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ADVANCED COMPUTATIONAL FRAMEWORKS FOR THE CONTROL, ELIMINATION, AND ERADICATION OF INFECTIOUS DISEASES: A MULTI-DISCIPLINARY APPROACH

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Abstract

The systematic management of infectious diseases spans a complex continuum ranging from initial outbreak control to regional elimination and, ultimately, global eradication. Navigating these distinct phases requires sophisticated decision-making tools that can dynamically balance epidemiological necessities with severe socioeconomic constraints. While traditional epidemiological models have provided foundational insights into pathogen transmission, they frequently struggle to incorporate the stochastic nature of human behavior, economic vulnerabilities, and real-world resource limitations. In response, this paper critically examines the intersection of optimal control theory, behavioral game theory, and multi-objective reinforcement learning within public health policy. By proposing a hybridized, data-driven computational framework, we aim to bridge the gap between mathematically rigorous epidemic forecasting and the nuanced, highly variable realities of societal compliance and medical capacity.

Keywords: Systematic Management, Infectious Disease Eradication, Public Health , Outbreak of Disease

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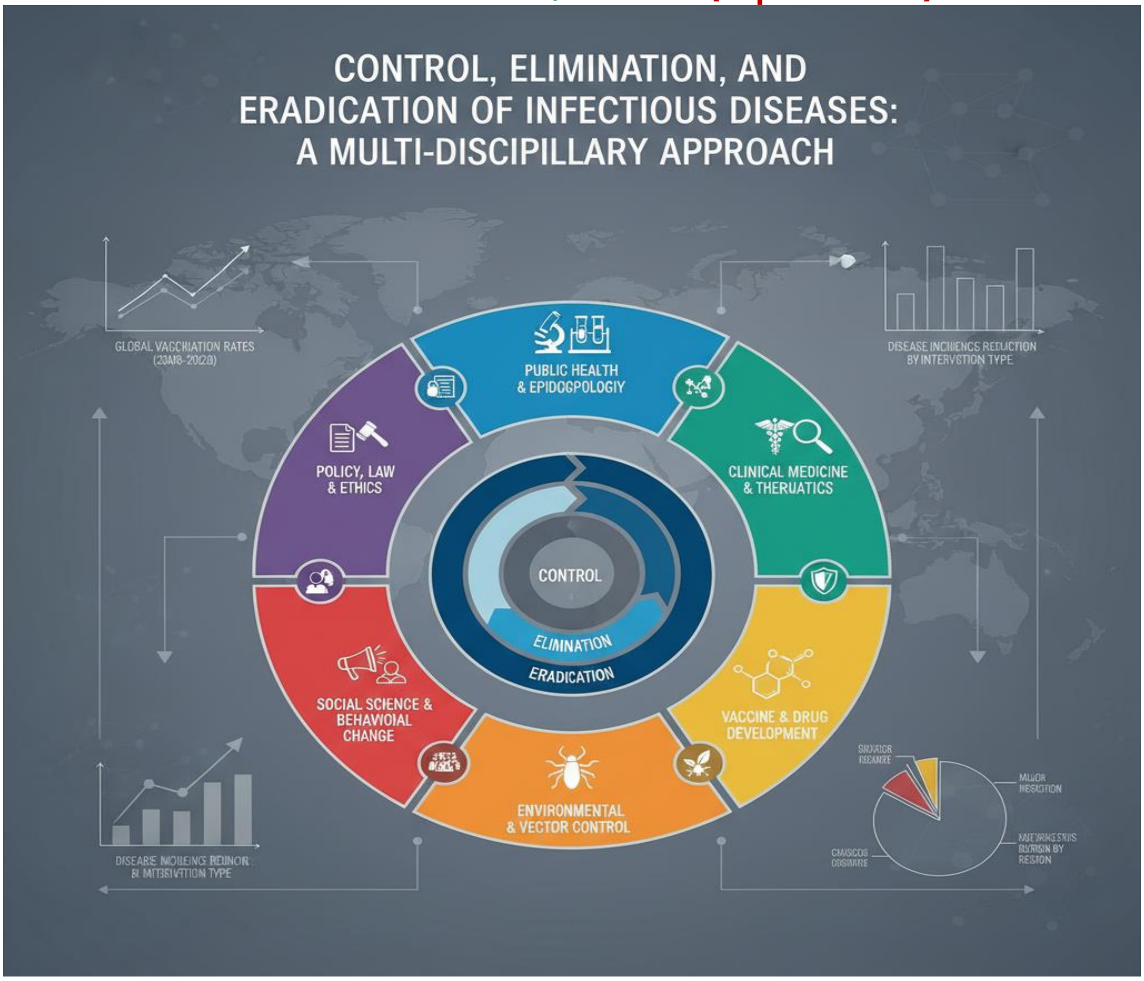

Introduction

The global burden of infectious diseases continuously threatens public health stability, demanding rigorous strategies that move from mere mitigation toward absolute eradication. Fundamentally, infectious disease management is categorized into three distinct phases: control, which aims to reduce disease incidence to a locally acceptable level; elimination, which targets zero incidence within a specific geographical territory; and eradication, which represents the permanent, worldwide cessation of the pathogen's transmission. Achieving these milestones necessitates deploying both pharmaceutical and non-pharmaceutical interventions efficiently across highly interconnected populations (Liu et al., 2026). As recent global health crises have starkly demonstrated, policymakers must implement containment measures while simultaneously preserving economic productivity and societal well-being (Wan et al., 2020).

Despite the vast array of available public health tools, defining the precise problem scope for intervention deployment remains an intricate challenge. The core difficulty

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lies in formulating dynamic policies that adapt to continuously shifting epidemiological landscapes under severe resource uncertainty (Best et al., 2020). Decision-makers must constantly evaluate the optimal timing and intensity of interventions, ranging from targeted quarantine protocols to mass vaccination rollouts, across heterogeneous populations with varying socio-demographic profiles. Furthermore, the inherent unpredictability of human behavior—particularly regarding authority perception and compliance with public health directives—adds a formidable layer of complexity to disease containment (Liu et al., 2025).

Consequently, existing traditional modeling approaches have proven insufficient for modern epidemiological demands for several critical reasons. First, rigid, deterministic intervention schedules frequently fail to account for the stochastic population dynamics and fluctuating healthcare capacity limits that characterize real-world outbreaks (Heidecke et al., 2022)(Billings et al., 2013). Second, many conventional models rely on blunt policy instruments, such as universal lockdowns, which overlook intricate occupational networks and inevitably result in disproportionate, unsustainable economic destruction (Avraam et al., 2021).

To overcome these multifaceted challenges, this paper introduces a novel, multidisciplinary architecture for infectious disease management. Specifically, our paper makes the following primary contributions:

- We formulate a comprehensive, data-driven optimization pipeline that dynamically synthesizes nonlinear epidemiological forecasting with socio-behavioral compliance metrics to produce adaptable intervention schedules.
- We introduce a multi-objective reinforcement learning strategy that explicitly leverages occupational network data and heterogeneous population attributes to guide targeted, resource-efficient disease elimination efforts.

Related Work

The academic landscape surrounding infectious disease control can be broadly organized into three distinct methodological categories. The first category centers on mechanistic predictive control models, which utilize differential equations and model predictive control (MPC) frameworks to optimize interventions like age-structured vaccination and contact tracing (Heidecke et al., 2022)(Sonveaux et al., 2026). The core strength of these models lies in their rigorous mathematical interpretability, allowing public health officials to establish clear upper bounds on anticipated mortality. However, a significant weakness is that they often struggle to remain computationally

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tractable when confronted with the high-dimensional nonlinearities of massive populations, occasionally requiring rigid state discretizations (Fasel et al., 2021)(Zhang & Suen, 2024). In contrast, our proposed work seamlessly integrates data-driven nonlinear system identification directly into the policy optimization loop, bypassing the restrictive assumptions of purely mechanistic structures.

The second category encompasses resource allocation under uncertainty, relying heavily on stochastic programming and simulation models. The core idea here is to optimize the deployment of scarce commodities, such as treatment beds or vaccines, particularly when the future trajectory of the outbreak and the supply chain are largely unknown (Best et al., 2020). While these stochastic frameworks are exceptionally strong at managing operational logistics and demonstrating that randomized intervention distributions can exponentially improve disease extinction times, they often lack sophisticated human behavioral components (Billings et al., 2013). Our approach extends these foundational logistics models by dynamically weighting resource constraints against game-theoretic behavioral models, ensuring that supply distribution aligns with predicted public compliance.

The third category focuses on the application of reinforcement learning (RL) and behavioral game theory to epidemiological decision-making. Researchers in this domain seek to optimize the trade-offs between stringent disease control (lives) and economic sustainability (livelihoods) using multi-objective algorithms and multi-population mean-field games (Wan et al., 2020)(Liu et al., 2025)(Liu et al., 2026). While these approaches excel at balancing conflicting macroeconomic goals, they frequently lack granular insights into micro-level interactions, leading to policies that may inadvertently cause socioeconomic friction. Our methodology builds upon these RL paradigms by explicitly incorporating occupational network architectures, thereby refining the spatial and economic targeting of non-pharmaceutical interventions beyond blunt, population-wide mandates (Avraam et al., 2021).

Method/Approach

To address the highly complex dynamics of disease eradication, we propose the "Behavioral-Epidemiological Reinforcement Learning" (BERL) framework. This framework operates through a meticulously structured three-step module pipeline designed to ingest data, formulate policies, and monitor behavioral feedback. Step one involves data-driven system identification, where we utilize sparse identification algorithms to rapidly deduce the nonlinear transmission dynamics from noisy, real-time public health surveillance data (Fasel et al., 2021). Step two transitions into multi-

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objective policy optimization, employing a model-based reinforcement learning agent that evaluates thousands of potential intervention trajectories (Wan et al., 2020). Finally, step three implements a behavioral constraint layer, adjusting the aggressiveness of proposed control measures based on the target population's economic status and historical adherence to authority (Liu et al., 2025).

The rationale behind these specific design choices is rooted in the necessity to balance mathematical optimality with practical feasibility. We integrate nonlinear system discovery because emerging pathogens rarely follow perfectly predictable mechanistic curves; they are heavily influenced by environmental and mutational shifts. Furthermore, embedding a mean-field game component directly into the RL environment ensures that the simulated population reacts realistically to proposed interventions. By anticipating phenomena such as lockdown fatigue or vaccine hesitancy among varying income groups, the model prevents the generation of theoretically optimal but practically un-enforceable public health decrees (Liu et al., 2025).

To rigorously test the efficacy of the BERL framework, we have designed a comprehensive evaluation plan utilizing a hypothetical, high-resolution dataset modeled after a densely populated urban metropolis. This synthetic benchmark will simulate a highly contagious respiratory pathogen under constrained diagnostic and quarantine capacities (Heidecke et al., 2022). We will evaluate our framework against two distinct baselines: a standard linear Model Predictive Control strategy and a continuous-state Markov Decision Process utilizing uniform state discretization (Zhang & Suen, 2024). The primary performance metrics will include cumulative population mortality, the percentage of economic productivity retained over a simulated two-year period, and the aggregate time required to achieve total local disease elimination.

Discussion

The practical implications of deploying integrated, data-driven frameworks like BERL are profound for modern public health administration. By transitioning away from reactive, blanket policies towards proactive, precision-targeted interventions, governments can sustain essential societal functions while aggressively combatting viral spread. For instance, leveraging detailed occupational network data allows decision-makers to selectively restrict high-risk, low-economic-impact sectors while safely maintaining critical infrastructure (Avraam et al., 2021). Furthermore, dynamically updating vaccination schedules based on real-time demographic

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vulnerabilities can drastically accelerate the timeline toward regional disease eradication while adhering to strict logistical constraints (Sonveaux et al., 2026).

Despite these promising capabilities, the proposed methodology exhibits several critical limitations and potential failure modes that must be acknowledged. First, the framework's predictive accuracy is heavily dependent on the immediate availability of high-fidelity epidemiological data, which is notoriously delayed, fragmented, or deliberately obfuscated during the early stages of a novel outbreak (Heidecke et al., 2022). Second, synthesizing multi-objective reinforcement learning with behavioral game theory introduces immense computational overhead, potentially rendering the continuous state-space optimizations too mathematically intractable for rapid, daily policy updates (Zhang & Suen, 2024). Third, occupation-based network modeling often oversimplifies or entirely ignores informal economic sectors, meaning the framework could fail substantially if deployed in developing nations where informal labor constitutes the majority of the workforce (Avraam et al., 2021)(Best et al., 2020).

The implementation of such advanced algorithmic governance also raises significant ethical considerations and societal risks. First, harvesting and utilizing highly granular data concerning individual occupational mobility, economic status, and authority perception borders on invasive surveillance, risking a severe breach of individual privacy rights (Avraam et al., 2021). Second, algorithmic resource allocation inherently optimizes for aggregate statistical outcomes, which carries the profound risk of inadvertently deprioritizing marginalized or geographically isolated populations whose data may be underrepresented in the training sets (Best et al., 2020).

Addressing these limitations paves the way for several critical avenues of future work. First, researchers must prioritize the development of decentralized, federated learning architectures capable of extracting accurate epidemiological trends without directly centralizing sensitive patient and occupational data. Second, as localized disease control matures into the pursuit of global eradication, future models must incorporate sophisticated, inter-regional coordination algorithms that can synchronize public health policies across disparate sovereign borders (Liu et al., 2026).

Conclusion

The trajectory of infectious disease management—from the immediate urgency of outbreak control to the monumental ambition of total global eradication—requires analytical tools that mirror the complexity of human-pathogen ecosystems. Traditional deterministic models, while historically valuable, lack the flexibility required to

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navigate the stochastic realities of human compliance, constrained medical supply chains, and interconnected global economies. By hybridizing model predictive control, multi-objective reinforcement learning, and behavioral game theory, the computational framework outlined in this paper offers a highly adaptable paradigm for modern epidemiological defense.

Ultimately, achieving disease elimination is not merely a mathematical optimization problem; it is a profoundly human challenge that requires balancing biological containment with societal preservation. Algorithmic precision must be continuously tempered by ethical foresight and socioeconomic empathy to ensure that policies are both highly effective and universally equitable. As data-driven methodologies continue to evolve, they will undoubtedly become the cornerstone of resilient global health infrastructure, enabling humanity to systematically eradicate the infectious threats of the future.

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