# VIRONIX

Virtual Care Management

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# The Challenges Facing Chronically Ill Patients

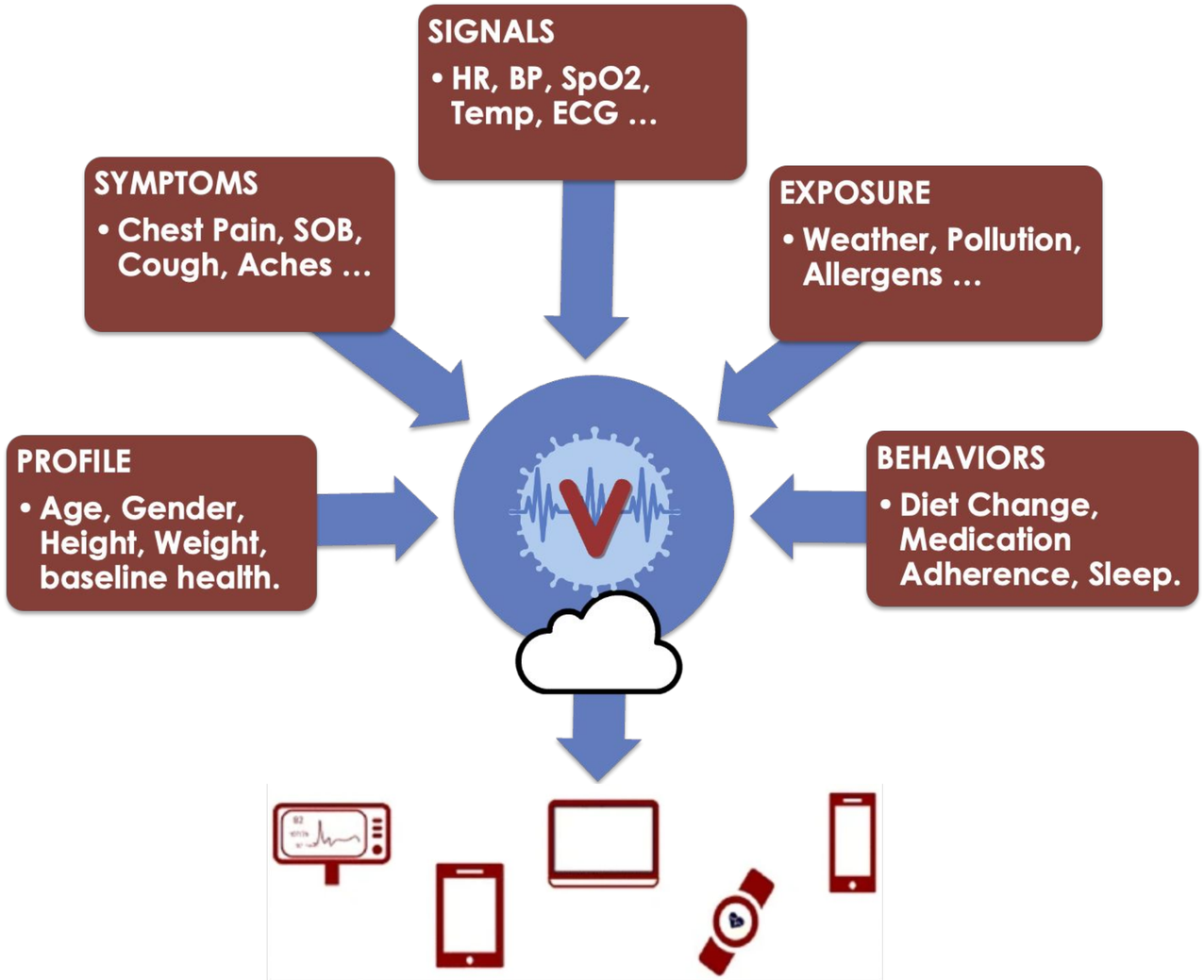

**Chronic disease patients experience dangerous and recurrent health deterioration episodes. When caught early, these are readily addressed by diet, sleep, and medication.**

**~1B** Global Heart, Lung, & Kidney Disease Patients

**~40M** US Patients

**~$2T** Global Hospitalization Cost

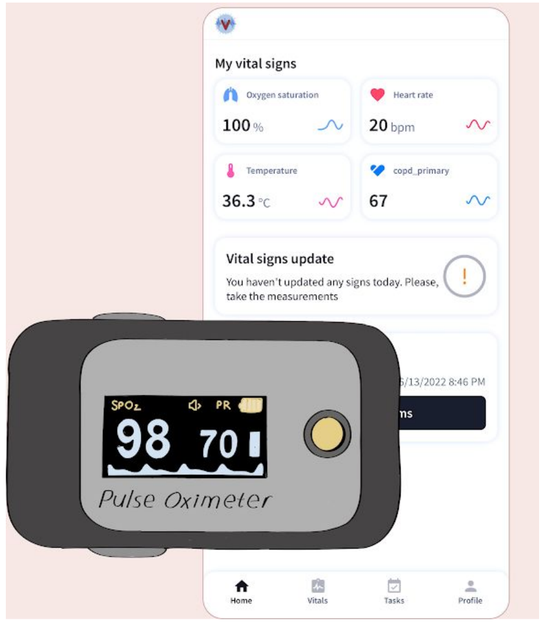
# The Solution: Vironix AI-APIs



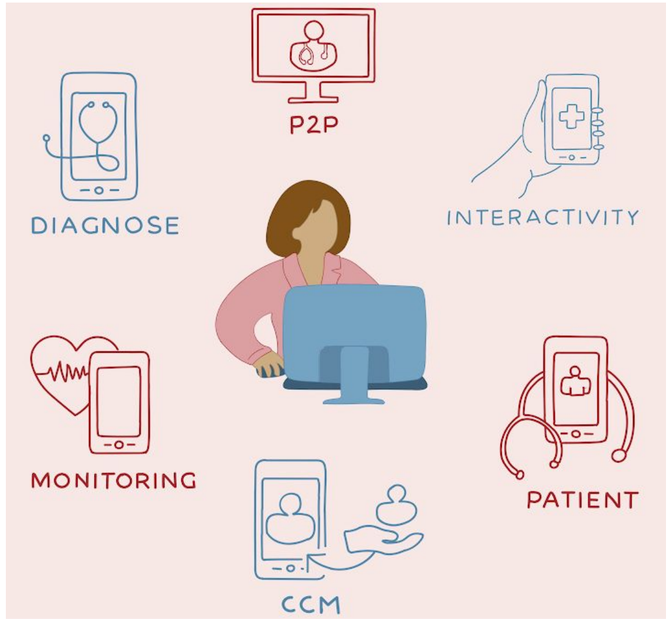

- Exacerbation Detection
- Biometric Irregularities
- Disease-specific Health Scores
- Vitals At A Glance
- Analytics & Trends
- Medication Step-Up Signals

# How Does Vironix Work?

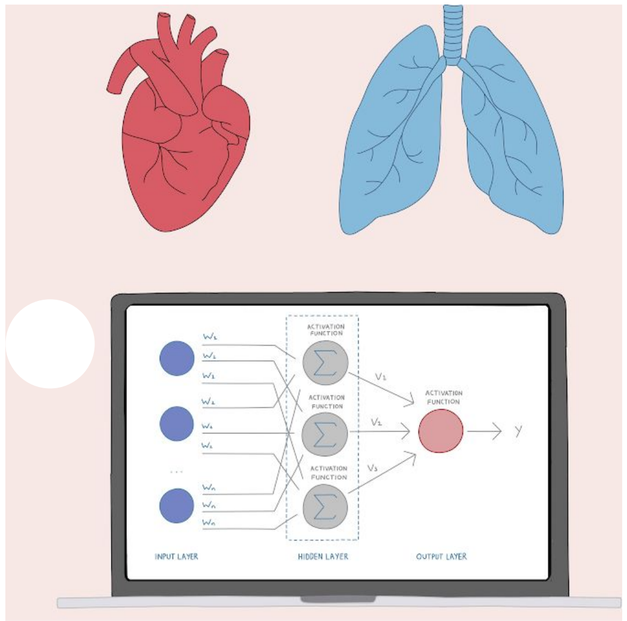
## We Sell To Physicians, Clinics, & Hospitals




**Remote Physiological Monitoring**




**Chronic Care Management**




**AI-Detection of Lung and Heart Failure**

- Paid for by health insurers
- Risk free: $0 upfront investment from customers
- Reduces hospitalizations and improves patient well-being

# Net Increase in Physician Revenues = $75 to $250/patient/month

Medicare introduced a set of Remote Patient Monitoring (RPM), Chronic Care Management (CCM), and Remote Therapeutic Monitoring (RTM) codes

**$19**
Initial Setup

**$42**
Chronic care

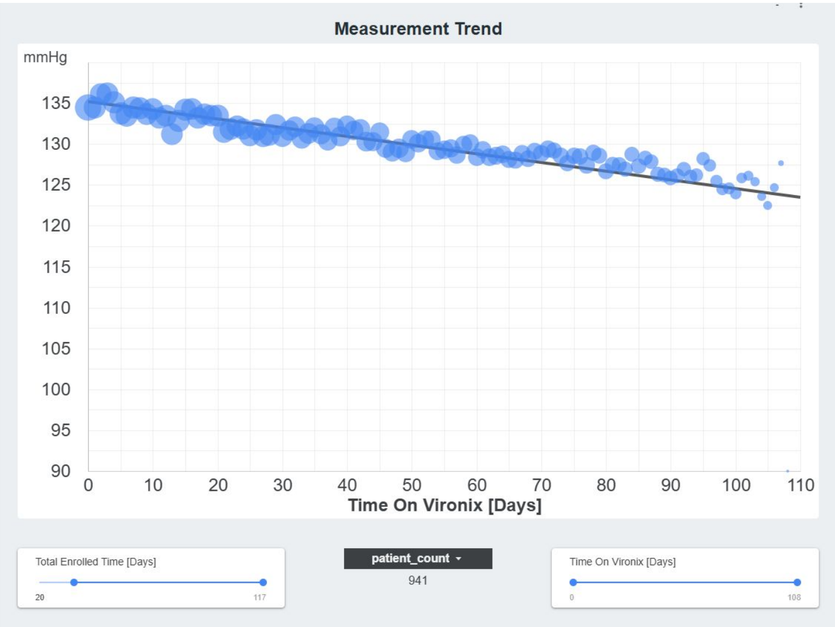
**$61**
Biometrics

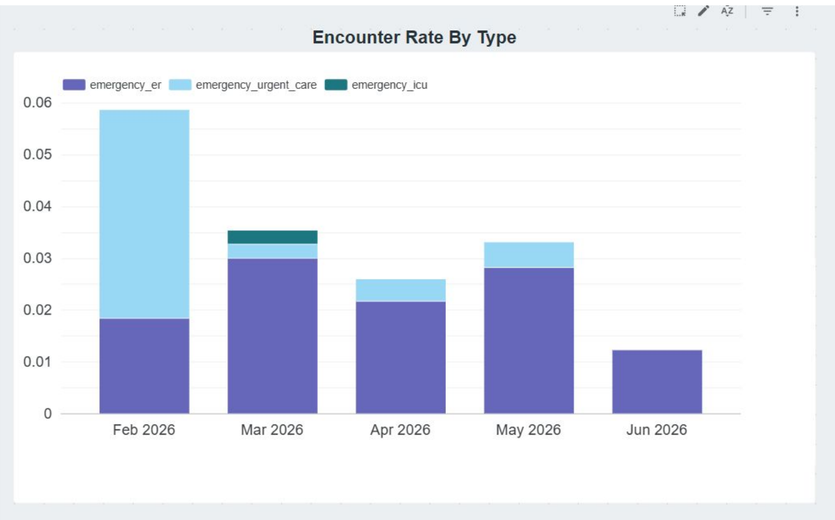
**$54**
Therapeutic

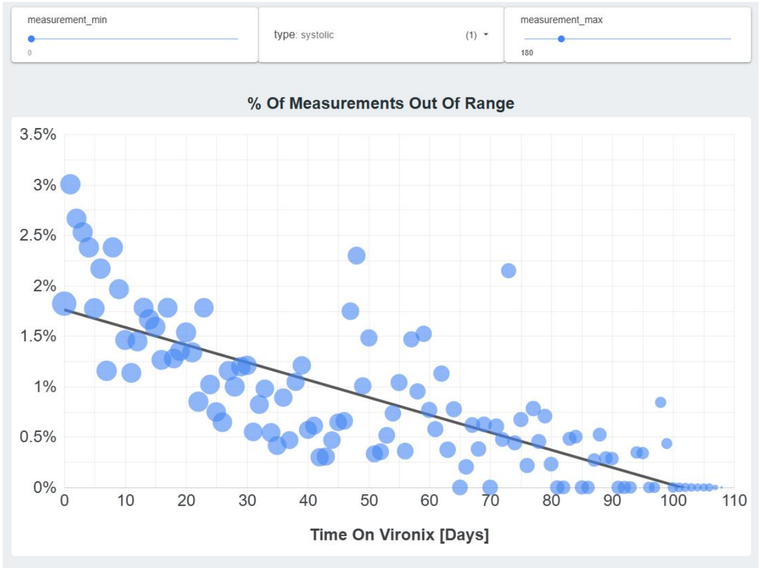
**$51**
Interpretation

Value-based care has quickly emerged as an alternative to traditional fee-for-service models of reimbursement. Designed to drive better patient outcomes and align payer/provider/patient incentives, value-based care introduces shared savings and risk

# Effect of Remote Patient Monitoring





We see statistically significant drops in systolic blood pressure the longer the patients are on the service.

The effect on reducing severe encounters (e.g. ER visits) and PROMIS GI scores is encouraging but less clear.

**“Down and to the right = Good”**

# THE MODELING PROBLEM: WHY THE VIRONIX APPROACH?

How do we build predictive models that consume consumer-level data and return accurate assessments of quality of life (QALY) and dangerous health deterioration?

## Data Access

1. Comprehensive, consumer available health data collected during disease degeneration is generally nonexistent.

2. Medical record data is widely unavailable/proprietary, generally incomplete, and gathered at point of care. (Which leads to sparse data).

## Complexity of Disease Degeneration

1. Building first principles models that can be leveraged by consumers at-home with measurable inputs is very challenging. (Measurements should be taken frequently and non-invasively).

2. In general, disease degeneration is a multi-scale problem involving multiple biological systems.

# MPI 2026 PROBLEM

## Modeling Chronic Digestive Diseases

# GI TRACT DISEASES: COMBINED OVERVIEW & BURDEN

## WHAT ARE THESE CONDITIONS?

### Inflammatory Bowel Disease (IBD)

- Crohn's & Ulcerative Colitis — chronic immune-mediated GI inflammation

### Irritable Bowel Syndrome (IBS)

- Functional GI disorder; recurrent abdominal pain & altered bowel habits

### Diverticular Disease

- Colonic pouches (diverticula) that can rupture/inflame (diverticulitis)

### Fatty Liver Disease (MASLD/NAFLD)

- Metabolic fat accumulation in liver; strongly linked to obesity & diabetes

## SHARED KEY SYMPTOMS

- Abdominal pain, cramping & bloating (universal across all 4 conditions)
- Altered bowel habits — diarrhea, constipation, or alternating patterns
- Chronic fatigue and reduced quality of life
- Nausea, appetite loss and unintended weight loss
- Rectal bleeding and bowel urgency (IBD, Diverticulitis)
- Early stages often asymptomatic (MASLD, Diverticulosis)
- Advanced stages: jaundice, ascites, systemic complications

## COMMON TRIGGERS & RISK FACTORS

- Western diet: low-fiber, high-fat, high-sugar, high-red-meat intake
- Obesity, metabolic syndrome & type 2 diabetes
- Chronic psychological stress and anxiety
- Gut microbiome dysbiosis (shared root across all 4 conditions)
- NSAID, opioid & antibiotic overuse
- Sedentary lifestyle & physical inactivity
- Aging — risk rises steeply after age 50 for most conditions

## COMBINED ECONOMIC BURDEN

**~$121–$154B**

combined annual direct US healthcare costs

- IBD: $14.6–$31.6B / yr
- IBS: $1.5–$10.0B / yr
- Diverticulitis: $2.2–$9.0B / yr
- MASLD: ~$103B / yr
- Massive indirect costs: lost workdays, caregiver burden, reduced productivity
- 500K+ combined US hospitalizations annually

## EXTENT OF THE PROBLEM

**~170M+**

Americans affected across all 4 GI conditions

### By Condition (US)

- IBD: ~3.1M diagnosed
- IBS: ~25 - 45M affected
- Diverticulosis: ~60M+ adults (35% > 60)
- MASLD: ~100M (38% of adults)

### Key Trends

- All 4 conditions have rising incidence in the US
- Western diet & obesity are common drivers
- Significant overlap & comorbidity between conditions
- Often undiagnosed or misdiagnosed for years
- GI disorders are the #3 cause of US hospitalizations

### Remote Monitoring Opportunity

- Symptom tracking & flare prediction
- Dietary & lifestyle behavior monitoring
- Medication adherence surveillance
- Reduced ER visits through early intervention

Sources: CDC, Gastroenterology (2019/2023), NIH/PMC, NIDDK, Diabetes Spectrum (2024), US Pharmacist — Vironix Health

# Challenge 1: Supplemental Research on Modeling

Research and Identify literature on mechanistic models of the GI tract and ML-based prognosis models for IBD and IBS.

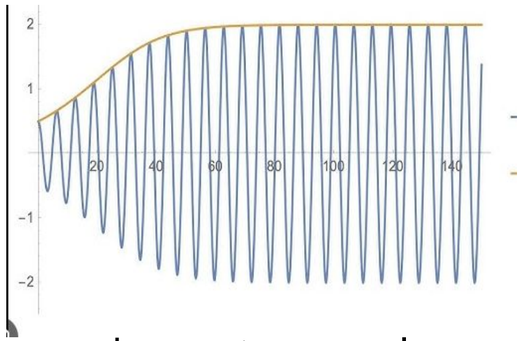
1. How do their assumptions differ?

2. What mechanistic details of the disease were used in the model?

3. What validation studies have been conducted?

# Challenge 2: Formulating models

Develop a hybrid "Disease Degradation Model" that integrates mechanistic foundations with statistical learning methods and clinical data.




The models are required to address two objectives:

a. Short term prediction - Identify active flares and forecast flare frequency within a short timescale.
   - Short term flares (time scale ~t [hours])
   - What markers lead to these flares? Markers = any signal we can detect.
   - How do the markers change in response to treatment protocols?
   - Likely a set of coupled differential equations is needed.

b. Long-term prediction - Mapping the progression of the chronic digestive disorder.
   - Long term scale (time scale ~εt [months])
   - How do short-term flares affect long-term risk (e.g. permanent damage, hospital visits, surgery)

# Challenge 3: Evaluating Model Performance

Propose methods to assess model input parameters and couple model outputs to predict flares and long-term progression using known patient longitudinal data. (e.g. use ML model to predict rate constants in a differential equation that models the patient disease state.)

1. Identify which model parameters are most sensitive to patient-specific data.
2. Identify which model parameters that are not relevant to the model.
3. How can we validate the mechanistic plausibility of your hybrid model?
4. Some data is sparse (measurements or assessments that are taken irregularly) which could involve an ML model to interpolate sparse data.

# Mechanistic Modeling Approaches

1. Models can describe a specific degradation process (e.g., the loss of intestinal barrier integrity or the depletion of short-chain fatty acids) and its response to a given treatment protocol.
   a) How do we map model outputs (e.g. decay rate of intestinal wall) to patient disease states?
   b) How can you incorporate the effect of treatment protocols into the modeling framework?

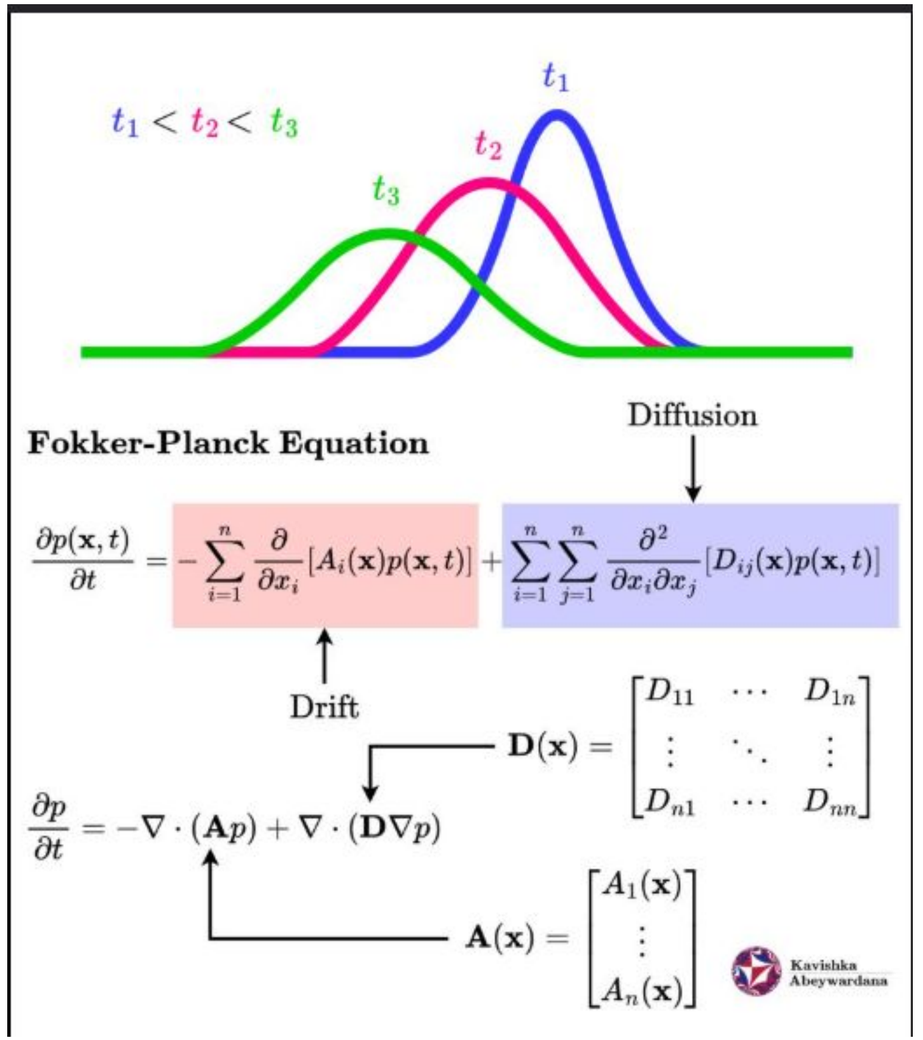
2. Markov-state-models/Fokker-Planck equation that model the time evolution of the probability density function P(x,t) of the patient disease state.
   a) Patient has a probability of being in a certain disease state.
   b) How do we calculate transition probabilities from one state to another from clinical data?

3. Develop a framework to translate patient disease state to predict risk for a flare-up.

Model inputs include patient biodata from a profile, longitudinal dataset of simple vitals and patient-reported symptoms, periodic tests, and treatment protocol information. [Vironix has this. But you have to ask nicely.]

S. Swaminathan, et al., Vironix: Remote Screening, Surveillance, Triage, and Management of Novel Coronavirus https://covidx.vironix.ai/CovidX_CoronaVirus_WhitePaper04052020.pdf

# Mechanistic Modeling Approaches

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# Modeling Disease Severity on Clinical Characteristic Data

| Characteristic | All Patients (N=1099) | Disease Severity | |
|---|---|---|---|
| | | Nonsevere (N=926) | Severe (N=173) |
| Age | | | |
| Median (IQR) — yr | 47.0 (35.0–58.0) | 45.0 (34.0–57.0) | 52.0 (40.0–65.0) |
| Distribution — no./total no. (%) | | | |
| 0–14 yr | 9/1011 (0.9) | 8/848 (0.9) | 1/163 (0.6) |
| 15–49 yr | 557/1011 (55.1) | 490/848 (57.8) | 67/163 (41.1) |
| 50–64 yr | 292/1011 (28.9) | 241/848 (28.4) | 51/163 (31.3) |
| ≥65 yr | 153/1011 (15.1) | 109/848 (12.9) | 44/163 (27.0) |
| Female sex — no./total no. (%) | 459/1096 (41.9) | 386/923 (41.8) | 73/173 (42.2) |
| Smoking history — no./total no. (%) | | | |
| Never smoked | 927/1085 (85.4) | 793/913 (86.9) | 134/172 (77.9) |
| Former smoker | 21/1085 (1.9) | 12/913 (1.3) | 9/172 (5.2) |
| Current smoker | 137/1085 (12.6) | 108/913 (11.8) | 29/172 (16.9) |

Disease severity scores based on health history (smoking history, etc.)

1. Acquire clinical characteristic data from human trials literature and software users.
2. Use Bayesian inference to convert characteristic data into vignettes for a training/validating prediction algorithm.
3. Build ML classification models for predicting health severity from a patient state.
   - k-nearest neighbor
   - support vector machine (SVM)
   - gradient descent

$$P(feature \mid severity) = \frac{P(severity \mid feature)}{P(severity)} \cdot P(feature)$$

Posterior probability

Prior probability

S. Swaminathan, et al., Vironix: Remote Screening, Surveillance, Triage, and Management of Novel Coronavirus https://covidx.vironix.ai/CovidX_CoronaVirus_WhitePaper04052020.pdf

# Starting References


1. Hypothesis: Mechanism of irritable bowel syndrome in inflammatory bowel disease, Yoshiharu Uno (https://doi.org/10.1016/j.mehy.2019.109324)
2. Physiological Data Collected From Wearable Devices Identify and Predict Inflammatory Bowel Disease Flares, Hirten et. al. (https://doi.org/10.1053/j.gastro.2024.12.024)
3. Emerging wearable technology applications in gastroenterology: A review of the literature, Chong and Woo (https://doi.org/10.3748/wjg.v27.i12.1149)
4. Machine Learning Prediction Model for Inflammatory Bowel Disease Based on Laboratory Markers. Working Model in a Discovery Cohort Study, Kraszewski et. al. (https://doi.org/10.3390/jcm10204745)
5. A Dynamic Quantitative Systems Pharmacology Model of Inflammatory Bowel Disease: Part 1 - Model Framework, Rogers et. al. (https://doi.org/10.1111/cts.12849)
6. Continuous time Markov chain approaches for analyzing transtheoretical models of health behavioral change: A case study and comparison of model estimations, Ma et. al. (https://doi.org/10.1177/096228021663985 9)

# Logistics

1. Programming Language Preferences:
   - Python (Strong Preference)
   - Matlab
2. Please comment code extensively and break code into functions/subroutines!
3. Try as much as possible to conform to PEP 8 style guide for python programming. https://www.python.org/dev/peps/pep-0008/
4. Remember to keep good records of citations used.
5. All data needs to be removed from your local machines by the end of the conference.
   - Fee free to use any data in the literature.
   - Any Vironix data is regulated by HIPAA and would need to be approved by the bossman.

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