

Designing Deployable Public Health Campaigns via Online Learning Techniques

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1 Introduction

Artificial intelligence (AI) is having a transformative impact on digital medicine, particularly in clinical diagnostics and personalized healthcare. Machine learning models, especially deep neural networks, are enhancing disease detection by analyzing medical images, electronic health records, and genomic data with unprecedented precision. These advancements enable earlier and more accurate identification of pathologies. Beyond diagnostics, AI-driven tools are transforming personalized treatment plans and clinical decision-making, demonstrating the technology's potential to augment healthcare delivery.

Recognized as a pivotal enabling technology, AI holds immense promise for addressing systemic societal challenges. This potential is formalized in the Artificial Intelligence for Social Impact (AI4SI) [29] paradigm, which shifts focus from purely technical innovation to context-aware, ethically grounded solutions. Aligned with frameworks like the UN Sustainable Development Goals [22], AI4SI emphasizes scalable interventions to improve quality of life, particularly for marginalized populations. Within these high-impact domains, public health stands out as both underexplored and uniquely challenging. This research specifically focuses on information-based behavioral interventions, i.e. campaigns that aim to change health behaviors through peer influence and health communication. Public health ecosystems have inherent uncertainties: incomplete data, unpredictable environmental factors, and complex socioeconomic determinants of health [24]. Recent policy developments [20] indicate growing recognition of AI's potential to revolutionize core public health functions. Building on this, this research explores fundamental algorithmic challenges in applying online learning to public health campaigns.

Many of these challenges can be formally framed as an influence maximization problem [14], where: (1) a social network represents relationships between individuals (nodes and edges), (2) selected individuals act as seed nodes that initiate information spread, (3) influence propagates according to probabilistic diffusion models (e.g., Independent Cascade [14]), and (4) the objective is to select a set of seeds that maximizes the expected spread of information. While influence maximization has been extensively studied under complete information assumptions, real-world applications require online learning algorithms that can adapt to partial observability, dynamic network changes, and formal constraints.

2 Research Directions

Applying AI to public health communication interventions reveals critical gaps between algorithmic theory and real-world practice. These gaps manifest as several key challenges. A primary concern is *partial observability*: in on-site information campaigns [19, 36, 33, 35, 34, 37, 13, 16, 4, 30, 31], organizations rarely possess complete data on the target population's social network, making it difficult to optimize intervention impact. Digital information campaigns [5, 12] face similar constraints, as social media data (e.g., from X) may be incomplete due to private profiles or offline interactions, rendering network reconstruction unreliable. Another critical challenge is *data security and privacy* [24]. AI applications in public health must navigate the risks of exposing sensitive information, particularly when integrating data from multiple sources, which increases reidentification risks. This challenge is further complicated by varying national privacy frameworks, as each country maintains its own regulations governing AI and health data usage [6], imposing additional constraints on data security measures and privacy protection in intervention design. Beyond data limitations, adaptive intervention strategies remain underdeveloped. While some algorithms account for non-participation in multi-round interventions [36, 33, 35], few explicitly address the *co-evolution* of interventions and dynamic population changes. Additionally, *personalization* efforts are unevenly applied. Although some health interventions leverage wearable data for tailored behavioral strategies [28, 8], health communication campaigns often fail to adapt messages to individual cognitive preferences. As highlighted by Faus et al. [10], message effectiveness depends on aligning content with recipients' information-processing styles (cf. the Elaboration Likelihood Model [25]), and targeting individuals receptive to behavioral change (cf. the Health Belief Model [3]). Deployability of public health campaigns is further complicated by the need for *credible peer influence*. Campaign success hinges on ambassadors embodying promoted behaviors [10], yet this alignment is frequently overlooked. Finally, resource allocation must balance *fairness* (avoiding algorithmic biases) and *justice* (equitable distribution across communities), a challenge underscored in recent work [24, 7, 17]. The challenges outlined above highlight the complex interplay between technical feasibility and real-world deployability in AI-driven public health interventions. Current solutions often treat these challenges in isolation. A unified framework is needed to address these interdependencies, particularly in resource-constrained settings where suboptimal decisions may exacerbate health inequities.

This research proposal will explore several promising directions for advancing AI in public health, as evidenced by the following re-

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search questions:

RQ1. *How can online learning algorithms effectively balance exploration-exploitation tradeoffs for network structure learning in partially observable influence maximization problems?*

RQ2. *How can online learning frameworks adapt to co-evolving network-agent systems while maintaining privacy guarantees and incorporating real-time feedback for dynamic strategy optimization?*

RQ3. *How can fairness constraints and incentive-compatibility mechanisms be formally integrated into online learning algorithms for influence maximization?*

3 Research Agenda

Motivating Example. To bridge the research objectives with methodological development, I anchor this approach in a real-world instance of preventive intervention, so that it is possible to reason in concrete terms. In many countries, the public health landscape faces a critical challenge: efficiently delivering HIV prevention services to marginalized groups, including migrants, people who use drugs (PWUD), and LGBTQIA+ communities, despite limited resources and structural barriers. In Italy, programs like Fondazione Villa Maraini’s integrated testing model [18] and ARCI-GAY’s nationwide peer-led outreach [1] demonstrate the importance of community-based strategies. Yet a persistent gap remains: *identifying the most effective peer educators or "seeds" within these populations to maximize health message diffusion*. A drop-in center serving homeless youth in a major U.S. city mirrored this challenge, aiming to face HIV transmission through peer-led awareness campaigns. They proposed an algorithmic solution to identify the optimal peer leader, which was really deployed and faced real-world constraints, such as peer leader absenteeism and unknown influence probabilities. Several methods were designed to address this problem. Among them, Wilder et al. [35] proposed the CHANGE agent, addressing this problem by combining network sampling, adaptive planning, and robust optimization. This method was tested in a pilot field study and proved to be effective in both peer leader selection and the reduction of data collection costs. Furthermore, it’s worth mentioning this work, also because it provides a comprehensive adaptive framework, while later works mostly focused on improving the network exploration task.

Methodological Components. The HIV prevention case serves as a concrete testbed, with all algorithmic contributions designed for broader applicability to influence maximization problems.

RQ1 will establish the foundational layer by advancing contextual bandit theory for influence maximization in largely unknown social networks. This research will frame the network exploration process as a Contextual Multi-Armed Bandit (ConMAB) [27, 15], problem, where queryable nodes are the "arms", the currently known subgraph provides the "context", and newly discovered edges serve as the "reward". Building on existing methods, this work will address a critical limitation of standard ConMABs in this setting: their tendency to over-exploit well-explored network regions while neglecting other potentially influential but less-known parts of the graph, a significant issue in networks with sparsely connected communities. To overcome this, this component will introduce an approach to dynamically choose the exploration strategy based on previous feedback. This will prevent local over-exploitation and maintain efficient global exploration, shifting the objective from simply maximizing the size of the discovered subgraph to identifying a more representative proxy network for effective influence maximization. Furthermore, RQ1 will

extend its scope to more complex, partially observed scenarios characterized by incomplete node metadata. To address this, the research will incorporate a Generative Surrogate Model for metadata imputation in active learning frameworks [2]. This model will leverage the observed network topology and available node attributes to infer probable feature vectors for nodes with missing data, thereby enriching the feature set and extending prior metadata-driven methods [30]. Another focus of this work will be the development of an online framework capable of navigating the trade-off between network exploration and feature acquisition. This framework will dynamically decide whether to expend its budget on querying nodes to uncover topological structure or on acquiring missing metadata, optimizing its strategy under explicit budget constraints.

RQ2 builds upon the network learning foundation from RQ1 to develop comprehensive online learning frameworks that capture the dynamic interplay between learning agents and evolving network structures. This component integrates the exploration capabilities established in RQ1 with real-time feedback mechanisms and cognitive models such as the Elaboration Likelihood Model [25] to enhance both exploration efficiency and influence maximization effectiveness. Privacy-preserving capabilities are achieved through Differential Privacy mechanisms [9] integrated with Federated Learning architectures [32], enabling distributed learning while maintaining formal privacy guarantees.

RQ3 completes the unified framework by incorporating fairness and incentive-compatibility constraints into the online learning algorithms developed in RQ1 and RQ2. This component advances theoretical foundations of constrained online learning by developing novel optimization techniques that maintain convergence guarantees while satisfying fairness constraints [7] and incentive-compatibility conditions derived from mechanism design theory [21]. The approach formalizes these constraints within the established online learning framework, creating algorithms that provably balance effectiveness with ethical considerations.

Ethical Considerations. Effective influence maximization algorithms could be misused for social manipulation or misinformation campaigns. Therefore, parallel research towards manipulation detection and countermeasures [11, 23, 26] is essential. However, such concerns should not halt algorithmic progress when applied to ethically sound public health interventions. This work will include explicit safeguards, restriction to verified public health contexts, transparent disclosure to participants, and institutional ethical oversight.

4 Preliminary Results and Conclusions

Preliminary results for RQ1 demonstrate significant advances in contextual bandits for network structure exploration. The proposed framework introduces a novel two-level bandit architecture that addresses fundamental exploration-exploitation challenges in partially observable influence maximization. The lower layer implements a contextual bandit with specialized state representations, while the upper meta-layer provides dynamic strategy selection between global and component-focused exploration. This hierarchical approach shows balanced exploration while preventing local over-exploitation. Empirical evaluation demonstrates significant performance improvements over state-of-the-art methods across diverse network topologies.

As far as concerns the scheduling, RQ1 was initiated during the first year of the PhD program with these preliminary results and will be completed during the second year alongside initiating work on RQ2. The third year will focus on RQ3’s constrained learning algorithms.

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