIRS model flow for AI-generated content sharing

The resulting system of differential equations describing the dynamics of AI-content spread is formulated as follows:

$$\frac{dU}{dt} = \nu N - \frac{\lambda U A}{N} - \nu U + \sigma K, \quad (1)$$

$$\frac{dA}{dt} = \frac{\lambda U A}{N} - \rho A - \nu A, \quad (2)$$

$$\frac{dK}{dt} = \rho A - \sigma K - \nu K, \quad (3)$$

This SIRS-type model captures the circulation of users between unawareness, active sharing, and knowledge, analogous to classical epidemiological processes, but applied to the digital spread of AI-generated content.

4. Model Parameters

Table 1 Parameters and compartment definitions in the SIRS-AIGC model

Symbol	Description
ν	User turnover rate (rate at which users join or leave the platform)
λ	Exposure rate (probability that an unaware user becomes active upon contact with AIGC)
ρ	Awareness rate (rate at which active users become knowledgeable and stop uncritical sharing)
σ	Forgetfulness rate (rate at which knowledgeable users revert to being unaware)
N	Total number of digital users in the ecosystem
$U(t)$	Unaware users at time t
$A(t)$	Active sharers of AIGC at time t
$K(t)$	Knowledgeable (IP-aware) users at time t

Model Interpretation

Equation (1) shows that unaware users increase by new user entry (ν) and those losing immunity (σK), but decrease when exposed to AI content or leave the system.

Equation (2) models active sharers $A(t)$. Users enter this compartment through exposure to AIGC (λUA) and leave it via awareness (ρA) or platform exit (νA).

Equation (3) captures the dynamics of knowledgeable users $K(t)$. This group increases as active sharers become aware (ρA) and decreases due to forgetfulness (σK) or leaving the system (νK).

This framework provides insight into the spread of AI-generated content and the effect of awareness strategies on controlling uncritical sharing.

To simplify the analysis, we can consider the proportions of users in each compartment relative to the total population. Let

$$u(t) = \frac{U(t)}{N}, \quad a(t) = \frac{A(t)}{N}, \quad k(t) = \frac{K(t)}{N}$$

represent the fractions of unaware, active, and knowledgeable users at time t. Assuming a constant total population N, the proportion-based system becomes:

$$\frac{du}{dt} = \nu - \lambda ua - \nu u + \sigma k, \qquad (4)$$

$$\frac{da}{dt} = \lambda ua - \rho a - \nu a, \qquad (5)$$

$$\frac{dk}{dt} = \rho a - \sigma k - \nu k, \qquad (6)$$

with the natural constraint: *u(t) + a(t) + k(t) = 1.*

5. Positivity and Well-Posedness of the Model

To ensure interpretability and practical relevance of the SIRS model for AI-generated content (AIGC) dissemination, we verify that the model yields non-negative and bounded solutions when initialized with realistic (non-negative) proportions of users in different digital states.

5.1 Digital Positivity of Solutions

We assume the initial conditions:

$$u(0) \geq 0, \qquad a(0) \geq 0, \qquad k(0) \geq 0, \qquad u(0) + a(0) + k(0) = 1$$

As the model is framed in normalized proportions, it reflects a digital population where the sum of all user states remains conserved over time.

To illustrate positivity, consider the infectious compartment. If at any time a(t) → 0, then:

$$\left.\frac{da}{dt}\right|_{a=0} = \lambda u \cdot 0 - \rho \cdot 0 - \nu \cdot 0 = 0$$

implying that *a(t)* cannot fall below zero. A similar argument holds for *u(t)* and *k(t)*. Hence, the system inherently ensures:

$$u(t),\ a(t),\ k(t) \geq 0 \qquad \text{for all } t \geq 0$$

This mathematical guarantee of non-negativity is critical for digital policy models, as it precludes the unrealistic scenario of negative users and ensures interpretability in AI content governance simulations.

5.2 Boundedness and Feasibility

Since *u(t)+a(t)+k(t) = 1,* all compartments remain bounded in [0,1]. The feasible solution space is:

$$\Omega = \{(u, a, k) \in \mathbb{R}^3_+ : u + a + k = 1\}$$

which is positively invariant under the dynamics.

6. Basic Reproduction Number and Equilibria

To understand the long-term behaviour of AI-generated content propagation in a digital population, we analyse the equilibria of the system and derive the basic reproduction number R_0, which determines whether the content dies out or becomes persistently shared.

6.1 Disease-Free Equilibrium (DFE)

At the Disease-Free Equilibrium (DFE), there are no infected users, i.e., *a* = 0. We seek steady-state values where the dynamics of the system vanish:

$$\frac{du}{dt} = \frac{da}{dt} = \frac{dk}{dt} = 0$$

substituting *a = 0,* we obtain:

$$\frac{da}{dt} = 0 \qquad \text{(trivially satisfied)}$$

From $\frac{dk}{dt} = 0$:

$$0 = \rho \cdot 0 - (\sigma + \nu)\, k \Rightarrow k = 0$$

From $\frac{du}{dt} = 0$

$$0 = \nu - \lambda u \cdot 0 - \nu u + \sigma k \Rightarrow u = 1$$

Hence, the Disease-Free Equilibrium is:

$$(u^0, a^0, k^0) = (1,0,0)$$

This equilibrium represents a fully susceptible digital population with no ongoing sharing of AI-generated content.

6.2 Basic Reproduction Number R_0

The basic reproduction number R_0 represents the expected number of secondary content sharers generated by a single''infected" user in an otherwise susceptible population. It is derived from the infection dynamics:

$$\frac{da}{dt} = a(\lambda u - \rho - \nu)$$

Evaluated at the DFE where u = 1, we have:

$$\left.\frac{da}{dt}\right|_{\text{DFE}} = a(\lambda - \rho - \nu)$$

Therefore, the basic reproduction number is:

$$R_0 = \frac{\lambda}{\rho + \nu}$$

This threshold parameter governs whether content proliferates ($R_0 > 1$) or fades away ($R_0 \leq 1$).

6.3 Endemic Equilibrium (EE)

The endemic equilibrium corresponds to a persistent level of AI content sharing, with $a > 0$. Setting all time derivatives to zero and using the steady-state assumptions:

From $\frac{da}{dt} = 0$:

$$\lambda u a - (\rho + \nu)a = 0 \quad \Rightarrow \quad u = \frac{\rho + \nu}{\lambda} = \frac{1}{R_0}$$

From $\frac{dk}{dt} = 0$

$$\rho a = (\sigma + \nu)k \quad \Rightarrow \quad k = \frac{\rho a}{\sigma + \nu}$$

Applying the normalization condition $u + a + k = 1$:

$$\frac{1}{R_0} + a + \frac{\rho a}{\sigma + \nu} = 1$$

Solving for a:

$$a\left(1 + \frac{\rho}{\sigma + \nu}\right) = 1 - \frac{1}{R_0} \quad \Rightarrow \quad a = \frac{1 - \frac{1}{R_0}}{1 + \frac{\rho}{\sigma+\nu}}$$

Then:

$$k = \frac{\rho}{\sigma + \nu} \cdot u$$

Thus, the endemic equilibrium is given by:

$$u^* = \frac{1}{R_0},$$
$$a^* = \frac{1 - \frac{1}{R_0}}{1 + \frac{\rho}{\sigma+\nu}},$$
$$k^* = \frac{\rho}{\sigma + \nu} \cdot u^*$$

Condition for Existence: The endemic equilibrium exists only when $R_0 > 1$, i.e., when the transmission rate of AI-generated content exceeds the combined removal rate due to awareness, regulation, or digital disengagement.

7. Stability Analysis

To assess the local behaviour of the system near its equilibria, we perform a linear stability analysis using the Jacobian matrix. This allows us to determine whether small perturbations around an equilibrium grow or decay over time-critical for evaluating the persistence or elimination of AI-generated content in a digital population.

7.1 Jacobian Matrix of the Reduced System

Since $k = 1 - u - a$, the normalized SIRS model reduces to a two-dimensional system:

$$\frac{du}{dt} = \nu - \lambda ua - \nu u + \sigma(1 - u - a)$$
$$\frac{da}{dt} = \lambda ua - (\rho + \nu)a \quad ,$$

Define the functions:

$f_1(u,a) = \nu - \lambda ua - \nu u + \sigma(1 - u - a)$, $\quad f_2(u,a) = \lambda ua - (\rho + \nu)\, a$

The Jacobian matrix is:

$$J(u,a) = \begin{bmatrix} \frac{\partial f_1}{\partial u} & \frac{\partial f_1}{\partial a} \\ \frac{\partial f_2}{\partial u} & \frac{\partial f_2}{\partial a} \end{bmatrix} = \begin{bmatrix} -\lambda a - \nu - \sigma & -\lambda u - \sigma \\ \lambda a & \lambda u - (\rho + \nu) \end{bmatrix} \quad (7)$$

7.2 Stability of the Disease-Free Equilibrium (DFE)

The Disease-Free Equilibrium is: $(u^0, a^0, k^0,) = (1,0,0)$.

Substituting u = 1, a = 0 into the Jacobian (7) yields:

$$J_{\mathrm{DFE}} = \begin{bmatrix} -(\nu + \sigma) & -(\lambda + \sigma) \\ 0 & \lambda - (\rho + \nu) \end{bmatrix}$$

The eigenvalues of this triangular matrix are:

$$\lambda_1 = -(\nu + \sigma), \quad \lambda_2 = \lambda - (\rho + \nu) = (\rho + \nu)(R_0 - 1), \quad R_0 = \frac{\lambda}{\rho + \nu}$$

Interpretation:

- $R_0 < 1$: both eigenvalues negative ⇒ DFE is locally asymptotically stable. Content spread dies out.
- $R_0 > 1$: $\lambda_2 > 0$ ⇒ DFE unstable. Content can spread virally.

8. Numerical Simulation and Sensitivity Analysis

We simulate the SIRS model using Python with normalized initial conditions:

$$u(0) = 0.9, \quad a(0) = 0.1, \quad k(0) = 0.$$

Here, $u(t)$, $a(t)$, and $k(t)$ denote the fractions of susceptible, infected, and recovered individuals, respectively, satisfying the constraint $u(t) + a(t) + k(t) = 1$ for all t.
For the simulation, the following parameter values (Table 1) are used:

$$\lambda = 0.6, \quad \rho = 0.2, \quad \sigma = 0.1, \quad \nu = 0$$

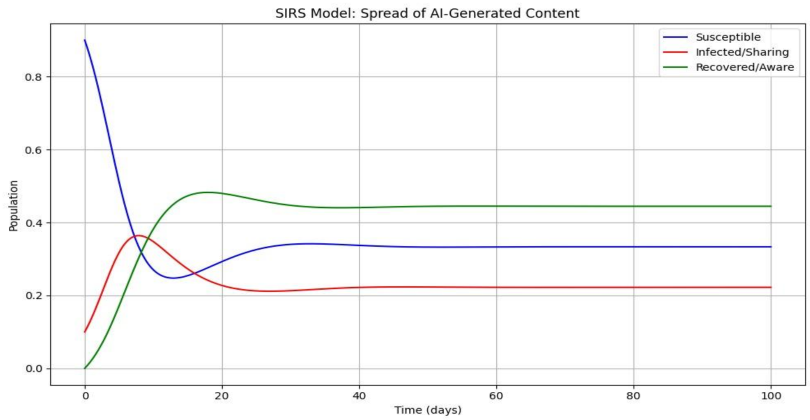

Figure 2: SIRS model simulation of AI-generated content spread: Susceptible (blue), Infected (red), and Recovered (green) over time.

Interpretation of the Simulation Initially, 10% of users are content sharers (a), while 90% are unaware (u). The infected fraction increases rapidly, then users recover ($\rho = 0.2$) or become susceptible again ($\sigma = 0.1$), producing cyclical dynamics. By day 100, the system stabilizes near $u \approx 0.33, a \approx 0.22, k \approx 0.44$.

Sensitivity of the Reproduction Number R_0 to Model Parameters

To assess the impact of intervention strategies, we analyze the sensitivity of a modified reproduction number:

$$R_0 = \frac{\lambda}{\rho + \nu}$$

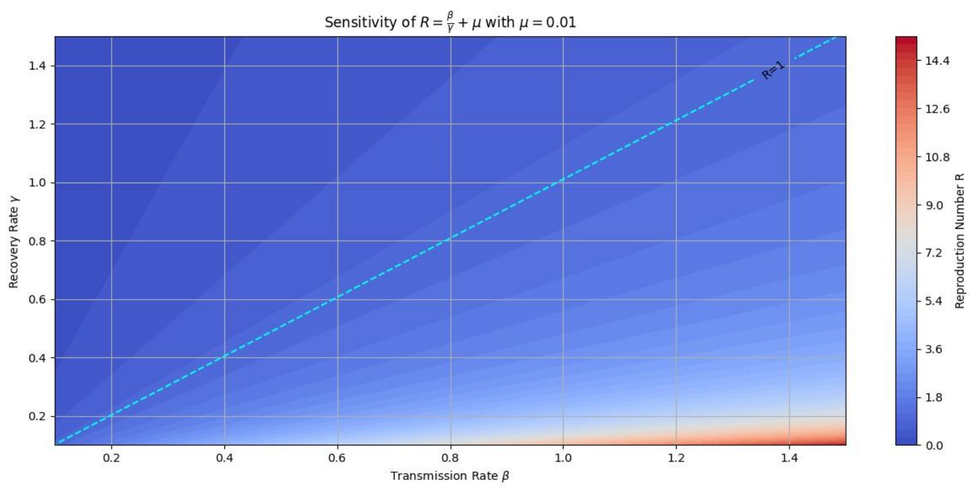

Figure 3: 2D contour plot showing sensitivity of reproduction number $R_0 = \frac{\lambda}{\rho + \nu}$ to variations in β and γ, with $\mu = 0.01$. The cyan dashed line marks the epidemic threshold $R_0 = 1$

Insights from Sensitivity Analysis: Figure 3 illustrates the threshold behavior of R_0. The cyan dashed line ($R_0 = 1$) separates regions of controlled (R_0< 1) and uncontrolled (R_0 > 1) spread of AI-generated content.

Insights:

- High λ or low ρ imples R_0 > 1, rapid content proliferation.
- Increasing ρ reduces R_0 , even if λ is high.
- Nonzero ν represents external content influx, potentially pushing R_0 > 1.

Implications for Intellectual Property Rights (IPR)

These findings have meaningful implications for IPR management in AI-driven digital environments:

- **Controlling λ**: Reducing unauthorized sharing (e.g., via watermarking, traceability, or algorithmic detection) limits the spread of infringing content.
- **Enhancing ρ:** Improving content recovery mechanisms (like awareness campaigns, automated flagging, or user training) increases the rate at which users disengage from or resist such content.
- **Addressing ν:** Persistent background content sources necessitate coordinated international frameworks to manage cross-platform content inflow and intellectual property compliance.

Hence, parameter tuning within the model framework aligns with real-world strategies for maintaining digital content integrity.

9. Conclusion

Normalized SIRS modeling with variables *u, a, k* shows that even with recovery mechanisms, some users remain susceptible. Small changes in λ or ρ can shift the system from controlled to uncontrolled content spread, providing guidance for IPR and digital content policies.

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