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A Precision Model for Colorectal Cancer Screening Adherence: Integrating Predictive Analytics and Adaptive Intervention Strategies

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Abstract

Colorectal cancer (CRC) remains a leading cause of cancer death despite consistent low adherence rates to screening compared to clinical guidelines. The article presents a novel conceptual model that integrates predictive analytics and precision intervention strategies for optimizing CRC screening adherence in three aspects. (a). As an initial step, the framework incorporates heterogeneous multi-source data - including high-dimensional electronic health records (EHRs), social determinants of health (SDoH) indices, and behavioral telemetry from mobile health platforms - into a unified graph-based knowledge representation via hypergraph neural networks. (b) Second, a temporal convolution attention-augmented multi-modal deep survival analysis model predicts time-varying nonadherence risks, explicitly handling both static covariates (e.g., genetic predispositions) and dynamic temporal trends (e.g., care access frequency decay curves). (c) Third, the intervention engine employs constrained reinforcement learning (CRL) with counterfactual fairness constraints to assign personalized nudges (e.g., automated reminders, navigator support) dynamically subject to time-varying resource constraints. A closed-loop feedback system enables model updating via adversarial validation against real-world data stream drifts with Wasserstein distance minimization. Theoretical contributions include (1) a topological embedding space using persistent homology for care pathway deviation modeling, (2) a non-Markovian decision process with provable approximation guarantees for longitudinal adherence optimization, and (3) an information-theoretic argument for minimal sufficient interventions based on rate-distortion theory. This system attempts to bridge computational epidemiology and health operations research to advance precision prevention paradigms.

Keywords: Colorectal cancer, hypergraph neural networks, multi-modal deep survival analysis, precision intervention, predictive analytics, reinforcement learning, screening adherence

Introduction

Colorectal cancer (CRC) is a public health issue and the second most common cause of cancer-related death worldwide (Brittain *et al.* 2018; Rex and Eid 2008; Pinheiro 2018; Miller-Wilson *et al.* 2021; Chen *et al.* 2017). Detection of CRC by screening in asymptomatic individuals significantly improves outcome by removal of premalignant lesions and early cancers (Chen *et al.* 2017). There are several screening modalities available – such as colonoscopy, fecal immunochemical testing, and others – and guidelines recommend routine screening for average-risk adults at specific ages. Despite evidence-based advantages and long-standing guidelines, screening compliance is suboptimal in numerous populations (Miller-Wilson *et al.* 2021). Many appropriate patients remain unscreened with recommended intervals, and opportunities are therefore lost to prevent or detect cancer earlier, at a more treatable stage. Adherence barriers to CRC screening are numerous and stretch beyond individual, to healthcare, to systemic. (Taheri-Kharameh *et al.* 2016)

At the patient level, factors such as poor understanding of screening applicability, worry or fear associated with procedures, and lack of comprehension of personal risk can deter patients from completing screening. Both health literacy and culture determine whether a patient will prioritize and follow screening recommendation (Tang *et al.* 2001). At the provider level, inconsistent provider recommendation or poor support can lead to patients delaying or not performing screening. System and logistical barriers only serve to exacerbate the issue: lack of access to screening services, scheduling of availability issues, cost and insurance limitations, and lack of reminders or follow-up may all prevent compliance (Green *et al.* 2017). Socioeconomic and sociodemographic factors intersect with such barriers to produce inequalities in screening rates. Take, for example, communities with limited healthcare access or historically underserved populations, which are often found to have lower screening rates

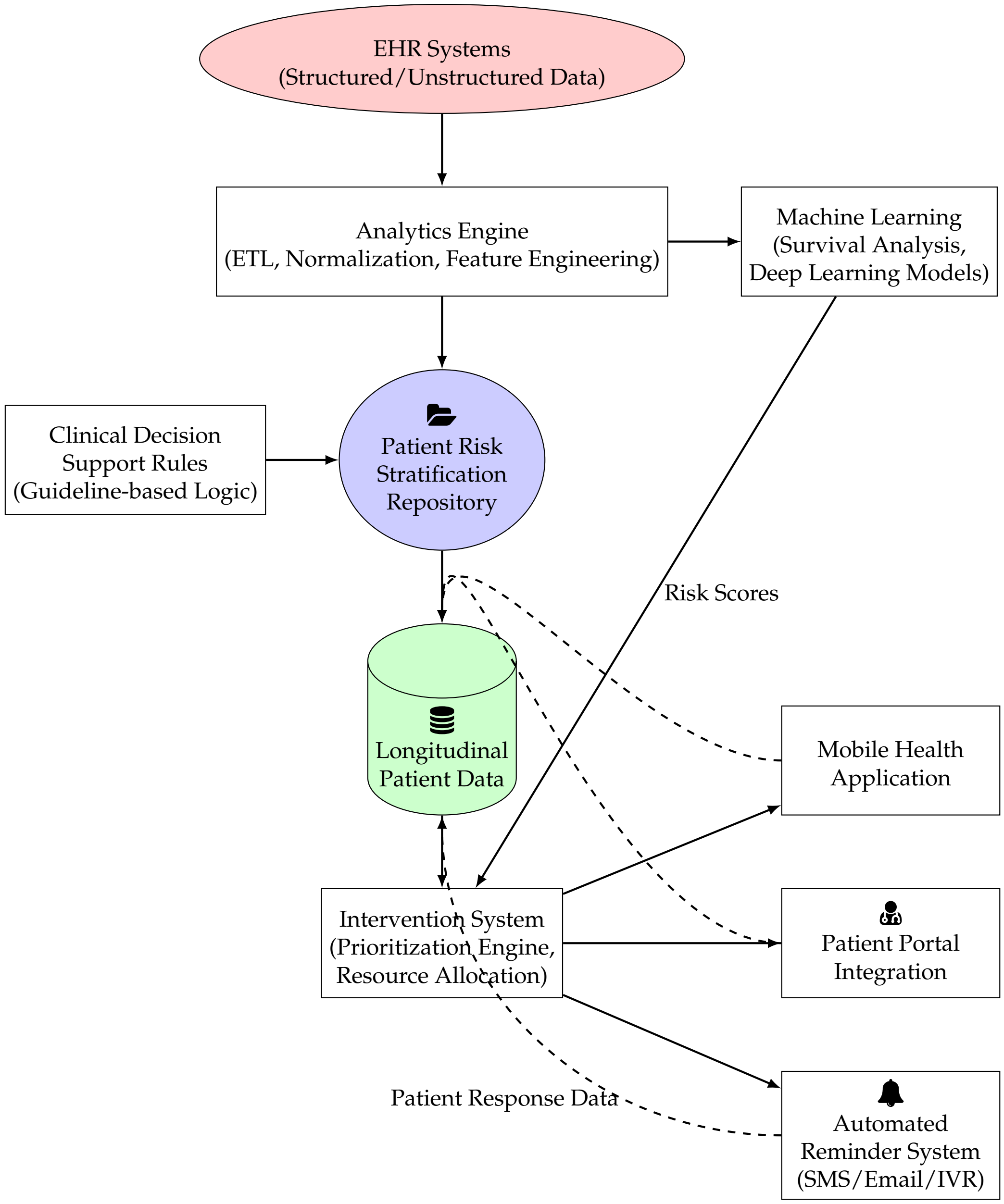

Figure 1 Architecture of AI-driven screening adherence system showing integration of EHR data, machine learning models, and digital intervention tools. The system demonstrates closed-loop feedback through patient response data collection.

Table 1 Barriers to Colorectal Cancer Screening

Category	Patient-Level Barriers	Provider-Level Barriers	Systemic Barriers
Knowledge	Lack of awareness, low health literacy	Inconsistent recommendations	Absence of public health campaigns
Psychological	Fear, anxiety, procedure aversion	Limited motivational strategies	Cultural stigma around screening
Access	Transportation, cost, insurance	Limited consultation time	Geographic disparities in healthcare access
Logistical	Scheduling conflicts, follow-up issues	Lack of reminder systems	Insufficient screening infrastructure

as a result of a confluence of these barriers (Doria-Rose *et al.* 2021). In the recent years, technological advances have emerged as potential enablers to support preventive care adherence, e.g., CRC screening.

The growth in the utilization of electronic health records (EHRs) and health information systems provides an opportunity to systematically screen patients due for screening and track their adherence longitudinally (Lieberman 2010). Electronic communication platforms – such as patient portals, mobile health applications, and automated reminder systems – enable providers to engage with patients beyond the clinic visit, sending individualized reminders or educational content about screening. Data analytics and artificial intelligence techniques offer new tools for studying large volumes of health data to identify patterns of non-adherence (Murff 2010). For instance, machine learning programs can be calibrated to predict who is most at risk of failing to attend their screening based on EHR information, allowing follow-up in a proactive manner. These technology facilitators vow to transcend some of the traditional challenges: reminders and educational messages are able to improve awareness and activation, and insights from data have the ability to direct resources where they will make the greatest difference (Rabeneck 2007). However, current models and strategies for improving CRC screening persistence have important limitations (Issa and Noureddine 2017). Most health systems employ basic rule-based reminders (e.g., sending form letters to all patients of a certain age) or general, algorithmic interventions that do not account for differences among patients.

Generic strategies may be of limited value, since they do not account for the specific reasons that a given patient is not up to date on screening (Heisser *et al.* 2021). Traditionally, improvement programs focused on a single element – for instance, the mailing of reminders – without leveraging the wealth of information that could shape a more tailored approach. In addition, models that do exist are immutable and fail to respond to changing patient health status, patient preferences, or life events over time (Price 2003). They are also able to disregard the timing of the interventions; an intervention made at the wrong time (e.g., when a patient is occupied with some other health issue) may be less efficient, but most current models fail to adjust the timing or method of contact dynamically. Further, the majority of predictive efforts at identifying non-adherent patients still use relatively simple algorithms or scoring systems that consider only a handful of risk factors, perhaps neglecting complex interactions that better define behavior (Bian 2016). Briefly, while there has been some progress, there remains a shortfall in capitalizing on current data integration and AI methods to build a stronger, adaptive model for CRC screening adherence. Traditional predictive models of adherence to CRC screening have classically employed straightforward statistical techniques (e.g., logistic regression) applied to claims data in order to provide summary risk estimates (Inadomi *et al.* 2019). As useful as early risk stratification was, these models are now limited by their capacity to capture the complexity of (a) multi-scale effects (from individual patient factors to larger contextual factors), (b) patients' patterns of healthcare contacts over time, and (c) dynamic resource constraints that influence the way a given intervention is delivered in practice. The proposed theoretical framework combines three computational paradigms—graph representation learning, deep survival analysis, and constrained reinforcement learning—to provide an end-to-end system for optimizing CRC screening adherence. The premise is that screening adherence is fundamentally a dynamic process influenced by time-varying risk profiles, resource limitations, and high-dimensional contextual data. By systematically modeling these factors, this framework transcends conventional one-size-fits-all interventions. (Kim *et al.* 2019)

The framework emphasizes: 1. Data Integration: Large-scale EHR data, social determinants of health (SDoH) external indicators, and mobile health app-based behavioral telemetry are brought together in a shared knowledge structure (Hay *et al.* 2003). Inter-relationships between patients, clinical concepts, providers, and community-level factors are represented using a hypergraph. 2. Predictive Analytics: A multi-modal survival prediction, based on deep learning, forecasts each individual's risk of nonadherence over time (Damiano and Cash 2013). Temporal attention and convolution kernels detect emergent patterns indicative of screening dropout, stagnation, or drifting health behaviors. 3. Optimization of Intervention: Constrained reinforcement learning (CRL) scales up a portfolio of interventions (e.g., reminders via text messages, patient navigators, provider alerts) under resource constraints, fairness, and shifting population needs (Honda and Kagawa-Singer 2006). The approach models improvement in adherence as a sequential decision problem and learns an adaptive policy that maximizes population-level adherence gains over time. (Maxwell *et al.* 2020)

These theoretical advances are reinforced by three theory results. First, we use topological data analysis to capture patient trajectories' subtle deviations from optimal screening patterns and develop a persistent homology–based quantification of how distinct care trajectories deviate from optimal screening patterns (Jin *et al.* 2019). Second, we demonstrate that Markovian assumptions commonly made are unable to capture the history dependencies in repeated screening periods and thus necessitate a non-Markovian decision-theoretic formulation. Third, an information-theoretic proof explains that there are minimal sufficient interventions—a lesser subset of interventions can frequently lead to near-optimal adherence levels, facilitating real-world resource allocation. (Menees and Fenner 2007)

Theoretical Foundation

Cancer screening guideline compliance has been explored from various theoretical frameworks in public health and behavioral science. Before proposing a new integrated model, it is required to review and synthesize prominent constructs of existing theories and models that have been applied to understand CRC screening compliance. These conceptual foundations are individual-level psychological models, interpersonal influence models, and ecological or systems models. All provide information on different aspects of adherence, highlighting the need for a multilevel perspective (Gonzalez *et al.* 2011). Classic health behavior theories have been widely used to explain why individuals choose (or not) to participate (or not) in preventive health behaviors like screening.

One of the most popular frameworks is the Health Belief Model (HBM), where it is assumed that an individual's likelihood of engaging in a health behavior, e.g., screening, relies on several core perceptions (Ford *et al.* 2006). These include perceived susceptibility (individual risk belief for CRC), perceived severity (seriousness belief for CRC and its consequences), perceived benefits (belief that screening will reduce risk or severity), and perceived barriers (barriers to screening, e.g., pain or cost). Cues to action (reminders or symptoms that prompt screening) and self-efficacy (belief in one's ability of performing screening) also enter the picture (Subramanian *et al.* 2004). HBM remains the most common theory in recent cancer screening research, and a recent systematic review found that its constructs were applied in a minimum of eight screening uptake studies during

Table 2 Technological Facilitators for CRC Screening Adherence

Technology	Function	Potential Benefits	Limitations
EHR-Based Alerts	Automated patient identification	Timely screening reminders	May generate alert fatigue
Patient Portals	Secure communication, education	Enhances patient engagement	Requires digital literacy
AI Predictive Models	Identify high-risk individuals	Targeted intervention strategies	Model biases, interpretability issues
Mobile Health Apps	Personalized notifications	Increases adherence via real-time engagement	Privacy concerns, data security
Reinforcement Learning	Optimized intervention policies	Adaptive strategies based on patient response	Computational complexity, resource allocation challenges

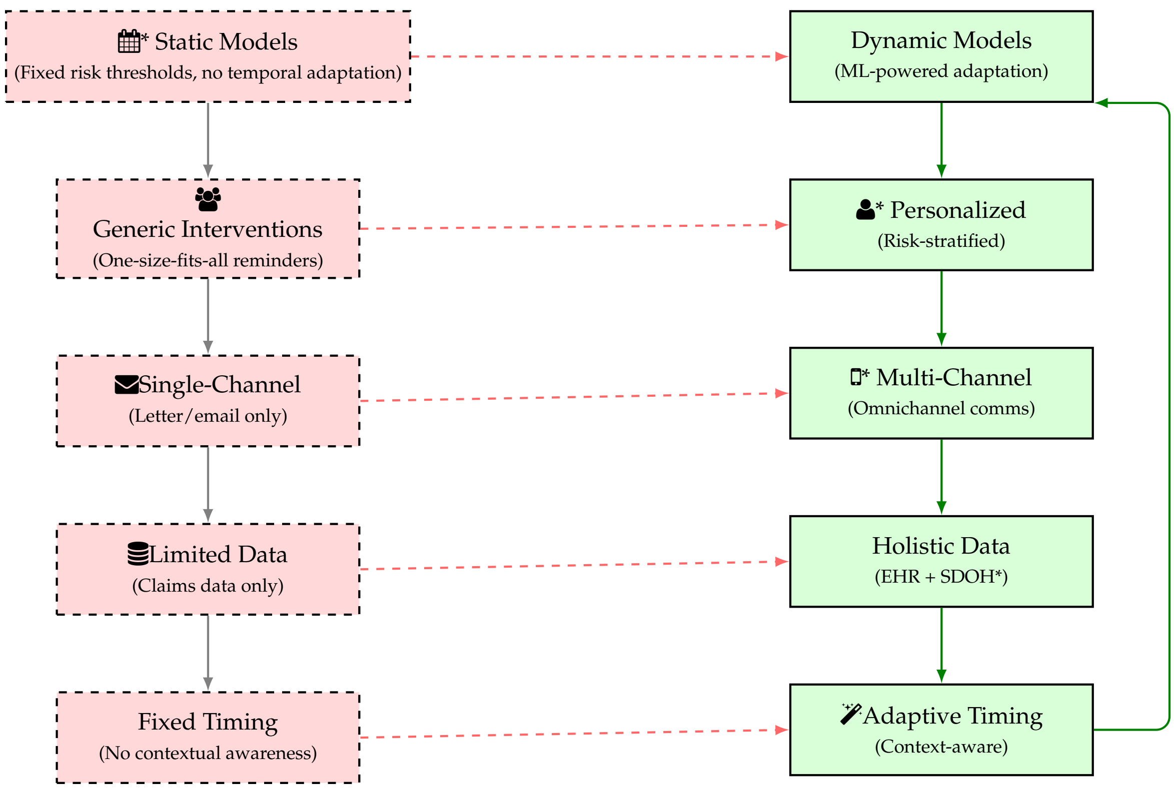

Figure 2 Evolution of CRC screening adherence systems: Current limitations (left) vs. desired AI-enhanced approaches (right).

the last five years. The model's enduring popularity is a result of its intuitive plausibility and empirical validity because time and again, studies have shown that individuals who feel at greater risk of CRC and believe screening is effective are more likely to adhere, and those who feel there are strong barriers to screening, such as fear, embarrassment, or lack of time, are less likely to adhere. HBM-based interventions generally aim to strengthen risk perception and highlight benefits, but reduce perceived barriers via education or streamlining of processes. The Theory of Planned Behavior (TPB) is another prominent model, with a focus on the priority of intention as the immediate behavior determinant (Lieberman 2006). TPB postulates that there are three key determinants that constitute an individual's intention to be screened: attitude towards screening (overall assessment of the behavior as good or favorable), subjective norms (opinions regarding whether significant others, such as relatives or doctors, think that they ought to undergo a screening), and perceived behavior control (perceived ease or hardiness of being screened, which closely correlates with self-efficacy). (Francisco 2014)

Experiments using TPB have shown that positive attitudes and strong social control, such as physician or family support, can strongly increase screening intentions, which in turn strongly predict screening behavior. The model also acknowledges external limits—if individuals don't feel they have control depending on limited availability of healthcare resources or can't afford to miss work time, their action and intention can be challenged despite favorable attitudes and social support (Messina 2011). TPB includes elements of social influence more explicitly than HBM and has been broadened in CRC screening research to encompass cultural elements, including perceptions of fate or medical distrust, that influence screening intentions among ethnic groups.

A number of individual-level theories are also useful for explaining screening adherence (Carlos *et al.* 2004). The Transtheoretical Model (TTM) or the "stages of change" model theorizes that individuals progress through stages—pre-contemplation, contemplation, preparation, action, and maintenance—to acquire a health behavior. Translating this to CRC screening, a patient may not know or be interested at first, form an intention to do it later on, move forward to decide and ultimately have it done, and hopefully, continue to have routine screenings recommended (Jones *et al.* 2019). Each phase is a response to various motivational and cognitive determinants, enabling interventions to be individually designed. For instance, individuals in contemplation may require additional education, and those in the preparation phase for screening might require assistance with overcoming logistical constraints. In like manner, Social Cognitive Theory focuses on observation learning and self-efficacy, which postulates that observing others successfully undergo screening or messages of encouragement from similar role models can enhance one's own confidence and positive expectations. Most interventions in the community utilize these principles by using survivor or community health worker testimonials to alter attitudes (Brittain and Murphy 2015). While beliefs and intentions at the individual level are crucial, CRC screening adherence is also heavily influenced by structural and healthcare-related determinants.

Andersen's Behavioral Model of Health Services Use is commonly used in healthcare utilization research, including screening (kuen Azor Hui *et al.* 2013). This framework puts factors into predisposing characteristics (e.g., gender, age, family history, education), enabling resources (e.g., transportation, income, insurance, having a regular medical provider to see), and need characteristics (e.g., family history or perceived symptoms prompting screening). Consistent studies show that enabling assets, particularly insurance and primary care access, are some of the best predictors of compliance with screening (Shneyderman *et al.* 2015). Lack of insurance and lack of access to a steady source of care are regularly reported as barriers to screening up-to-dateness. Policy change, such as the expanded insurance coverage through the Affordable Care Act, has been associated with increases in screening rates, thus emphasizing the role of structural determinants (Rawl *et al.* 2015). Among healthcare-related factors, provider recommendation of screening is especially key to CRC screening adherence. Multiple research studies have established that a doctor's recommendation is the one most important and influential predictor of screening behavior. (Ritvo *et al.* 2015)

Screening is carried out with far higher probability by individuals who recall being reminded that a screening test had been advocated on their behalf by their doctor (Weissfeld *et al.* 2002). Likewise, non-receiving persons are among the most important sets of individuals declining screening. Physicians inform and encourage patients by educating them on screening, recommending the best modality, and explicitly advocating the need to act (Schmidtknecht 2017). Behaviorally, a recommendation from an agent is an action cue in HBM and affirms a social norm in TPB. Opportunity is lost, however, when time constraints, other issues of priority, or failure in follow-up decrease opportunities for providers to recommend screening (Fendrick *et al.* 2021). To address this, clinical counseling approaches such as the 5A's model—Ask about screening status, Advise the patient to be screened, Assess preferences or barriers, Assist in overcoming barriers, and Arrange follow-up—have been proposed to guide provider-patient interactions. Success in following each of these steps can greatly enhance adherence, but failure at any step can cause a patient to not be screened.

Increasingly, there is evidence supporting a multilevel framework to CRC screening adherence, a concept of which is that screening behavior is not always determined by individual choice or by provider actions but by a constellation of influences at multiple levels: individual, interpersonal, organizational, and policy. Socio-ecological models consistently take into account the reality that individuals are nested within broader social structures (Shete *et al.* 2021). For CRC screening, individual elements cross with family, community, healthcare providers, healthcare system attributes, and public policies. As an example, family and community values shape attitudes toward screening—some communities readily discuss colon health and encourage screening, whereas other communities have fatalistic or shame-based attitudes towards cancer (Siantz *et al.* 2016). At the organizational level, organization-level features of healthcare systems, including patient navigators, reminder systems, and specialized screening programs, can significantly impact adherence. At the most general level, public campaigns and policies, such as national awareness campaigns or state-sponsored screening programs, create an environment for prioritizing and normalizing screening (Winawer 2012). A recent systematic review highlighted that barriers and facilitators exist in all three individual, clinical, and socio-contextual domains, and interventions must target more than one level to be most effective. Most commonly cited factors are knowledge and health beliefs at the individual, healthcare access and insurance at the system, and provider activation and reminder at the clinical (Hirko *et al.* 2020). In the following paragraphs, the architecture is explained fully: Section 2 outlines conceptual framework architecture (data integration, predictive analytics, and intervention optimization).

Section 3 outlines in full the three main theoretical innovations (topological manifold embeddings, non-Markovian decision modeling, and minimal intervention proofs) (Inadomi 2008). Section 4 addresses ethical and operational matters, including bias mitigation and explainability. Section 5 offers a more general account of the framework's potential impacts on specific public health, and Section 6 concludes with a concise summary of significant conceptual contributions (Gaglia *et al.* 2010).

Conceptual Framework Architecture

This sub-section describes the overall architecture of the proposed CRC screening compliance framework. It is divided into three important layers: 1. Data Integration Layer: Responsible for aggregating and mapping multi-source, heterogeneous data into a hypergraph representation that is amenable to downstream analytics. 2. Predictive Analytics Engine: Employs multimodal deep survival analysis and network propagation to derive dynamic nonadherence risk. 3. Intervention Optimization: Implements constrained reinforcement learning with fairness constraints to allocate interventions with limited resources.

Both are theoretically independent but interdependent. The data integration layer ensures the predictive analytics engine has high-quality, temporally aligned data. The predictive analytics engine produces time-varying risk estimates that drive the intervention engine and the policy decision process. Finally, the outputs of the intervention engine (e.g., what interventions are rolled out, who complies or not) create new data, which filters back through to the data integration layer—a closed loop.

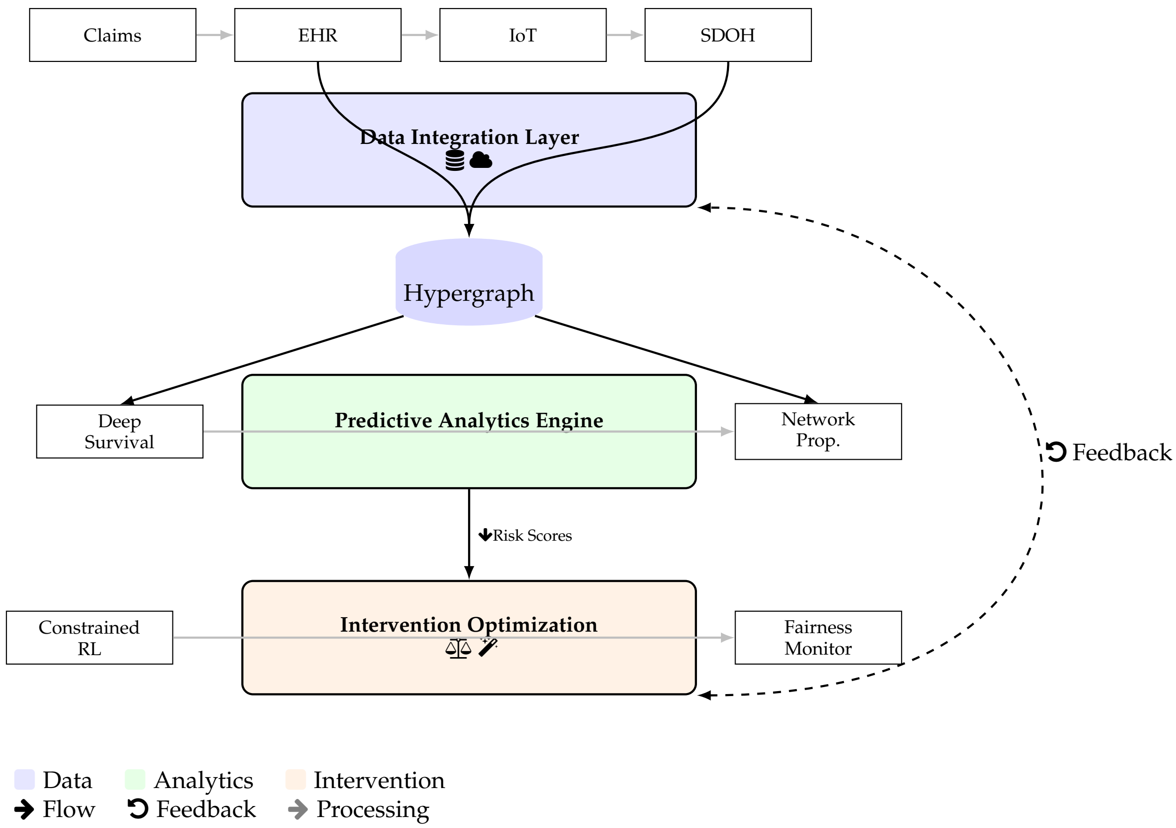

Figure 3 Architecture of CRC screening framework with three optimized layers.

Data Integration Layer

Overview of Multi-Source Data CRC screening compliance cannot be fully understood from a single stream of data. The decision of a person to undergo screening is a combination of clinical factors, psychosocial reasons, community influences, and often technology-facilitated behavior (e.g., responding to app reminders). The proposed framework leverages:

- Electronic Health Records (EHRs): Ordered fields (diagnosis codes, procedure codes, lab results) and unstructured text (provider notes) to capture longitudinal clinical histories. - Social Determinants of Health (SDoH): Population-based measures including access to transportation, income or socioeconomic status, distance to healthcare facilities, and local screening outreach programs. - Behavioral Telemetry: Mobile health app engagement metrics (e.g., steps per day, logins, response time to medication reminders) that supply rich data on patient self-care activity and technology use.

Entity Resolution and Identity Matching One of the foundational steps is entity resolution across heterogeneous data sources. Patients are typically represented under various identifiers (medical record numbers, insurance IDs, etc.). We use a probabilistic matching algorithm to merge these different representations and map them to a common patient ID. The Fellegi-Sunter approach, or a variant thereof, is typically applied, with attributes such as name similarity, birth date, address, and phone numbers being used to calculate matching weights.

Once consolidated, each patient's data from EHR, SDoH databases, and mobile health app logs can be mapped to a single entity, eliminating redundancy and offering consistent linking.

Temporal Tensorization and Imputation Following entity resolution, the data is converted into a temporal tensor $\mathcal{T} \in \mathbb{R}^{N\times T\times F}$, where: - N = number of patients, - T = number of discrete time slices (e.g., biweekly or monthly intervals) spanning the horizon for potential CRC screening (often 5–10 years), - F = number of features extracted from raw data (including clinical, behavioral, and geospatial variables).

Because health data are frequently missing, the model incorporates coupled matrix-tensor factorization (CMTF). In CMTF, a shared latent factor pattern is sought in multiple related data tensors, one for each type of input. CMTF is able to recover missing values by imputing them from correlated signals in other slices of data or other side information. For instance, if we lack a patient's SDoH index for certain time points but we have steady SDoH readings for similar patients or for previous intervals, the factorization can impute plausible values with low-rank patterns.

We aim to minimize:

$$\min_{\mathbf{U},\mathbf{V},\mathbf{W}} \|\mathcal{T} - \mathbf{U},\mathbf{V},\mathbf{W}\|_F^2 + \lambda(\|\mathbf{U}^\top\mathbf{S}\|_F^2 + \|\mathbf{V}\|_*),$$

where $\mathbf{S}$ is a matrix of socioeconomic covariates used to regularize the factorization, and $\|\cdot\|_*$ denotes the nuclear norm, encouraging a low-rank temporal pattern.

Dynamic Time Warping for Sequence Alignment EHR event logs can be asynchronous, with procedures or visits occurring on patient-specific timelines. To account for these variations, the framework employs dynamic time warping (DTW) with derivative transforms (DTW-D). DTW "stretches" or "compresses" timelines to align similar clinical sequences, decreasing misalignment

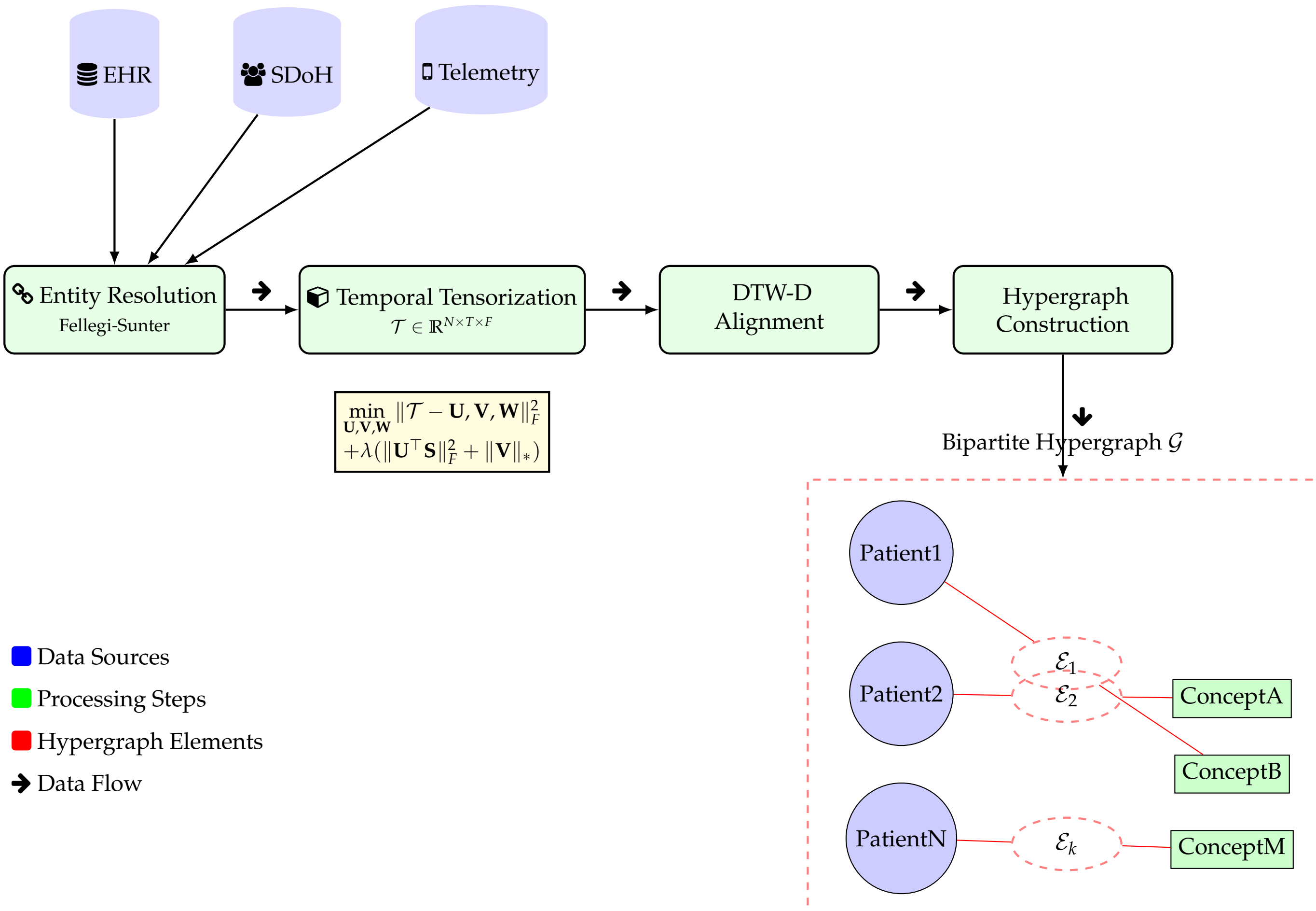

Figure 4 Data integration pipeline showing multi-source data processing through entity resolution, temporal tensorization with CMTF imputation, dynamic time warping, and hypergraph construction. The bipartite hypergraph structure enables relationship modeling between patients and clinical/social concepts.

errors. This alignment step is crucial for creating consistent intervals for subsequent tensor representation and for defining meaningful event-based patterns (e.g., how quickly after an abnormal fecal immunochemical test a patient returns for follow-up).

Hypergraph Construction The final step in data integration is constructing a bipartite hypergraph $\mathcal{G} = (\mathcal{V}_p \cup \mathcal{V}_c, \mathcal{E})$. Here: - $\mathcal{V}_p$ are patient nodes, - $\mathcal{V}_c$ are concept or feature nodes (clinical codes, social indicators, and key events), - $\mathcal{E}$ denotes edges or hyperedges connecting multiple nodes.

Compared to a normal bipartite graph, a hypergraph may express multi-way relationships. As an example, a hyperedge could connect a patient node, a specific location node, and a time segment node to report that a screening colonoscopy was performed there during that period. Weights on these edges can be derived from TF-IDF scores of terms in clinical notes or from the frequency of applicable events (e.g., number of visits for certain diagnoses). Representing data in a hypergraph, we can represent many-to-many relationships (one patient can have multiple applicable concepts simultaneously, and one concept can be applicable to multiple patients) more naturally than the structure of a normal graph would allow.

Predictive Analytics Engine

Deep Survival Transformers Building on the integrated dataset, the framework employs a multi-modal deep survival analysis model to estimate the time-to-nonadherence hazard, $\lambda(t|\mathbf{x}_i)$. Classical survival models, such as Cox proportional hazards, cannot fully capture complex, time-varying covariates or multi-modal data structures. Hence, we use a deep learning model with transformer-based architectures.

The survival model can be written conceptually as:

$$\lambda(t|\mathbf{x}_i) = \exp\big(g(\mathbf{h}_i(t)) + \sum_{k=1}^{K} \int_0^t \phi_k(t-s)\, dN_i^k(s)\big),$$

where $g(\cdot)$ is implemented by a transformer network with multi-head attention that scans a patient's clinical history. The term ϕ_k represents temporal convolution kernels (TCNs) capturing different event types (e.g., missed appointments, prior abnormal tests, changes in mobile health engagement). The integrated hidden state $\mathbf{h}_i(t)$ is updated via recurrent units (e.g., GRU cells) that aggregate past observations. The transformer's multi-head attention architecture subsequently decides how much of the past sequence is most significant to employ in order to predict near-future risk of nonadherence.

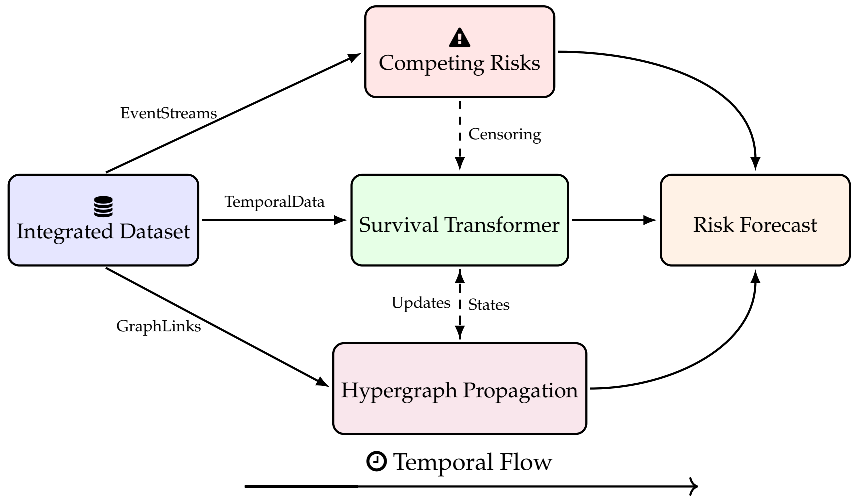

Figure 5 Architecture of the predictive analytics engine combining: (1) Neural survival analysis with temporal attention, (2) Competing event modeling, and (3) Graph-enhanced feature propagation. Arrows show primary data flows between components.

Competing Risks Modeling In CRC screening compliance, we have competing results: 1. Develop CRC (or have a clinically significant event), 2. Non-CRC mortality, 3. Loss to follow-up (e.g., patient relocates or no longer participates), 4. Continuous healthy follow-up.

Rather than modeling a single hazard for "nonadherence," the model provides for competing risks with cause-specific hazard functions:

$$h_c(t) = \lim_{\delta \to 0} \frac{P(t \leq T < t + \delta, C = c \mid T \geq t)}{\delta},$$

where c indexes each competing event. This allows the survival component to differentiate whether a patient drops out because they have died of another cause, moved away, or simply fallen out of contact with screening.

Hypergraph Neural Network Propagation To incorporate the topological structure introduced by the hypergraph, we use a graph isomorphism network (GIN) or similar message-passing approach. Each node (patient or concept) has an embedding $\mathbf{h}_v$. At iteration k, the update rule is:

$$\mathbf{h}_v^{(k)} = \text{MLP}^{(k)}\Big((1 + \epsilon^{(k)}) \cdot \mathbf{h}_v^{(k-1)} + \sum_{u \in \mathcal{N}(v)} \mathbf{h}_u^{(k-1)}\Big),$$

where $\mathcal{N}(v)$ are the neighbors (or co-members in hyperedges) of v, and $\epsilon^{(k)}$ is a learnable parameter controlling how much of the previous representation is retained. This process iterates until the node embeddings stabilize or reach a designated iteration limit.

The trained final node embeddings (specifically for patient nodes) can subsequently be incorporated into the survival model as additional features or used to fine-tune the hidden state $\mathbf{h}_i(t)$. In practice, the representation of the hypergraph conveys cross-patient and cross-concept relations that can potentially be informative for adherence (e.g., patients sharing the same linked provider cluster or living in the same socioeconomically underserved zip code can have risk factors to enable finer prediction).

Intervention Optimization

Formulation as a Constrained Markov Decision Process (CMDP) Having approximated each patient's time-varying risk, the system must choose which interventions to dispense, to whom, and when—subject to scarce resources. We express this as a constrained Markov decision process (CMDP). The state s_t includes: - The patient's dynamic state embedding $\mathbf{h}_i(t)$ (as per the survival model), - The history of interventions from times 1 through $t-1$, - Resource utilization up to time $t-1$.

Actions a_t belong to a set of possible interventions: $\{\text{Text Reminder}, \text{Navigator Assignment}, \text{Provider Alert}, \ldots\}$. Each action has an associated cost $c(a_t)$. The reward function $R(s_t, a_t)$ reflects the expected improvement in adherence (e.g., predicted probability of screening completion), adjusted by any negative factors such as patient disutility or cost. Symbolically:

$$R(s_t, a_t) = \mathbb{E}[Y_{\text{adhere}} \mid \text{do}(a_t)] \; - \; \beta \cdot (\text{QALY Loss}) \; - \; c(a_t),$$

where $\text{do}(a_t)$ indicates the hypothetical setting in which the chosen intervention is applied, and β is a scaling parameter. Over a time horizon T (e.g., multiple screening cycles or intervals), we want to find a policy π that maximizes cumulative reward. However, we also have constraints: limited budgets, staff capacity, or fairness constraints. This leads us to a Lagrangian relaxation:

$$\max_{\pi} \min_{\lambda \geq 0} \; \mathbb{E}_{\pi}\Big[\sum_{t=0}^{T} \gamma^t \big(R(s_t, a_t) \; - \; \lambda\big(c(a_t) - B/T\big)\big)\Big],$$

where B is a total resource budget (e.g., total funds or staff hours), and γ is a discount factor. The inner optimization finds the smallest λ such that the budget constraints hold in expectation. The outer optimization attempts to maximize reward given those constraints.

Counterfactual Fairness and Constrained Reinforcement Learning Fairness constraints are necessary in healthcare to avoid increasing disparities. The framework incorporates counterfactual fairness constraints, i.e., that the intervention suggested by the policy to a patient should not differ based on protected attributes (e.g., race or ethnicity) alone if all other clinical and behavioral attributes are the same. One way is to train an adversary model that attempts to predict protected attributes from the policy's recommended action. By dampening the predictive power of the opponent, we force the intervention policy to rely on clinically important factors rather than demographic factors.

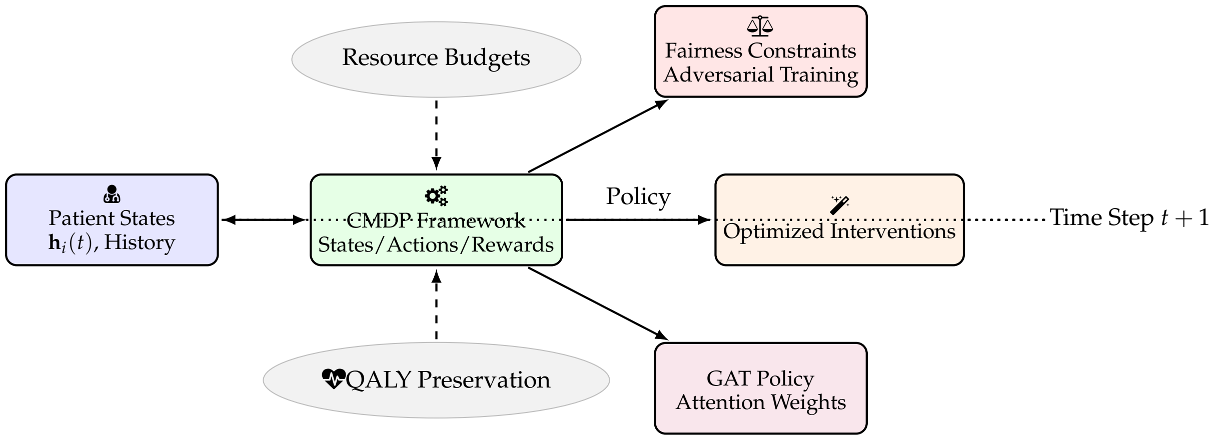

Figure 6 Intervention optimization architecture combining: (1) Constrained MDP formulation with resource/QALY constraints, (2) Counterfactual fairness through adversarial training, and (3) Graph attention networks for relational decision-making. Dashed lines indicate constraint incorporation, dotted lines show temporal progression.

Mathematically, we add a term $\mathcal{L}_{adv}$ that penalizes the policy's capacity to separate patients by race/ethnicity. We can write:

$$\min_{\theta} \max_{\phi} \Big(\mathbb{E}[\mathcal{L}_{\text{task}}(\theta)] \; - \; \lambda \, \mathbb{E}[\mathcal{L}_{\text{adv}}(\phi)] \Big).$$

Here, θ parameterizes the policy π_θ, and ϕ parameterizes the adversarial network. By setting up the problem in this min-max fashion, we encourage the policy to become fair under the definition that protected attributes cannot be recovered from policy outputs alone.

Graph Attention Policy Networks To incorporate relationships among patients and resources, the policy π_θ is implemented with a graph attention network (GAT) that dynamically updates intervention decisions. For a patient node i connected to neighbors $\mathcal{N}(i)$ (e.g., provider node, community node, or other relevant patient clusters), the attention coefficients are calculated by:

$$e_{ij} = \text{LeakyReLU}\big(\mathbf{a}^\top [\mathbf{W}\mathbf{h}_i \,\|\, \mathbf{W}\mathbf{h}_j]\big),$$

and are normalized (via softmax) to produce attention weights α_{ij}. These attention weights capture the system's learned relative significance of neighboring node states in deciding on an intervention for node i. Encoding the connectivity structure allows us to understand, for instance, how a cluster of patients seen by the same under-resourced clinic might require a special intervention or how an individual's risk can be mitigated to some extent by intense community support.

Thus, at every time step, the system: 1. Updates patient states via the survival model and neural updates hypergraph. 2. Plugs these novel embeddings into the GAT-based policy to select an intervention action for each patient. 3. Monitors resource usage and verifies constraints to avoid any budget or fairness requirement violation. 4. Monitors outcomes (did the patient receive screening within the interval?), switches state, and repeats.

Theoretical Innovations

This section gives a thorough explanation of three theoretical aspects that are new in the suggested framework: (1) an introduction to topological embeddings to study care pathways, (2) a non-Markovian generalization of standard reinforcement learning for sequential screening decisions, and (3) an information-theoretic proof of minimal sufficient interventions.

Topological Adherence Manifold

Motivation for Persistent Homology Patient trajectories could be regarded as paths within a high-dimensional state space, where each point represents the patient's clinical and behavioral state at a particular point in time. Standard metrics (e.g., Euclidean distance) might fail to detect nuanced structural deviations from an "ideal" screening path, especially if such paths include multiple cycles of care, care gaps, or partial engagement. Persistent homology of topological data analysis (TDA) gives a robust means of detecting and measuring shapes or holes in high-dimensional manifolds of data.

Constructing Simplicial Complexes for Adherence For each patient i, we: 1. Compile a list of occurrences (e.g., episodes that were screened, atypical results, offer for intervention). 2. Construct a simplicial complex by adding vertices for every event and edges for temporally successive or clinically correlated events. 3. Define a distance or filtration function representing how "near" events are in time or concept space.

Multiple runs of the Vietoris-Rips process at different distance thresholds yield a nested sequence of complexes, and persistence diagramsD_i represent birth and death of topological features (connected components, loops, voids). In a loose sense, a "loop" might describe a cyclic recurrence (e.g., cyclic missed follow-ups or cyclic unsuccessful test completion attempts before full screening success).

Wasserstein Metric for Trajectory Comparison We then embed each patient's persistence diagram D_i into a metric space $\mathcal{M}$ via the Wasserstein metric:

$$d_{\mathcal{M}}(i,j) = \inf_{\eta : D_i \to D_j} \sum_{x \in D_i} \|x - \eta(x)\|_2^2.$$

By comparing the topological signature of a particular patient to that of an "ideal" adherence pathway (which might have minimal loops or direct intervals to completed screening), we can quantify how dissimilar a patient's path is. This quantification can be used in risk models or policy decision; e.g., high topological divergence might trigger more aggressive interventions.

Non-Markovian Decision Theory

Limits of the Markov Assumption Most reinforcement learning methods assume Markovian dynamics, i.e., the future state only depends on the current state and action. However, CRC screening is inherently history-dependent: if a patient consistently ignores reminders, that record of non-response is relevant to future prediction, in addition to the current observation in itself. Similarly, a patient's past colonoscopy experiences (positive or negative) may affect future decisions in ways not fully captured by a Markov state.

Approximation via L-Length Memory We formalize a non-Markovian process by letting the transition kernel P depend on a finite memory window L. Concretely:

$$P(s_{t+1} \mid s_{0:t}, a_{0:t}) \neq P(s_{t+1} \mid s_t, a_t).$$

One practical approach is the ϵ-approximation: if there exists an L such that:

$$\|P(s_{t+1} \mid s_{0:t}, a_{0:t}) \; - \; P(s_{t+1} \mid s_{t-L:t}, a_{t-L:t})\|_1 \leq \epsilon,$$

then we can regard the system as *approximately* Markovian in the extended state space (the last L states and actions). The Kolmogorov extension theorem tells us that the appropriate selection of L can cause the policy to converge to almost optimal behavior. In practice, we put a cut-off history of past interventions and consequences into the state representation. Our abstract design therefore acknowledges that memory-bounded modeling trumps naive Markov assumptions on repeated screening situations.

Minimal Intervention Proof

Information Bottleneck Perspective One of the constant questions of operations is: *How many distinct interventions must a health system deploy in order to achieve almost optimal adherence?* Suppose we have many possible interventions, but it costs to implement all of them. We'd like to identify a minimal subset $\mathcal{I}^*$ that preserves almost all of the predictive power in producing adherence.

From an information-theoretic perspective, any intervention can be interpreted as a channel operating on the random variable Y (compliance outcome). The rate-distortion view prompts us to look for an encoding of the space of interventions that preserves information of interest regarding Y. Symbolically:

$$I(Y; \mathcal{I}^*) \; \geq \; I(Y; \mathcal{I}_{full}) - \epsilon,$$

where $\mathcal{I}_{full}$ is the full set of interventions, and $\mathcal{I}^*$ is the minimal cardinality subset. The existence of $\mathcal{I}^*$ is guaranteed by standard rate-distortion arguments: in a large set of partially redundant interventions, certain subsets can replicate the coverage of relevant states.

Rate-Distortion Formulation Concretely, we define a distortion measure $d(\cdot)$ that quantifies how well an intervention set approximates the ideal outcome. We then solve:

$$R(D) = \min_{p(\hat{\mathcal{I}}|\mathcal{I})} I(\mathcal{I}; \hat{\mathcal{I}}) \quad \text{s.t. } \mathbb{E}[d(\mathcal{I}, \hat{\mathcal{I}})] \; \leq \; D.$$

Near-equivalence of results forces a channel $\hat{\mathcal{I}}$ with near capacity of the full intervention set under a small distortion D. However, when we allow for a small ϵ margin, a lower-capacity subset emerges. This theoretical result accounts for resource allocation: the system need not utilize all nudges and outreach methods comprehensively to get near-optimal population compliance when faced with limited budgets and personnel time.

Operational Considerations

Real-world implementation of this conceptual framework necessarily leaves regulatory, and managerial matters. Two considerations we address and think are important are: (1) prevention of bias and (2) explainability—both crucial to the ethical deployment of advanced analytics in population health.

Bias in underlying health data can be learned by data-driven screening adherence models. For example, if ethnic minorities had fewer interactions with primary care in the past (due to systemic inequalities), an unconstrained model would allocate fewer outreach resources to them—assuming they will not respond, reinforcing inequities. To address this, the model includes adversarial debiasing. In addition to being optimized for the main predictive task, we have an adversarial network that attempts to predict protected characteristics (race, ethnicity, or socio-economic status) from intermediate representations of the model or policy outputs. A gradient reversal layer subsequently backpropagates a penalty every time the adversary succeeds, forcing the model to eliminate predictive signals with respect to these characteristics. Formally:

$$\min_{\theta} \max_{\phi} \Big(\mathbb{E}[\mathcal{L}_{task}(\theta)] \; - \; \lambda \, \mathbb{E}[\mathcal{L}_{adv}(\phi)] \Big).$$

Here, θ parameterizes the main model (survival or policy) and ϕ parameterizes the adversary. By controlling λ, one adjusts the trade-off between overall predictive accuracy and demographic parity. In practice, health care systems can enforce fairness definitions such as demographic parity (equal false negative rates for all subgroups) or equal opportunity. These restrictions can be incorporated in the CMDP formulation by penalizing or preventing policies that adversely affect some protected groups systematically. Being computationally costly, however, the integration of adversarial fairness with CRL is one direction towards ethically aligning resource allocation without compromising overall adherence rates.

As transformer-based survival models and hypergraph neural networks are complicated, it is essential to provide high-level interpretability. Integrated gradients is one of the techniques which attributes each feature's contribution to the final output through the comparison of model outputs along a path from a baseline input to the actual input. For individual patients, the system can generate local explanations (e.g., using SHAP—Shapley Additive Explanations). A standard explanation can reveal that high neighborhood disadvantage and frequent missed appointments both strongly raise the risk of high nonadherence, while frequent mobile app use lowers the risk. Beyond feature attribution, counterfactual explanations offer a "what-if" analysis: if the patient (or system) were to change some factor, would the risk of nonadherence go down? For instance, the model can estimate that the provision of a direct patient navigator visit at month 3 would have reduced the estimated nonadherence risk by 40%. This perspective assists clinicians in identifying the most promising alterations to care or contact.

Discussion

Through the integration of EHR, social determinants, and behavioral telemetry, the design is cognizant that screening adherence is not just dependent on clinical aspects but also on patients' daily environments and moment-by-moment behaviors (Heisser *et al.* 2020). This data-driven approach facilitates nuanced patient stratification on the basis of the potential to be helped by low-touch interventions (e.g., text message reminders) vs. high-touch navigator support. The use of hypergraph neural networks and transformer survival models highlights the importance of preserving temporal dynamics (how risk of non-adherence evolves over time) and relational structures (patients with common providers or neighborhoods) (Melnitchouk *et al.* 2018). Traditional logistic models or even simple recurrent nets are not well suited to learning multi-way relationships that evolve over time. Constrained reinforcement learning acknowledges real-world constraints, including budget constraints, personnel limitations, and fairness constraints.

It casts the problem of delivering interventions as an optimization problem under uncertainty, leveraging partial observability and approximate memory to handle repeated screening interactions (Mema *et al.* 2016). The emergence of topological data analysis for pathway comparison, and non-Markovian RL, provides mathematical frameworks to control high-dimensional, long-range dependencies. The information-theoretic minimal intervention proof reassures decision-makers with the guarantee that a best-chosen subset of interventions can achieve near-optimal results, dispelling concerns about unlimited resource expansion. AI Alignment Forum. Merging these together, the described framework is a conceptual plan towards precision public health—where screening recommendations are dynamically tailored, updated, and systematically implemented (Levin 2012).

While this is a conceptual paper, it has several implications for healthcare organizations and policymakers. Policy structures that facilitate data integration and data sharing are necessary. The system relies on full EHR data, as well as external social determinants measures—often scattered across multiple agencies or systems (Petersen 2002). Having regulatory environments permit secure, ethical data linkage is important. From the vendor side, companies building population health management platforms could integrate hypergraph-based analytics modules and policy engines based on CRL. The architecture provides a roadmap for the next generation of "smart care coordination" platforms that not only display static risk scores but proactively suggest and compare intervention policies subject to constraints on resources.

Applying the conceptual framework in practice would most likely be incremental application to existing healthcare information technology (HIT) (Recio-Boiles *et al.* 2019). For example, an integrated health system may: 1. Adopt the hypergraph-based data integration pipeline as an add-on to its existing data warehouse. 2. Add a deep survival transformer module to generate dynamic nonadherence risk scores. 3. Phase in a CRL policy manager to coordinate outreach campaigns, perhaps starting with a subset of interventions (e.g., call reminders vs. calls). 4. Establish a feedback loop to measure outcomes and retrain models.

The potential synergy is tremendous: as the system refines its predictions, it more effectively personalizes interventions, which boosts engagement and still further refines subsequent predictions. (Butterly 2020)

With all the promise, though, comes prudence. The very data-driven nature of this approach might reinforce biases if not well managed—hence the emphasis on fairness constraints and adversarial debiasing. In addition, too-frequent or obtrusive interventions (e.g., everyday text messages) might compromise patient autonomy or trust (Carlos *et al.* 2005). An effectively tuned policy would have to balance aggressiveness (pressing for increased compliance) against patient choice respect, a consideration extending beyond algorithmic strictures into the area of clinical ethics and best practices of patient activation.

Although the focus in this essay is on CRC screening, the model is designed to be applied to other preventive health behaviors with periodic time intervals (e.g., breast cancer mammography, diabetic retinopathy screening, adult immunization). Any domain with time-based reminders, resource-limited interventions, and multi-faceted data streams can benefit from the combination of hypergraph representations, survival analysis, and RL policy optimization. The long-term vision is to bring about an era of "smart prevention," where interventions are not only tailored at onset but also continuously revised as new data become available. (Ladabaum *et al.* 2013)

Conclusion

This work has proposed a new conceptual framework to boost colorectal cancer screening adherence by the synergistic application of hypergraph-based data integration, multi-modal deep survival analysis, and constrained reinforcement learning. Conceptualizing screening adherence as a time-varying, resource-restricted, and context-sensitive problem reflects the imperatives confronted by healthcare systems aiming to maximize population health gains. Three critical contributions support the framework's value: (Chagpar and McMasters 2008) Enabling a joint representation of heterogeneous data (clinical, social, behavioral) that preserves multi-way relationships and aligns them over time. Not only encoding static risk factors but also dynamic event histories, competing risks, and cross-patient correlations. The temporal attention mechanism ensures the discovery of valuable past patterns and uses them to make risk predictions. Proposing an adaptive intervention policy which recognizes constrained resources, ensures equitable distribution of care, and is aware of a non-Markovian world (Vernon 1997). The theory extensions—integrating care trajectories onto a topological manifold, formalizing non-Markovian decision processes, and applying rate-distortion principles to intervention sets—improve the conceptual foundation of this approach. Operational aspects, including prevention of bias, interpretability, and workflow integration into clinical practice, have been highlighted as being indispensable to safe, ethical, and effective deployment.

Even while actual deployment and empirical testing are left to future work, the framework itself forms the basis for the next generation of precision public health systems (Ellison *et al.* 2011). By systematically incorporating state-of-the-science computational approaches, it provides a blueprint to rectify the long-standing issue of suboptimal CRC screening adherence—and, by extension, a model for addressing analogous adherence challenges in preventive care. Through data-informed evolution at the moment and resource-appropriate intervention planning, these programs can potentially transform population health outcomes, ultimately reducing CRC and other preventable illnesses.

From the business perspective – i.e., healthcare companies, insurers, employers, and technology entrepreneurs – theoretical knowledge on screening compliance can power innovation and new applications. The private sector has a key role to play in developing tools and services that can support screening and putting strategies in place in healthcare provision (Ferrer *et al.* 2010). Several industry and technology consequences are: Development of Patient-Centered Screening Modalities: Having realized that perceived barriers (inconvenience, discomfort) prevent many from getting colonoscopy has led industry to invent new screening tests. An example is development by a biotech company of the multi-target stool DNA test (Cologuard being the brand name) that can be done at home and only requires a colonoscopy if the test is positive. The identification of barriers and acceptance as key factors by the conceptual model merits such innovations – by bypassing the barrier of an invasive test, such alternatives aim to increase overall adherence (Hay *et al.* 2015). Similarly, companies are creating blood-based screening tests for CRC (sometimes called "liquid biopsies"). If successful, an CRC screening blood test would be a game-saver for uptake, as one would only require a simple draw of blood. The model expects that presenting individuals with a range of options and permitting patient choice (in accordance with physician guidance) can get each person closer to an acceptable method, making the overall take-up higher. Areas of work that are diagnostic in purpose should also retain human factors (like convenience and comfort) on the same plane as sensitivity and specificity in developing tests, as both dimensions play a key role in making an impact among populations (Rutter and Inadomi 2017). Digital Health and Reminders: The Activation component of compliance (reminder and prompt) is an area awaiting technology intervention. Health technology companies can implement mobile apps, messaging programs, and integration with electronic health records to remind patients promptly. For instance, one app might remind a person that their yearly FIT is overdue, provide them with directions, and even allow them to order a kit or schedule pickup (Milà *et al.* 2012). Current patient portals and electronic medical records can also send reminders for patients (via email/text) as well as providers (via dashboard notifications) automatically. Industry can make them more powerful by using behavioral science techniques – e.g., crafting the message content to include persuasive elements (e.g., a social norm message: "90% of patients in your age group at this clinic are up-to-date with screening" or a loss-framing: "Screening now could save your life by catching cancer early"). These tactics are associated with the psychological elements of the patient within the model, trying to influence attitudes and perceived norms at the point of decision. Customer relationship management (CRM) software used in other sectors is also usable in healthcare to track and remind patients about the screening process (initial contact, taking the test, follow-up) (Kadiyala 2009). Healthcare communication businesses can stand a possibility to provide integrated screening adherence solutions to clinics and health systems. Provider Workflow Tools and Decision Support: Industry can assist providers by intermingling screening adherence reminders in their workflow. This could be EHR-based clinical decision support that notifies a provider about patients who are due for screening and even pre-orders a test on their behalf to be signed during the visit (Winawer *et al.* 2016). There are already platforms that use AI or data analysis to identify patients overdue for screening and generate lists or alerts. An extension would be predictive analytics: using machine learning on patient data to predict who is most unlikely to take a generic invite and may need additional intervention (such as a personalized call or guidance). Predictive models might use variables like history of no-shows, comorbidities, or socio-demographic data to stratify patients according to risk of non-adherence, so that health providers (or payers) can allocate resources optimally – so-called "precision public health" or personalized intervention.

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