FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 9, May, 2026, pp 295 – 298
DOI: https://doi.org/10.33003/fjs-2026-1009-5262

A Game-Theoretic Framework for Coupling Behavioral Dynamics with Compartmental Epidemiological Models: An Overview

[1*]Ezeh, Francis Chigozie and [2]Okuonghae, Daniel Uhunoma

[1]Department of Statistics University of Benin, Benin City, Nigeria.
[2]Department of Mathematics University of Benin, Benin City, Nigeria.

*Corresponding authors' email: chigozie.ezeh@uniben.edu

ABSTRACT

Classical compartmental models of infectious diseases, such as SIR model and its extensions, often assume that intervention-related parameters are fixed and independent of population behavior. However, in real epidemic settings, the uptake of interventions like, vaccination, hand hygiene, and isolation is highly influenced by individual decision-making. This study presents a structured game-theoretic approach for coupling behavioral dynamics with compartmental disease models. The framework outlines the steps in the construction of payoff functions that capture the interplay between intervention costs and disease risk and their dependence on the disease prevalence. These payoff structures are incorporated with epidemiological models through evolutionary game theory, yielding coupled systems in which disease dynamics and behavioral changes evolve. Through an illustrative example based on the classical SIR model, the steady-state behavior of the coupled system is interpreted using the concept of Nash equilibrium. Unlike classical compartmental models that uses fixed intervention parameters, the coupled framework accounts for adaptive behavior changes and provides a procedure for integrating decision-making into infectious disease models. By giving a clear outline of the steps involved in disease-behavior coupling, this overview provides a guide for developing adaptive behavioral disease models and enhances the design and evaluation of effective public health intervention strategies.

Received: 15 June 2026

Accepted: 24 June 2026

Published: 30 June 2026

Keywords: Game-Theoretic models, Behavioral changes, Disease-behavior Coupling, Intervention Strategies, Payoff Construction, Compartmental models

INTRODUCTION

Mathematical modeling has been applied rigorously in understanding the transmission dynamics of infectious diseases (Okuonghae & Omame ,2020; Cooper et al., 1999; Anderson & May,1991). Classical compartmental models, such as SIR and its extensions, partition population into different classes and describe the movements between these classes using systems of differential equations. These models gave insights into key concepts for understanding the disease dynamics, like basic reproduction number, equilibrium thresholds and impact of intervention methods (Kermack & McKendrick, 1927; Hethcote, 2000). Despite the wide applicability of these models, there are still limitations especially the assumption that epidemiological parameters are fixed throughout the course of an epidemic. In many existing models intervention-related parameters like, vaccination (d'Onofrio, 2002), isolation (Towers and Feng, 2012), hand hygiene (Ezeh & Okuonghae, 2026), are influenced by individual perception of disease risk, cost of intervention and observed behavioral changes (Bauch & Earn, 2004; Reluga, 2010). These types of responses can determine the dynamics of a disease and may also present outcomes that are outside what is predicted by compartmental models.

To address this drawback, there has been a growing interest in models that incorporate behavioral changes in modeling dynamics of infectious diseases using game theory (Bauch & Earn, 2004; Reluga, 2010; Funk et al. 2010; Chang et al., 2020; Verma, et al., 2025, Zhang et al., 2026). These models provide conceptual framework for modeling situations where individuals make decisions based on benefits while interacting with others in the population. During epidemic individuals are left with the choice to adopt or not adopt an intervention strategy, which invariably influences disease transmission dynamics. Recent studies like (Wang, et al. 2025; Schimit, et al., 2025; Zhang et al., 2026) have applied the concept of evolutionary game theory to model and predict the transmission of a disease during an outbreak. These models show that behavioral changes can lead to outcomes that differ substantially from those predicted by models with fixed intervention parameters. However, these studies focused mainly on classification of existing models, reviewing different applications and discussing various theoretical developments. While these studies have made numerous contributions to the subject, less attention has been devoted to presenting a step-by-step methodological approach that can guide researchers through the construction of payoff functions, formulation of behavioral dynamics, and coupling of game-theoretic models with compartmental epidemic models. As application of game-theoretic models continue to grow, a structured systematic overview becomes useful for researchers seeking to develop new coupled disease-behavior models.

In addressing this need, the present study provides an overview of game-theoretic framework for coupling behavioral changes with compartmental epidemic models. The aim is to outline the key steps involved in constructing payoff functions, formulating behavioral dynamics, and integrating these with standard disease models. This overview will serve as a useful reference for developing game-theoretic epidemic models and other extensions.

MATERIALS AND METHODS

Game-Theoretic Build-Up

The coupling of a game theoretical model with a compartmental epidemiological model depends on the source of information, type of information and behavioral changes associated with the model (Funk et al., 2010). The source of information can also be global (like, television, internet) or local (like, rumors, information from relatives and friends). The type of information could be prevalence-based (from disease status of individuals in the population) or belief-based (from cultural belief, press, and social perception of the disease risk). In this framework, the behavioral change is represented as the decision to either take up or not take up an intervention strategy. For example, in a vaccination model individuals who choose to vaccinate may move from the susceptible class to the immune or vaccinated class (Hethcote, 2000).

Game theory provides a framework for modeling situations where individuals make decisions while interacting with other individuals (players). The players are considered intelligent entities trying to make decisions in the presence of many uncertainties, primarily the decision of the opposing player. Here each player tends to optimize its profit or payment known commonly as payoff, which represents the perceived benefit or cost associated with each strategy. To maximize payoff, each player takes a decision among several available decisions, otherwise known as strategies. The best strategy that will yield optimal payoff depends largely on the decision or strategy of the competing player (Chang et al., 2020). A key concept in game theory is the Nash equilibrium, which represents a state where no individual can improve their payoff by solely changing their strategy (Osborne & Robinstein, 1994; Nash, 1951). In epidemiology, this is equivalent to a situation where individuals have no incentive to change their intervention behavior given the current state of the disease and the behavior of others.

Payoff Construction

To couple behavioral decision with disease dynamics, payoff functions are constructed to represent the interplay between the cost of intervention and the risk of infection, where all individuals in a given population have access to information on the intervention. Let the cost associated with adopting an intervention strategy be denoted by $-f_y$ (where f_y denotes the direct cost of the intervention). The negative arises from the fact that maximizing payoff is the same as minimizing the adverse effect (Bauch et al., 2013). Similarly, let the risk of infection be denoted by $f_n p(t)$, where $p(t)$ is the proportion of infectious individuals in the population and f_n the mortality associated with the disease risk. Then the payoff for adopting the intervention is expressed as a function that incorporates both the direct cost of the intervention and the reduction in infection risk due to its effectiveness. The payoff function is,

$$-f_y - (1-\omega) f_n p(t) \qquad (1)$$

where $\omega \in [0,1]$ is the effectiveness of the intervention.

In equation (1) individuals who are adopting the intervention strategy will bear the direct cost f_y but will be compensated by a reduction in the risk of infection resulting from the impact of the intervention effectiveness.

Conversely, the payoff for not adopting the intervention implies full exposure to infection risk without the intervention cost. The payoff function is ,

$$-f_n p(t) \qquad (2)$$

Therefore in equation (2), those who are not adopting the intervention strategy will bear the full cost of the infection $f_n p(t)$. The difference between these payoffs determines the attractiveness of each strategy.

Payoff functions serve as a bridge between individual decisions preferences and population disease dynamics. Since these payoffs depend on epidemiological variables, it enables the incorporation of behavioral responses in infectious disease models. If incorporated, the coupled model presents scenarios where the disease spread depends on the level of intervention, the uptake of an intervention strategy and the state of the disease dynamics (Funk et al., 2010; d'Onofrio et al., 2007).

Behavioral Dynamics

The evolution of behavioral strategies over time can be modeled using the replicator equation (Taylor & Jonker, 1978; Hofbauer & Sigmund, 1998). Let $y(t) \in [0,1]$ be the proportion of the population adopting the intervention strategy at time(t). Then, the rate of change of $y(t)$ is determined by the difference in the payoff for adopting the strategy and the average payoff in the population as in equation (3) below,

$$\frac{dy}{dt} = y(1-y)(\pi_y - \pi_n) \qquad (3)$$

Where $\pi_y \; and \; \pi_n$ are the payoffs for adopting and not adopting the intervention strategy respectively.

Substituting equations (1) and (2) into equation (3) we have that,

$$\frac{dy}{dt} = y(1-y)[-f_y - (1-\omega) f_n p(t) + f_n p(t)] \qquad (4)$$

That is, $\frac{dy}{dt} = y(1-y)[-f_y - f_n p(t) + \omega f_n p(t) + f_n p(t)]$

Therefore, $\frac{dy}{dt} = y(1-y)[-f_y + \omega f_n p(t)] \qquad (5)$

The formulation in equation (5) gives the standard two-strategy replicator dynamics with respect to the payoff functions defined in equations (1) and (2). It entails that the proportion of individuals adopting the intervention strategy increases when the payoff associated with intervention exceeds that of non-intervention strategy, and decreases otherwise (Taylor & Jonker, 1978). Also, as the disease prevalence, $p(t)$, changes, the associated payoffs change, leading to adjustment of behavioral responses. This implies that, increase in infection prevalence may increase the uptake of intervention strategies, while decrease in prevalence may lead to reduced uptake. This interplay is core to the coupling of behavioral and disease models.

Illustrative Example: Coupling with SIR Model

To demonstrate how behavioral dynamics can be incorporated into a compartmental model, we consider the classic SIR model (Kermack and McKendrick, 1927), given by:

$$\left.\begin{aligned} \frac{dS}{dt} &= -\beta SI \\ \frac{dI}{dt} &= \beta SI - \gamma I \\ \frac{dR}{dt} &= \gamma I \end{aligned}\right\} \qquad (6)$$

where $S(t), I(t)$ and $R(t)$ represent the proportions of susceptible, infectious and recovered individuals in the population, respectively. The parameter β is the transmission rate and while γ is the recovery rate.

This model assumes a constant transmission rate, independent of the population behavior. To incorporate the impact of behavioral changes in the model, the intervention strategy is added to the transmission parameter β through a time-dependent variable $y(t) \in [0,1]$ defined earlier and the intervention effectiveness (ω) , as given below,

$$\beta(y) = \beta(1-\omega y) \qquad (7)$$

The expression in equation (7) assumes that increased adoption of the intervention strategy leads to a proportional reduction in the disease transmission. It is adopted here for illustrative purposes because of its simplicity and ease of interpretation. Although, this linear behavior-dependent transmission function is been widely used in behavioral-epidemic models, other formulations, like nonlinear, saturating, and threshold-dependent transmission functions, have also been proposed in the literature. The choice of a functional form for the transmission parameter depends on the disease under consideration and the behavioral pattern being modeled.

Substituting the time dependent behavior-based transmission rate in equation (7) into the SIR model in equation (6) we have a modified SIR model as,

$$\left.\begin{aligned} \frac{dS}{dt} &= -\beta(1-\omega y)SI \\ \frac{dI}{dt} &= \beta(1-\omega y)SI - \gamma I \\ \frac{dR}{dt} &= \gamma I \end{aligned}\right\} \quad (8)$$

This modified model incorporates the impact of behavioral changes due to intervention. The transmission rate here is not constant as it decreases with increasing proportion $y(t)$.

The behavioral model in equation (5) and the modified disease model in equation (8), gives the coupled model as:

$$\left.\begin{aligned} \frac{dS}{dt} &= -\beta(1-\omega y)SI \\ \frac{dI}{dt} &= \beta(1-\omega y)SI - \gamma I \\ \frac{dR}{dt} &= \gamma I \\ \frac{dy}{dt} &= y(1-y)[-f_y+\omega f_n I] \end{aligned}\right\} \quad (9)$$

where $p(t) = I(t)$.

This coupled framework captures the feedback interaction between the disease dynamics and the behavioral responses. As the number of infectious individual's increases, the perceived risk of infection rises, which may lead to increased adoption of the intervention strategies. In contrast, as intervention uptake increases, the effective transmission rate decreases, this may influence the spread of the disease. The coupled framework in this study is intended to illustrate the general methodology for integrating behavioral dynamics with compartmental epidemic models rather than to analyze any specific infectious disease.

Table 1: Comparison Betwenn Classical Compartmental Models and the Coupled Game-theoretic Framework

Attributes	Classical Compartmental Models	Coupled Game-Theoretic Models
Intervention parameter	Constant	Behavior-dependent
Transmission rate	Fixed	Modified by behavioral changes
Human behavior	Not modeled	Explicitly modeled
Decision making	Absent	Present
Payoff function	Absent	Present
Behavioral evolution	Absent	Replicator Dynamics
Equilibrium	Epidemiological equilibrium	Epidemiological and Nash equilibria
Feedback system	Absent	Disease – Behavior feedback

Nash Equilibrium

The concept of Nash equilibrium provides a useful way to interpret the steady-state behavior of the coupled behavior-disease model. Consider the coupled system in equation (9), when $\frac{dy}{dt} = 0$, this condition is satisfied in three possible ways:

(1) $y = 0$: No individual adopts the intervention strategy. This may occur when the cost of the intervention is perceived to be more than the disease risk making non-adoption of the intervention a preferred strategy.

(2) $y = 1$: All individuals adopt the intervention strategy. This occurs when the benefit of the intervention outweighs its cost making the uptake of intervention a dominant strategy.

(3) $\pi_y = \pi_n$: The payoff of both strategies is equal. In this case, individuals have no benefit to change their current strategy, leading to an equilibrium state where both strategies exist together.

These steady-state conditions correspond to Nash equilibrium state, where no individual can improve their payoff by solely changing strategy, given the behavior if others (Nash, 1951). In the coupled model, the Nash equilibrium is determined though the epidemiological variables such as the proportion of infectious individuals in the population. This creates a feedback relationship where disease prevalence influences the behavioral equilibrium and the behavioral equilibrium also, affects the disease transmission. Generally, the equilibrium of the coupled model emanated from the interaction between the epidemic and behavioral models, whereby distinguishing the framework from classical compartmental models, where intervention parameters are fixed and are independent of the population behavior.

Discussion

This study presents a structured game-theoretic framework for coupling behavioral changes and compartmental models of infectious diseases. Unlike classical models, where intervention-related parameters are fixed, the proposed framework treats intervention uptake as a dynamic variable that evolves in response to disease prevalence and individual decision-making. Consequently, individuals respond to disease prevalence by weighing the options available to them based on the associated cost of taking up the intervention and the severity of the disease risk.

The framework demonstrates that payoff functions play a central role as a link between epidemiological processes and behavioral responses. These payoff functions depend on assumptions on how individuals perceive risk of disease and cost of intervention, which varies across population and diseases. The resulting behavioral dynamics, represented through the replicator equation allow intervention uptake to evolve depending on the popular strategy.

The Nash equilibrium offers useful interpretations of the steady-state behavior of the coupled model. At equilibrium, individuals find it non-useful to change their strategy given the current state of the epidemics. However, unlike classical compartmental models, these steady states emerge from the mutual interaction between disease dynamics and strategic human behavior.

Previous studies have shown that disease models that integrated behavioral changes can generate qualitative dynamics that differs reasonably from those predicted by classical compartmental models. Depending on the nature of the disease and the behavioral assumptions adopted, coupled disease-behavior models may exhibit characteristics (like, multiple equlibria, sustained oscillation, delayed epidemic waves, and other complex phenomena) not captured by the fixed parameter models. These findings also elucidate the importance of accommodating adaptive human behavior when evaluating intervention strategies and designing public health policies.

In general, the framework presented in this study gives a methodological foundation for integrating evolutionary game theory with compartmental epidemic models. The study outlined the steps involved in the construction of payoff functions, behavioral dynamics, and disease-behavior coupling, which serves as a practical guide for developing behavioral-based epidemic models extendable to a wide range of infectious diseases and intervention studies.

CONCLUSION

In this study an overview of how game-theoretic approach can be used to incorporate behavioral changes into compartmental models of infectious diseases is presented. The framework demonstrates that intervention strategies can be modeled as dynamic variables influenced by individual decision-making, rather than as fixed parameters in classical compartmental models.

The coupled model derived by combining payoff functions from behavioral changes and epidemiological model, captures the interplay between disease prevalence and intervention uptake. The replicator equation used provides a systematic description of how behavioral changes evolve over time and the Nash equilibrium provides an insight into the steady-state behavior of the coupled model.

The illustrative example based on SIR model highlights the practical steps involved in implementing the coupling approach. The framework in general offers a useful foundation for extending classical epidemic models to incorporate behavioral responses, particularly in situations where individual decision-making plays a significant role in intervention uptake. Additionally, the framework has potential use in informing the design and evaluation of public health interventions during emerging infectious disease outbreaks, where adaptive human behavior influences disease transmission. Further studies may extend this framework to more complex settings capturing, stochastic epidemic models, network-based transmission models and multi-strategy behavioral games, for investigating vast disease-behavior interactions.

REFERENCE

Anderson, R. M., & May, R. M. (1991). *Infectious diseases of humans: Dynamics and control*. Oxford University Press.

Bauch, C.T., d'Onofrio, A., & Manfredi, P. (2013). Behavioral epidemiology of Infectious diseases: An Overview. Physics of Life Reviews, 10(1), 1-20. https://doi.org/10.1016/j.plrev.2011.07.001

Bauch, C. & Earn, D.J.C (2004). Vaccination and the theory of games. *Proc. Natl. Acad. Sci. 101,* pp. 13391-13394 https://doi.org/10.1073/pnas.0403823101

Chang, S. L., Piraveenan, M., Pattison, P., & Prokopenko, M. (2020). Game theoretic modelling of infectious disease dynamics and intervention methods: a review. *Journal of Biological Dynamics*, *14*(1), 57–89. https://doi.org/10.1080/17513758.2020.1720322

Cooper, B.S., Medley, G.F., & Scott, G.M. (1999). Preliminary analysis of the transmission dynamics of nosocomial infections: stochastic and management effects. *J Hosp Infect 43(2), 131-47* https://doi.org/10.1053/jhin.1999.0647

d'Onofrio, A. (2002). Stability properties of pulse vaccination strategy in SEIR epidemic model. *Mathematical Biosciences,* *179*(1), 57–72. https://doi.org/10.1016/S0025-5564(02)00087-8

d'Onofrio, A., Manfredi, P. & Salinelli, E. (2007). Vaccinating behavior, information and the dynamics of SIR vaccine preventable diseases. *Theor. Popul. Biol. 71, pp. 301-317* https://doi.org/10.1016/j.tpb.2006.09.003

Ezeh, F. C., & Okuonghae, D. U. (2026). Nosocomial infections and their models: A narrative review. *Transactions of Nigerian Association of Mathematical Physics, 24*, 189–202. https://doi.org/10.60787/tnamp.v24.685

Funk, S., Salathe, M., & Jansen, V.A (2010). Modeling the influence of human behavior on the spread of infectious diseases: a review. *J. R. Soc. Interface 7, pp. 1247 -1256* https://doi.org/10.1098/rsif.2010.0142

Hethcote, H. W. (2000). The mathematics of infectious diseases. *SIAM Review,* *42*(4), 599–653. https://doi.org/10.1137/S0036144500371907

Hofbauer, J., & Sigmund, K. (1998). *Evolutionary games and population dynamics*. Cambridge University Press.

Kermack, W. O. & McKendrick, A. G., (1927). Contributions to the mathematical theory of Epidemics:part 1. *Proceedings of the Royal Society of London A 115, 700- 721.*

Nash, J. (1951). Non-cooperative games. *Annals of Mathematics, 54*(2), 286–295.

Okuonghae D., & Omame A. (2020). Analysis of a mathematical model for COVID-19 population dynamics in Lagos, Nigeria. *Chaos Solitons Fractals, 139 , 110032* https://doi.org/10.1016/j.chaos.2020.110032

Osborne, M. J., & Rubinstein, A. (1994). *A course in game theory*. MIT Press.

Reluga, T. (2010). Game theory of social distancing in response to an epidemic. *Plos Comput. Bio. 6, pp. 1-9* https://doi.org/10.1371/journal.pcbi.1000793

Schimit, P.H.T., Sergio, A.R. & Fontoura, M.A.R.(2025) Vaccination as a Game: Behavioural Dynamics, Network Effects, and Policy Levers - A Comprehensive Review. *Mathematics , 13, 2242.* https://doi.org/10.3390/math13142242

Taylor, P. D., & Jonker, L. B. (1978). Evolutionarily stable strategies and game dynamics. *Mathematical Biosciences, 40*(1–2), 145–156.

Towers, S., & Feng, Z. (2012). Social contact patterns and control strategies for influenza in the elderly. *Mathematical Biosciences, 240*(2), 241–249. https://doi.org/10.1016/j.mbs.2012.07.007

Verma, P., Kumar, V., & Bhattacharyya, S. (2025). Modelling behavioural interactions in infection disclosure during an outbreak: An evolutionary game theory approach. *Mathematical Biosciences and Engineering,* *22*(8), 1931–1955. https://doi.org/10.3934/mbe.2025070

Wang, J., Zhang, X., Li, Y., & Liu, Z. (2025). Modeling and analysis of infectious diseases based on behavioral game theory in two-layer networks. *PLOS ONE*, *20*(5), e0323076. https://doi.org/10.1371/journal.pone.0323076

Zhang, W., Li, Y., Li, Q., Huang, G., & Feng, M. (2026). Modeling epidemic dynamics of mutant strains with evolutionary game-based vaccination behavior. *Chaos, Solitons & Fractals*, *205*, 117849. https://doi.org/10.1016/j.chaos.2025.117849