Journal of Computer Science and Frontier Technologies
ISSN Print: 3104-4204
ISSN Online: 3104-4212
CD ISSN: 3104-4220
https://doi.org/10.63313/JCSFT.9078

Transmission Dynamics Model Incorporating Risk Perception and Behavioral Fatigue

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How to cite this paper: Zhu, R. X. (2026). Transmission dynamics model incorporating risk perception and behavioral fatigue. Journal of Computer Science and Frontier Technologies, 3(2), 144-153. ISSN Print: 3104-4204, ISSN Online: 3104-4212.
https://doi.org/10.63313/JCSFT.9078
Published: 2026-05-21

Abstract

The classical SIR model provides a foundational framework for studying transmission dynamics, but its standard form often assumes a fixed transmission rate and therefore cannot directly represent adaptive changes in human behavior. In real transmission processes, individuals may reduce contact when perceived risk rises, while prolonged protection may also generate behavioral fatigue and weaken adherence. To describe this coupled mechanism, this paper extends the classical SIR model by introducing two bounded behavioral variables: risk perception and behavioral fatigue. The effective transmission rate is specified as an exponential function of these variables, which guarantees positivity and captures two opposite effects: risk perception suppresses transmission, whereas fatigue amplifies transmission. Ideal numerical simulations are conducted to compare the classical SIR model, a risk-perception-only model, and a full risk-perception-fatigue model. The results show that risk perception substantially lowers the infection peak and final epidemic size, while behavioral fatigue partially offsets the protective effect and delays the infection peak. Sensitivity analysis further indicates that increasing the risk-perception suppression coefficient reduces the epidemic scale, whereas increasing the fatigue amplification coefficient produces stronger rebound effects. The model offers a compact and interpretable framework for studying behavioral feedback in transmission dynamics.

Keywords

Transmission Dynamics; SIR Model; Risk Perception; Behavioral Fatigue; Behavioral Feedback; Numerical Simulation

1. Introduction

Compartmental models are widely used to analyze infectious disease transmission, information diffusion, rumor propagation, and other spreading processes. The SIR model introduced by Kermack and McKendrick remains one of the most influential mathematical frameworks for epidemic modeling [1]. Later work on infectious disease dynamics further clarified the role of threshold quantities, reproduction numbers, and compartmental transitions in epidemic analysis [2].

A major simplification in the classical SIR model is the assumption that the transmission rate is constant. This assumption is analytically convenient, but it neglects the fact that human behavior often changes endogenously as the perceived transmission risk changes. Reviews of behavior-disease modeling have emphasized that awareness, risk perception, information, and behavior change can reshape epidemic trajectories [3]. Awareness-based models also show that information and perceived risk may reduce contacts and affect outbreak size [4].

Risk perception is particularly important because individuals may reduce social contacts or strengthen protective behaviors when infection prevalence increases. Earlier models of spontaneous behavioral change and risk perception showed that uncoordinated individual responses can alter epidemic peaks and final epidemic sizes [5,6]. More recent COVID-19 studies reached similar conclusions: risk-driven contact reduction and adaptive social contact rates can generate complex dynamics, delayed peaks, and multiple waves [7,8].

At the same time, behavioral response is not always stable. During long-lasting public health crises, adherence to costly protective behaviors may decline. Empirical studies during COVID-19 examined hypothesized pandemic fatigue and found meaningful changes in protective behaviors across countries [9]. Other modeling work explicitly incorporated adherence fatigue together with risk-driven contact reduction, showing that fatigue can help explain multiple waves and time-varying transmission [7]. These findings suggest that a model containing only risk perception may overestimate the long-term effectiveness of protective behavior.

Recent studies and reviews have increasingly argued that epidemic models should incorporate endogenous human behavior rather than treating behavioral response as an external fixed input [10,11]. Motivated by this literature, this paper proposes a simple extension of the SIR model that jointly considers risk perception and behavioral fatigue. The model is not intended to reproduce a specific real outbreak; rather, it provides a concise theoretical and numerical framework for illustrating how protective response and fatigue can jointly shape transmission outcomes.

The contribution of this paper is threefold. First, it constructs a bounded behavioral feedback model in which risk perception suppresses the effective transmission rate and fatigue increases it. Second, it presents ideal simulation experiments comparing the proposed model with two baseline models. Third, it provides sensitivity analyses of the risk-perception suppression coefficient and the fatigue amplification coefficient, thereby clarifying their opposite roles in transmission dynamics.

2. Model Construction

2.1. Classical SIR Model

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The classical SIR model divides a closed population into susceptible, infected, and removed compartments [1,2]. Let S(t), I(t), and R(t) denote the numbers of susceptible, infected, and removed individuals at time t, respectively. The total population size is denoted by N, and

$$N = S(t) + I(t) + R(t).$$

The standard SIR model is written as

$$\frac{dS}{dt} = -\frac{\beta SI}{N}, \quad \frac{dI}{dt} = \frac{\beta SI}{N} - \gamma I, \quad \frac{dR}{dt} = \gamma I$$

Here, β is the transmission rate and γ is the recovery rate. The classical model is useful as a baseline because it clearly describes infection and removal mechanisms. However, the fixed value of β cannot reflect endogenous behavioral responses such as risk avoidance, social distancing, or fatigue-driven relaxation [3,10].

2.2. Behavioral Assumptions

The population is closed during the study period, so births, natural deaths, immigration, and emigration are not considered.

Homogeneous mixing is assumed. Each individual has the same average probability of contact with other individuals.

Infected individuals recover or are removed at a constant rate γ, and removed individuals no longer participate in transmission.

Risk perception is denoted by P(t), with P(t) in [0, 1]. A higher infected proportion activates stronger public risk perception, while risk perception decays naturally when transmission pressure decreases. This assumption is consistent with behavioral epidemic models in which awareness or perceived risk changes with epidemic states [4,6].

Behavioral fatigue is denoted by F(t), with F(t) in [0, 1]. Sustained high risk perception and long-term protection lead to fatigue accumulation, while fatigue naturally relaxes over time. This assumption is motivated by studies of adherence fatigue and pandemic fatigue [7,9].

The effective transmission rate depends on both behavioral variables. Risk perception decreases the transmission rate, while fatigue increases the transmission rate by weakening sustained protective behavior.

2.3. Improved Transmission Dynamics Model

Based on these assumptions, the proposed model is

$$\frac{dS}{dt} = -\frac{\beta(P,F)SI}{N},$$

$$\frac{dI}{dt} = \frac{\beta(P,F)SI}{N} - \gamma I,$$

$$\frac{dR}{dt} = \gamma I,$$
$$\frac{dP}{dt} = a\left(\frac{I}{N}\right)(1 - P) - bP,$$
$$\frac{dF}{dt} = cP(1 - F) - dF.$$

The effective transmission rate is defined as

$$\beta(P, F) = \beta^0 exp(-\alpha P + \eta F).$$

In this expression, β_0 is the baseline transmission rate in the absence of behavioral response, α is the suppression strength of risk perception, and η is the amplification strength of behavioral fatigue. The exponential form guarantees $\beta(P,F) > 0$, which avoids the mathematical problem of negative transmission rates. This structure also follows the general idea of using state-dependent or time-varying contact/transmission rates to represent adaptive behavior [8,10,11].
The risk perception equation contains an activation term and a decay term. The activation term $a(I/N)(1 - P)$ increases with the infected proportion I/N, while the factor (1 - P) keeps P(t) bounded. The decay term -bP indicates that risk perception declines when the epidemic signal weakens. The fatigue equation follows a similar bounded structure: cP(1 - F) accumulates fatigue under sustained risk perception, whereas -dF represents natural recovery from fatigue.

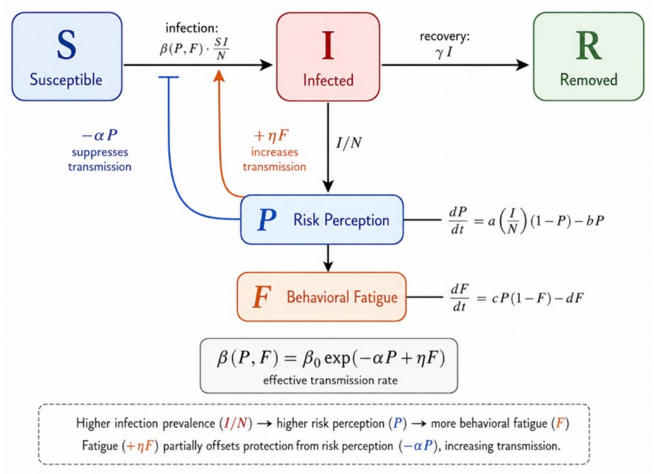

Figure 1. Conceptual framework of the proposed transmission dynamics model with risk perception and behavioral fatigue.

2.4. Parameter Definitions

Table 1. Model parameters and meanings

Parameter	Meaning	Interpretation
N	Total population size	Set to 100000 in the ideal simulation

β_0	Baseline transmission rate	Transmission strength without behavioral response
γ	Recovery rate	Rate at which infected individuals enter the removed state
α	Risk-perception suppression coefficient	Larger values imply stronger protective response
η	Fatigue amplification coefficient	Larger values imply stronger fatigue-driven rebound
a	Risk-perception activation rate	Effect of the infected proportion on risk perception
b	Risk-perception decay rate	Natural decline of risk perception
c	Fatigue accumulation rate	Fatigue induced by sustained risk perception
d	Fatigue relaxation rate	Natural recovery from behavioral fatigue

2.5. Basic Properties

Adding the first three equations gives

$$\frac{dS}{dt}+\frac{dI}{dt}+\frac{dR}{dt}= 0.$$

Therefore, $S(t) + I(t) + R(t) = N$ remains constant over time. This shows that the model preserves the closed-population assumption.

If the initial conditions satisfy $S(0) \geq 0$, $I(0) \geq 0$, $R(0) \geq 0$, $P(0) \in [0,1]$, and $F(0) \in [0,1]$, then all epidemiological variables remain nonnegative and $P(t)$, $F(t)$ remain in $[0,1]$. For example, when $P = 0$, $dP/dt = aI/N \geq 0$; when $P = 1$, $dP/dt = -b \leq 0$. Similarly, when $F = 0$, $dF/dt = cP \geq 0$; when $F = 1$, $dF/dt = -d \leq 0$. Thus, the interval $[0,1]$ is positively invariant for both behavioral variables.

The instantaneous effective reproduction number can be expressed as

$$R_t = \left[\frac{\beta(P,F)}{\gamma}\right]\cdot\left[\frac{S(t)}{N}\right].$$

When $R_t > 1$, the number of infected individuals tends to increase; when $R_t < 1$, it tends to decrease. Unlike the classical SIR model, R_t in the proposed model changes not only with the susceptible fraction but also with risk perception and fatigue.

3. Numerical Simulation Design

3.1. Purpose of the Simulation

The numerical simulation has three purposes. First, it compares the classical SIR model, the risk-perception-only model, and the full risk-perception-fatigue model. Second, it evaluates whether risk perception can reduce infection peaks and final epidemic size. Third, it examines whether fatigue can weaken the protective effect and lead to delayed or rebounding transmission. The numerical values used in this section are ideal simulation values, not empirical estimates from a specific country or region.

3.2 Initial Conditions and Baseline Parameters

The total population is set to N = 100000. The initial number of infected individuals is I(0) = 20, the initial number of removed individuals is R(0) = 0, and the initial number of susceptible individuals is therefore S(0) = 99980. The initial levels of risk perception and behavioral fatigue are both set to 0. The baseline parameters are shown in Table 2.

Table 2. Baseline simulation parameters

Parameter	Value	Explanation
N	100000	Total population size
S(0)	99980	Initial susceptible individuals
I(0)	20	Initial infected individuals
R(0)	0	Initial removed individuals
P(0)	0	Initial risk perception
F(0)	0	Initial behavioral fatigue
β_0	0.36	Baseline transmission rate
γ	1/7	Average infectious period of about 7 days
α	2.00	Risk-perception suppression strength
η	0.90	Fatigue amplification strength
a	8.00	Risk-perception activation strength
b	0.15	Risk-perception decay rate
c	0.08	Fatigue accumulation strength
d	0.04	Fatigue relaxation rate

Under these values, the baseline reproduction number without behavioral response is approximately $R_0 = \beta_0/\gamma = 0.36/(1/7) = 2.52$. This indicates that, in the absence of behavioral response, the transmission process has a strong tendency to spread.

3.3 Model Scenarios

Three scenarios are compared. The first scenario is the classical SIR model, in which the transmission rate is fixed at β_0. The second scenario is the risk-perception-only model, obtained by setting $\eta = 0$. The third scenario is the full model, in which both risk perception and behavioral fatigue are included. The simulation horizon is 160 days, and the outcome indicators include infection peak, peak time, final epidemic size, maximum risk perception, and maximum fatigue.

4. Results and Discussion

4.1. Comparison of Model Scenarios

Table 3. Comparison of transmission outcomes under different models

Model	Infection peak	Peak time (days)	Final infected	Final infected ratio	Peak P	Peak F

Model	Infection peak	Peak time (days)	Final infected	Final infected ratio	Peak P	Peak F
Classical SIR model	23648	41.2	89525	89.53%	—	—
Risk-perception-only model	1459	41.1	24326	24.33%	0.435	—
Risk-perception-fatigue model	2808	65.7	42686	42.69%	0.599	0.538

Table 3 shows that the classical SIR model produces a large outbreak, with a peak of 23648 infected individuals and a final infected ratio of 89.53%. After risk perception is introduced, the infection peak drops to 1459 and the final infected ratio drops to 24.33%. This confirms that adaptive protection can strongly suppress transmission, which is consistent with studies emphasizing risk-driven behavior and awareness effects [4,6,8].

When behavioral fatigue is further introduced, the infection peak rises to 2808 and the final infected ratio rises to 42.69%. Compared with the risk-perception-only model, the full model produces a larger and later outbreak. This pattern supports the interpretation that fatigue weakens sustained protective behavior and may partially offset the benefit of risk perception [7,9].

4.2. Sensitivity to Risk-Perception Suppression

Table 4. Sensitivity analysis of the risk-perception suppression coefficient α

α	Infection peak	Peak time (days)	Final infected ratio	Peak P	Peak F
0.5	23203	44.1	91.55%	0.925	0.628
1.0	11789	54.2	77.99%	0.863	0.621
1.5	5355	62.1	60.33%	0.740	0.589
2.0	2808	65.7	42.69%	0.599	0.538
2.5	1768	68.0	30.67%	0.485	0.487

Table 4 indicates that increasing α decreases both the infection peak and the final infected ratio. When $\alpha = 0.5$, risk perception is too weak to substantially suppress transmission, and the final infected ratio remains above 90%. When $\alpha = 2.5$, the final infected ratio falls to 30.67%. This result means that risk perception itself is not sufficient; it must be translated into effective behavioral protection to reduce transmission.

The peak values of P and F decline as α increases. This occurs because stronger suppression prevents the infected proportion from becoming very high, which in turn reduces subsequent risk perception and fatigue accumulation. Thus, a stronger early behavioral response may reduce not only infections but also the later behavioral burden.

4.3. Sensitivity to Behavioral-Fatigue Amplification

Table 5. Sensitivity analysis of the fatigue amplification coefficient η

η	Infection peak	Peak time (days)	Final infected ratio	Peak P	Peak F

0.0	1459	41.1	24.33%	0.435	0.449
0.3	1727	52.5	29.19%	0.479	0.479
0.6	2168	61.6	35.27%	0.536	0.510
0.9	2808	65.7	42.69%	0.599	0.538
1.2	3711	67.4	51.29%	0.664	0.564

Table 5 shows that increasing η raises both the infection peak and the final infected ratio. When η = 0, the model reduces to the risk-perception-only case. When η increases to 1.2, the final infected ratio rises to 51.29%. This demonstrates that fatigue-driven relaxation can significantly weaken the long-term effectiveness of behavioral protection.

Peak time also tends to move later as η increases. This suggests that fatigue does not dominate early transmission immediately. Instead, early risk perception initially suppresses transmission, and fatigue accumulates gradually. Once fatigue becomes sufficiently strong, the effective transmission rate rebounds and the infection peak appears later. Similar delayed and complex dynamics have been observed in models with adaptive contact rates and delayed behavioral response [8].

4.4. General Discussion

The results support the central mechanism of the proposed model: risk perception and fatigue have opposite effects on transmission. Risk perception suppresses effective transmission by reducing contact or increasing protection, whereas behavioral fatigue increases transmission by weakening sustained protection. Therefore, the complete model produces richer dynamics than the classical SIR model.

The proposed model also clarifies why fixed-transmission-rate models may be insufficient for long-duration outbreaks. If behavior is treated as constant, the model may fail to capture early voluntary contact reduction, late fatigue, and delayed rebound. Recent systematic and comparative studies of behavioral epidemic models similarly emphasize that endogenous behavior can improve the interpretation of epidemic trajectories and forecasts [10,11].

However, the simulation values in this paper are ideal values and should not be interpreted as real-world estimates. Their purpose is to demonstrate internal model mechanisms. To apply the model to real data, parameters would need to be estimated using case data, mobility data, survey data, or other behavioral indicators. In particular, the variables P(t) and F(t) would require empirical proxies such as risk-perception surveys, search behavior, policy-adherence surveys, or mobility indicators [9,12].

5. Conclusion

This paper develops an improved SIR-type transmission dynamics model incorporating risk perception and behavioral fatigue. The effective transmission rate is modeled as $\beta(P,F) = \beta_0 \exp(-\alpha P + \eta F)$, so that risk perception suppresses transmission and fatigue amplifies transmission while the rate remains positive.

Ideal simulation results show that risk perception can greatly reduce infection peaks and final epidemic size compared with the classical SIR model. However, when behavioral fatigue is included, the infection peak and final infected ratio increase relative to the risk-perception-only model, and the peak time is delayed. Sensitivity analysis further shows that stronger risk-perception suppression reduces the epidemic scale, while stronger fatigue amplification increases rebound risk.

The model provides a simple but interpretable framework for describing the feedback loop of rising risk, stronger protection, accumulated fatigue, and weakened protection. It is suitable for theoretical analysis, classroom projects, and preliminary studies of behavioral transmission dynamics. Future work may estimate parameters from real data, incorporate heterogeneous groups or networks, and add policy intervention variables to distinguish voluntary behavior from externally imposed control measures.

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