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INTELLIGENCE FOR IMAGINATION

Preventing unnecessary emergency room visits to reduce health care costs

ABSTRACT

The sole purpose of the Emergency Room (ER) is to save lives by providing immediate attention to people with life threatening situations. With 24x7 access, a broad array of services, and the latest technology at hand, ER teams are well equipped and trained in treating medical urgencies, stabilizing patient conditions, and preventing further damages.

Today, many ERs are overcrowded[i] as:

- Unlike other treatment facilities, ERs have a federal mandate to provide care to any patient requesting treatment
- Primary care physicians (PCPs) are in short supply
- Poor patient knowledge and socio-economic conditions drive more patients to seek medical care in ERs

An increasing abuse of ERs, either due to patient ignorance or convenience, demands urgent attention from both payers and providers. There is a lot of documented evidence where patients have used ERs for situations that could have been treated in a more cost-effective care setting such as Urgent Care Clinics (UCCs) or Patient-Centered Medical Homes (PCMHs). A study from Project HOPE[ii] estimated that 13% to 27% of all emergency department visits in the US could be managed in alternative sites, with a potential cost savings of approximately $4.4 billion annually.

This paper presents a comprehensive end-to-end solution to reduce ER utilization for non-emergent conditions. The proposed data-driven solution leverages predictive analytics to develop a framework to identify members likely to use the ER for avoidable reasons in the near future, and the solution recommends designing specific interventions to prevent future visits. During the process, we will have also built a case to leverage analytics in an agile way to rapidly derive maximum value.

[i]Barish RA, Mcgauly PL, Arnold TC. Emergency Room Crowding: A Marker of Hospital Health. Transactions of the American Clinical and Climatological Association. 2012;123:304-311.

[ii]Copyrighted and published by Project HOPE/Health Affairs as Weinick RM, Burns RM, Mehrotra A. Many emergency department visits could be managed at urgent care centers and retail clinics. Health Aff (Millwood). 2010;29(9):1630-1636. The published article is archived and available online at www.healthaffairs.org.

THE ER HEALTH CARE LANDSCAPE

In 2016, America spent more than $3.3 trillion on health care, or approximately $10,348 per person. This was a 4.3% increase from the previous year, contributing 17.9%[1] to overall US GDP. More importantly, the health care expenses grew 1.5% faster than the rise in GDP. This faster growth in total spending was partly driven by strong growth in spending for private health insurance, hospital care, physician and clinical services, aging population, and the expansion of coverage through the Affordable Care Act (ACA).

While health care experts and economists are still debating the long-term and exact impact of the probable causes, in a recent study published in JAMA,[2] the Obama administration claimed that since the ACA became law, the uninsured rate has declined by 43%—from 16% in 2010 to 9.1% in 2015— with most of that decline occurring after the law's main coverage provisions took effect in 2014 (see Figure 1 for details). Further, the Department of Health and Human Services (DHSS) estimated that 20 million more people had health insurance in early 2015 because of the law.

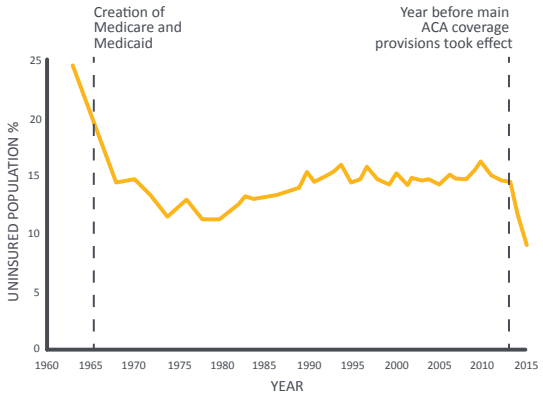


FIGURE 1. Percentage of Individuals in the United States Without Health Insurance, 1963-2015

However, having more insured people under the health care safety net without improving supporting infrastructure is expected to put significant pressure on the entire delivery system. A Center for Disease Control and Prevention (CDC) report[3,4,5] estimated that in 2011 there were over 136 million emergency room (ER) visits, for an average of 44.5 visits per 100 persons. Now, with an additional 20 million members getting coverage in 2015 and many more expected to have it in the following years, there will be an increased spotlight on ER utilization.

A finding from the National Hospital Ambulatory Medical Care Survey (NHAMCS) cites that nationally, 39.5% of ER visits among the general population are primary care sensitive in nature and therefore preventable.[6] A Truven study[7,8] estimates that only 29% of ER visits required emergency attention, with a rough cost estimate of $1,233 per ER visit,[9,10] wasting billions of dollars in health care costs. Another study projected $4.41[9,11] billion in annual savings if non-urgent visits are better managed in alternate care settings.

Ideally, ER usage should drop when there is an efficient health care system with better access to care and affordable costs, as expected by ACA provisions. However, ERs are not a substitute for primary care relationships, nor can they address the broader socio-economic factors driving health care costs.[11,12]

THE SCOPE OF THE ER PROBLEM

The scope of this paper is to dig deep and answer three broad questions:

1. Which members are likely to make avoidable ER visits in the near future?
2. Why are these members more likely to make an avoidable ER visit than others?
3. How can we prevent such visits in the future?

FIGURE 2. Three Broad Questions

LITERATURE REVIEW

Academia and organizations have been studying parts of this equation for years. We started with a systematic review of the existing literature to leverage present-day knowledge to understand:

1. ER utilization trends: What has been the historic trend and what do experts say about future use?
2. Emergent vs. non-emergent ER visits: What factors drive non-emergent visits?[iii]
3. Interventions: What can be done to reduce non-emergent ER visits?
4. Efficacy: What works vs. what does not with respect to environment (type of payer) and care delivery settings?

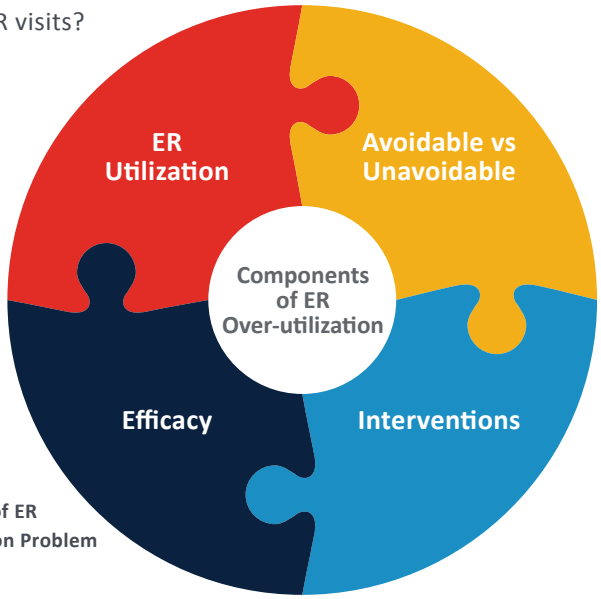


FIGURE 3. Components of ER Over-Utilization Problem

[iii]Cases where immediate care is not required within 12 hours (e.g., sore throat).

ISSUES AND CHALLENGES IN EXISTING SOLUTIONS

- Complexity of the problem
- Limited scope
- Limited data
- High cost of using analytical solutions
- No early cost benefit analysis
- Analytics in isolation without synergies in interventions
- Solutions specific to population cohorts under study and cannot be generalized
- No attempt to answer "So what?"

We found that due to the complexity of the problem, the inherent restrictions on sharing patient data, and the vast variety of health care delivery settings (Medicare, Medicaid, Employer Sponsored, Commercial, Individual, etc.), most of the studies answered only some of the questions that we set out to answer. The limited evidence from the academic studies did suggest that age, ease of access to ER compared with other care alternatives, perceived severity, and socio-economic settings all play a role in decisions to seek care in the ER for non-urgent problems.

The usual research studies focused on identifying:

1. How the visits should be classified: emergent and non-emergent? Or...

2. What are the factors driving non-emergent usage? Or...

3. What intervention may work for a select population through statistical analysis, review of patient charts, or survey techniques?

We observed that there was no systematic end-to-end approach that addressed all parts of the problem holistically. Further, most of the studies were not focused on demonstrating ROI from such initiatives which may, in part, be attributed to the nature of their funding itself: academic or through grants from non-profit organizations.

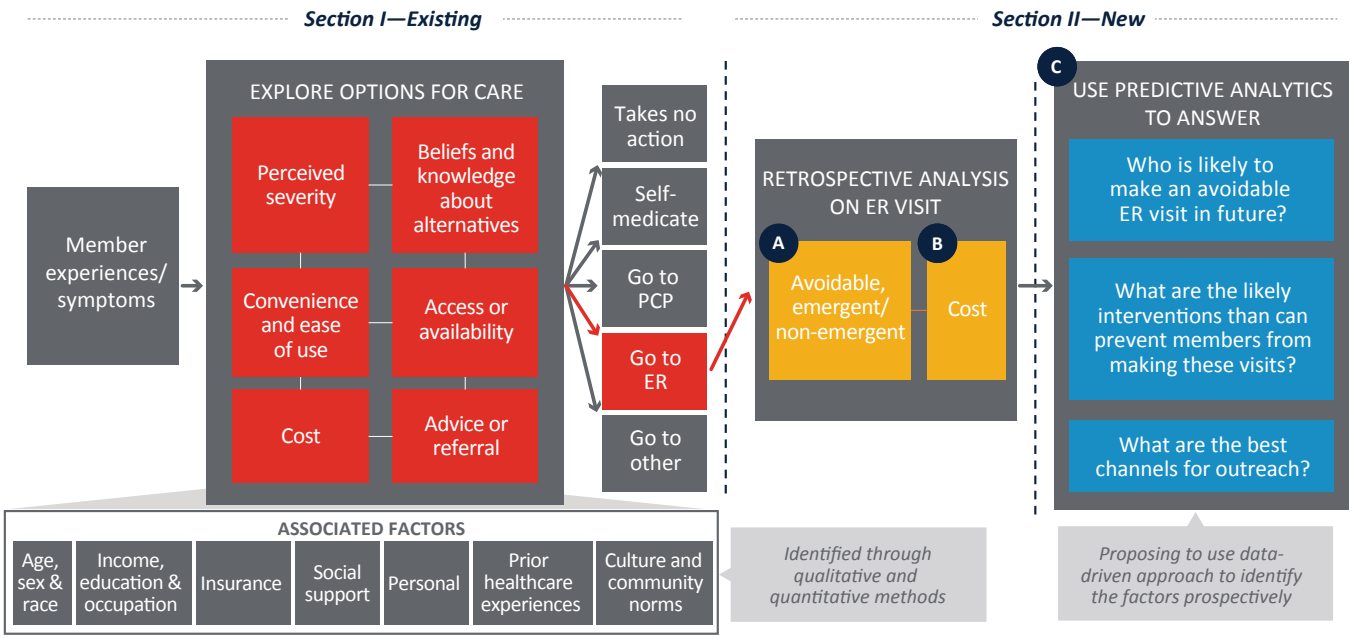
THE ANALYTICS DRIVEN ER UTILIZATION SOLUTION

CONCEPTUAL FRAMEWORK

In a study funded by the California Healthcare Foundation to understand factors influencing an individual's decision to visit an Emergency Department (ED) for a non-urgent condition, authors Lori Uscher-Pines et al[13] proposed a conceptual framework[iv] to show how a patient arrives at a decision to seek care in an ER by consciously or unconsciously weighing several considerations. The decision to go to an ER is influenced by an array of causal pathway factors and associated factors. See Section I of Figure 4 for details.

The associated demographic, socio-economic, and lifestyle factors (Section I of Figure 4) can be determined through qualitative and quantitative techniques. We will limit our study to patients who chose the "Go to ER" path and algorithmically determine the associated factors. Then, we will extend the framework (Section II of Figure 4) to identify which visits, retrospectively, were avoidable and what was the dollar impact of it. Finally, we will show how advanced AI/ML techniques will help to prospectively identify members likely to make an avoidable ER visit in the near future.

FIGURE 4. Conceptual Framework



American Journal of Managed Care: Emergency Department Visits for Non-urgent Conditions

[iv]Conceptual Model of Non-Urgent ED Use. Deciding to Visit the Emergency Department for Non-Urgent Conditions: A Systematic Review of the Literature. Am J Manag Care. 19(1):47-59.

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METHODOLOGY

ALGORITHM AND TECHNIQUES TO CLASSIFY ER VISITS

The foremost problem is to classify ER visits as emergent (unavoidable) or non-emergent (avoidable). The gold standard is to have a panel of clinical experts review patient charts for the selected population and then classify each visit accordingly. However, this process is very resource intensive and not feasible when quick results are needed. There can be multiple alternative approaches to classify ER visits as avoidable or unavoidable:

Option 1: Developing an independent algorithm

Here, a statistically large sample of claims is selected, and the frequency of primary diagnosis codes is analyzed in a "regular setting" vs. an "ER setting." Diagnosis codes that were more often treated in a "regular setting" and were also present in an "ER setting" are flagged. A threshold value is chosen to further trim down the selection, and then claims with flagged diagnosis codes are considered as "avoidable."

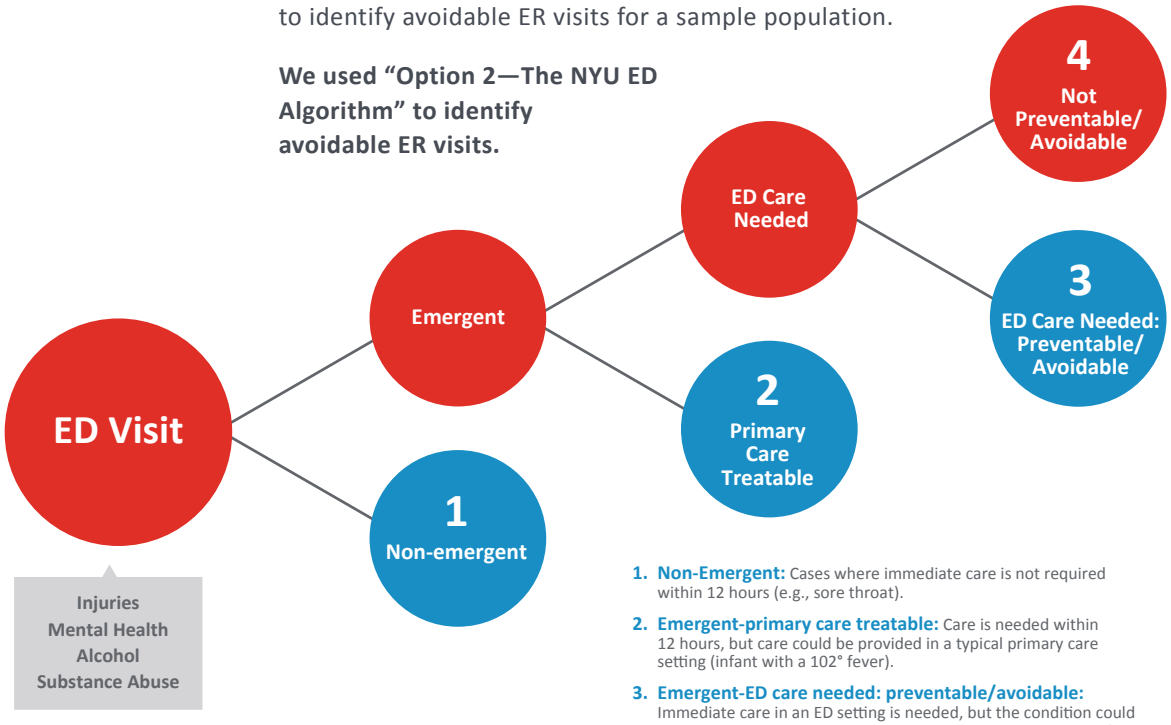
Option 2: Leveraging a publicly available algorithm

The NYU ED algorithm[v] is widely used to identify diagnosis codes which are avoidable (with greater than 90% probability). There are other variants of the NYU algorithm: The Billings/Ballard algorithm[14] and, more recently, the Minnesota algorithm.

Option 3: Leveraging in-house learning to create a hybrid algorithm

Leverage an in-house clinical research team's prior experience to identify avoidable ER visits for a sample population.

We used "Option 2—The NYU ED Algorithm" to identify avoidable ER visits.



1. **Non-Emergent:** Cases where immediate care is not required within 12 hours (e.g., sore throat).
2. **Emergent-primary care treatable:** Care is needed within 12 hours, but care could be provided in a typical primary care setting (infant with a 102° fever).
3. **Emergent-ED care needed: preventable/avoidable:** Immediate care in an ED setting is needed, but the condition could potentially have been prevented or avoided with timely and effective ambulatory care (asthma, diabetic ketoacidosis, and so on).
4. **Emergent-ED care needed: not preventable/avoidable:** Immediate care in an ED setting is needed, and the condition could not have been prevented/avoided with ambulatory care (heart attacks, multiple trauma, and so on).

FIGURE 5. NYU Algorithm

[v] NYU ED Algorithm, NYU Wagner, New York University, wagner.nyu.edu/

IDENTIFYING THE ANALYSIS POPULATION AND EXPECTED ROI

For our pilot study, we selected members with a specific chronic disease and then segmented the entire population into homogenous groups across several key dimensions such as plan (HMO, Non-HMO), health conditions, geography, age groups, etc. We also checked two key factors for the selected population:
a) Is there enough opportunity (avoidable ER visits) to begin with
b) Is support available to drive intervention programs and traverse the last mile

Highly sophisticated algorithms with super rich data quality are certainly expected to deliver the best of outcomes. However, in the real world there is a need to balance research and implementation costs with expected benefits and ROI.

Figure 6 below shows an illustrative approach to do a quick ROI estimation before moving ahead.

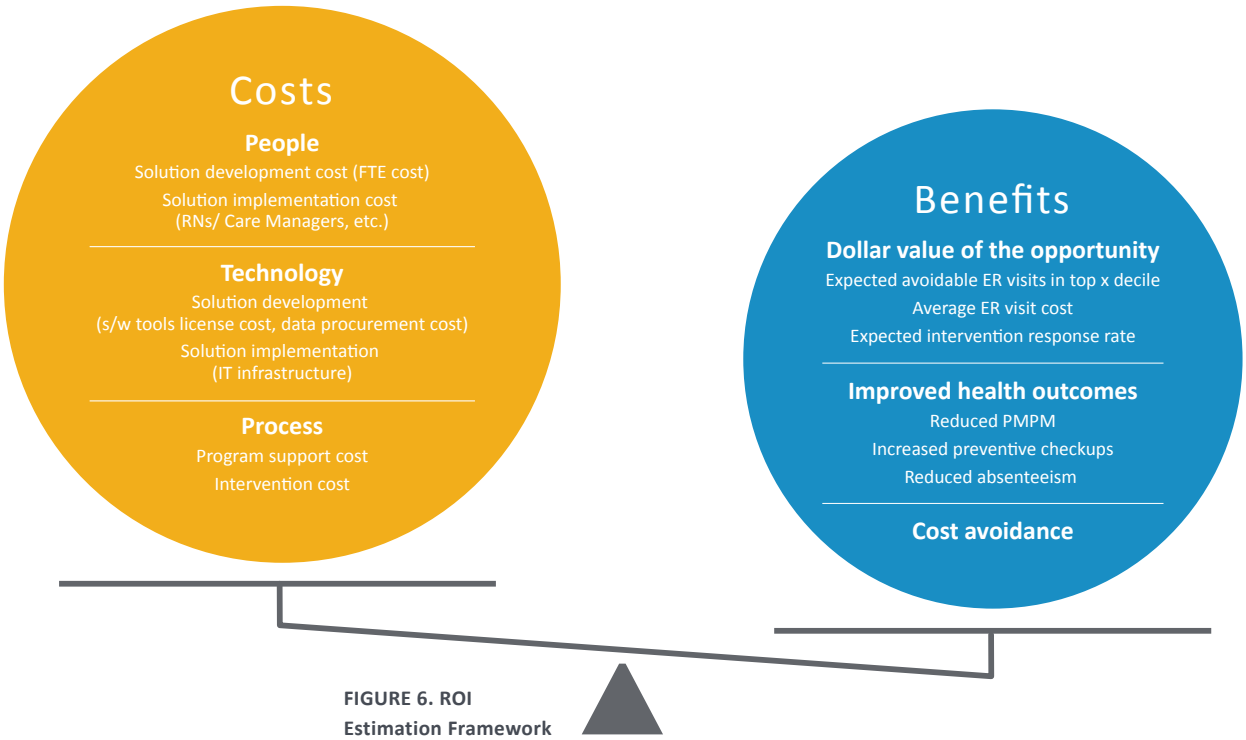


FIGURE 6. ROI Estimation Framework

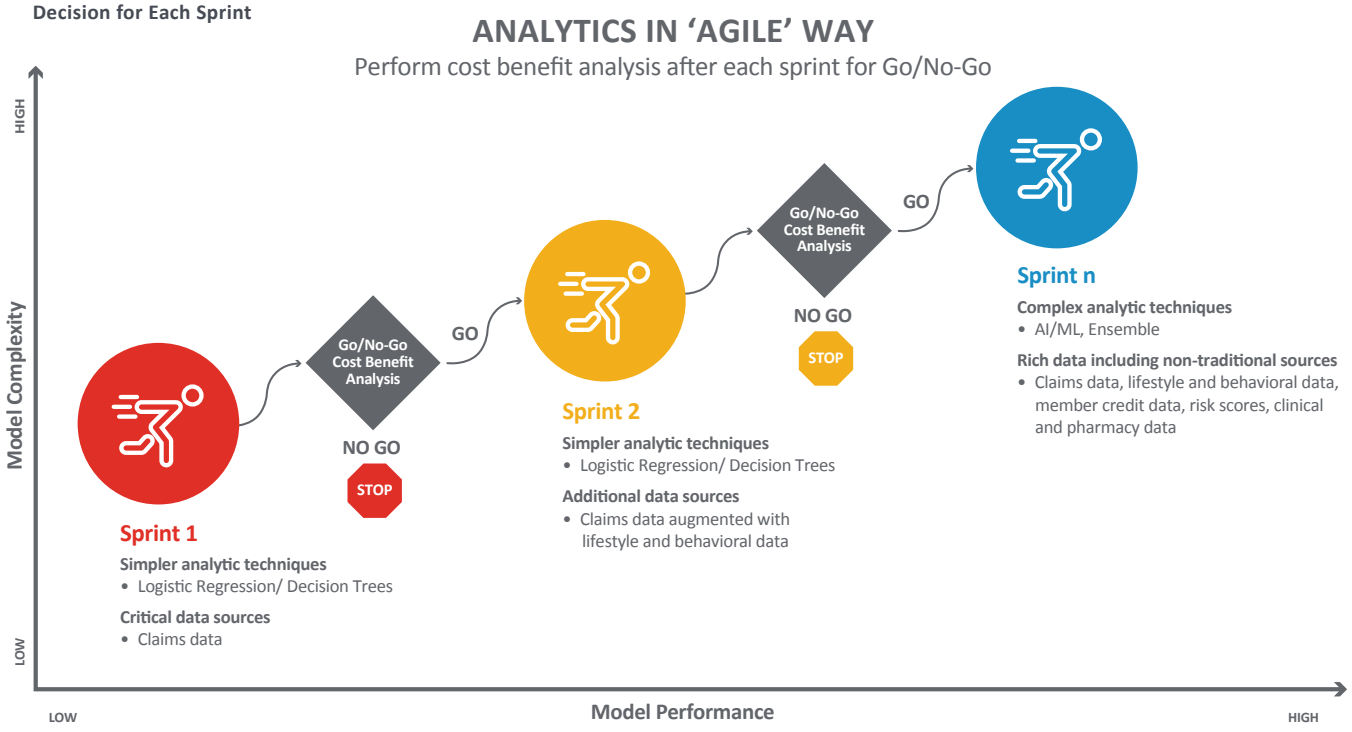
LEVERAGING PREDICTIVE ANALYTICS IN AN AGILE WAY

- What proportion of ER visits are avoidable?
- Is intervention program support readily available?
- What are the potential benefits?
- What is the expected cost?

Traditionally, predictive modelling exercises follow a waterfall approach. The requirements must be frozen and all stakeholders aligned before moving to design, development, and validation phases. This methodology lacks the necessary flexibility to rapidly react to evolving business needs. Further, the cost of failure is relatively high, as benefits cannot be established until the model results are field validated.

We recommend developing predictive solutions in an agile way: start with small data (e.g., claims) and simpler techniques to establish initial value. After each sprint, reassess the benefits to validate the necessity of the next sprint. Once the incremental gains are established, explore options to add either new data sources and/or complex predictive algorithms to further maximize the returns. See Figure 7 for more details.

FIGURE 7. Go/No-Go Decision for Each Sprint



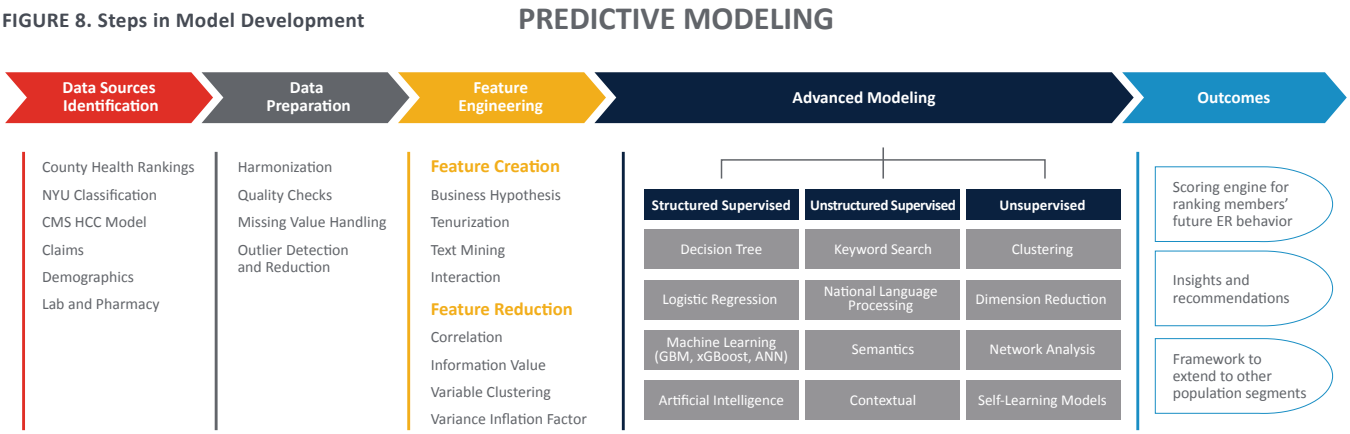
Using the agile approach shown above, we used traditional analytical steps to develop our models, starting from logistic regression and claims data to artificial intelligence (AI)/machine learning (ML) techniques with non-traditional data sources, e.g., augmenting traditional claims data with lifestyle and behavior information, bringing in zip-level socio-economic information, adding macroeconomic indicators, temperature, pollution information, etc. Refer to Figure 8 for more details.

Our final solution consisted of an ensemble of machine learning and logistic models. The solution was able to capture 50% of all avoidable ER members within top two deciles.

Below are some selected insights/validated hypotheses for members likely to make an avoidable ER visit:

a. Comorbid conditions, such as Congestive Heart Failure (CHF) or Chronic Obstructive Pulmonary Disease (COPD)
b. History of frequent ER use
c. Behavioral conditions such as drug or substance abuse, alcohol dependency, etc.
d. Depression and other bipolar disorders
e. Certain ethnic groups
f. Poor educational levels
g. Obesity and others

FIGURE 8. Steps in Model Development



THE SOLUTION IMPLEMENTATION

This phase involved identifying the right set of interventions that would benefit the member population identified from our predictive model.

IDENTIFYING THE RIGHT SET OF INTERVENTIONS

Once the top "x" decile members had been selected, we wanted to further segment this population based on its propensity to respond to a specific intervention to maximize the return on intervention. However, due to challenges outlined below, such information was not readily available:

- Delivered in a specific care setting
- Targeted at a specific geographic region for a certain ethnic group
- Broad disease-specific interventions are force fitted for selected population segment
- No longitudinal study that tracks outcome of historic care management (CM) or disease management (DM) programs linked with predictive models—e.g., impact of diabetes management program on members with high risk scores from a predictive model
- Limited employer workforce performance related data—e.g., how a certain wellness program resulted in member performance: absenteeism, productivity, etc.

In the real world, there are additional practical limitations, such as cost to execute, limited resources in the care management team, limited time to execute, and the need for rapid realization of benefits from the experiments.

Analytics can help organizations in optimizing the entire value chain of experiments: planning, designing, and execution. We need to leverage analytic techniques to fully mine information that the traditional care management/disease management programs have collected so far, and if not, design experiments to gather such intelligence.

QUESTION:

What can you do about the in-house information that your care management/disease management teams already have?

A BIGGER QUESTION IS:

What can you do about the information that you don't have?

APPROACH

In our case, we divided interventions into two broad categories (Figure 9):

1. Known interventions linked with member profiles identified through profiling
2. Experiential interventions to test and learn new programs through secondary research

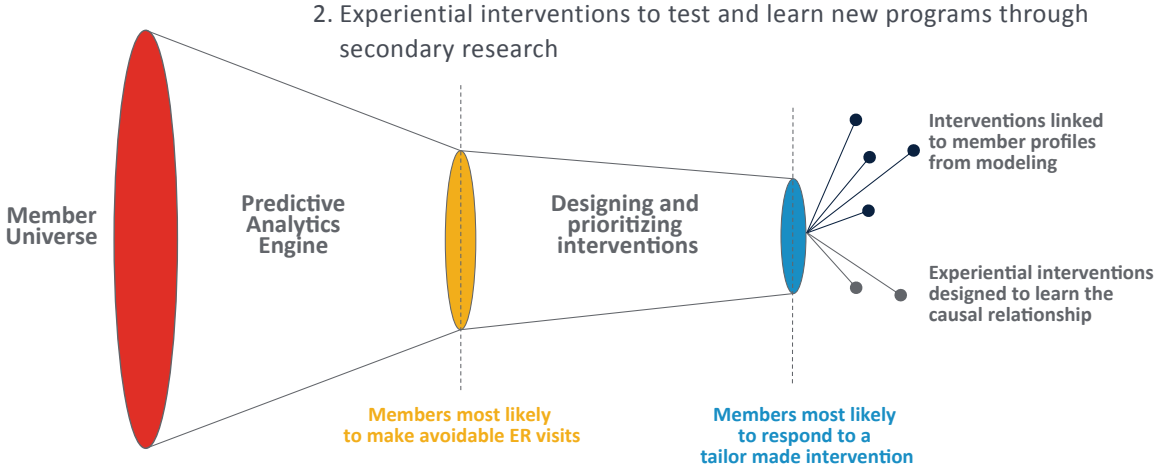


FIGURE 9. Designing Prioritized Interventions

We used below steps to identify and design the right set of interventions:

STEP 1:
Identify key themes from predictive model results

We identified key themes by reviewing patient profiles from our predictive models. We then reviewed them against the existing medical literature and selected interventions that were most relevant to our study population. See Table 1 for details.

TABLE 1

EMERGING THEMES	MODEL PREDICTORS	SUGGESTED INTERVENTIONS	LEARNING SOURCE
Past Visit Pattern **Disease Awareness** **Medication Adherence**	· Has history of making frequent avoidable ER visits · Has had few to no preventive tests in the last one year · Has comorbid conditions—CHF, COPD · Has major depressive, bipolar, and/or paranoid disorders · Sees multiple doctors	· Video and telephone counselling on importance of preventive exams[15] · Bi-weekly automated assessment and self-care education calls with telephonic follow-up by a nurse[16] · Group visits and depression counselling[17,18] · Pharmacist-led education[19,20]	Claims Data
Education Level **Lifestyle** **Ethnicity**	· Has low literacy levels · Has poor income levels or is less likely to afford the medical costs · Cannot afford quality meals · Is of African-American or Hispanic origin · Is obese	· Provide low-literacy level booklets, pamphlets, multi-media training, etc.[15,21] · At least one free annual testing of HbA1c and serum creatinine, and annual screenings for hypertension[22] · Diabetes/asthma self-management training using diet counselling and lifestyle modification[23] · Culturally tailored disease management, program with bilingual/cultural (Spanish, English), African-American or Mexican Registered Nurses and Community Health Workers (CHWs)[24-27] · Phone calls and/or text reminders[16]	Lifestyle, socio-economic and behavioral data

STEP 2:
Design collaborative interventions for experiential learning

Here, our objective was to identify which pilot interventions would help most in getting the right data for future interventions. Sample experiential interventions linked with emerging themes identified in step 1 are listed below:

- Smoking cessation program for members in a select Accountable Care Organization (ACO), Patient Centered Medical Home (PCMH), Skilled Nursing facility (SNF), or Long-Term Acute Care Facility (LTAC)
- Pharmacist-led education on early parents or members residing in a rural area
- Providing free nebulizers to asthma population—this will help in seeing (if) an increased medication adherence results in increased response to DM program

STEP 3:
Prioritizing interventions

Once we had a broad set of interventions linked to members' medical, socio-economic, behavioral, and lifestyle data, we prioritized the specific interventions for maximum ROI within the constraints of time, effort, and budget. See Figure 10 for an illustrative framework.

PRIORITIZE INTERVENTIONS ALIGNED WITH ORGANIZATIONAL FOCUS

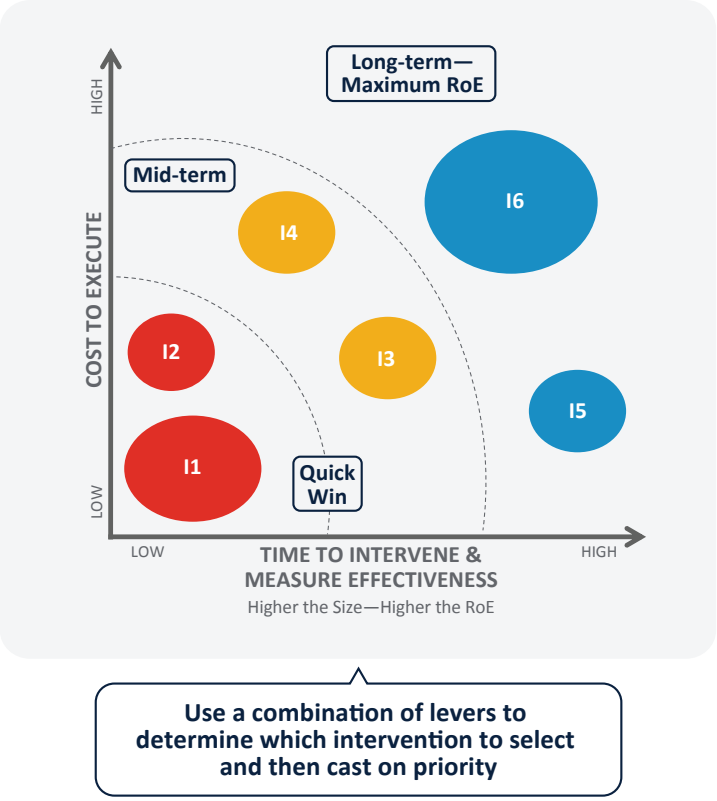


FIGURE 10. Prioritization Framework

STEP 4:
Efficacy of the interventions

As a final step, we designed a detailed IT system to capture the data from the experiments. Our ultimate aim is to use the collected intelligence to evaluate the efficacy of the program and also as an input to future predictive models.

CONCLUSION

Reducing avoidable ER visits is a complex problem requiring a collaborative effort from multiple functions. Early identification of the problem through a sophisticated predictive analytics solution can provide a competitive edge in mitigating revenue leakage and containing health risks.

To balance between program costs and potential benefits, we recommend using analytics in an agile approach and accounting for below critical success factors:

Ensure strong executive sponsorship for end-to-end program support: Predictive models have little value if the CM/DM teams cannot timely use the results. A multi-divisional collaboration for program execution and implementation is a must.

Perform early ROI estimation through baseline vs. benchmark comparison to ensure that there is value in pursuing the initiative.

Start small but be specific: Identify the right population segments where the problem is severe, and establish clear metrics and thresholds to measure success.

Develop the solution iteratively, starting with easily available small data: Leverage external data to fill in gaps due to lack of internal data, and use non-traditional data sources such as lifestyle, behavioral, and socio-economic data to enrich data quality.

Start with simpler analytic techniques to show value for executive buy-in before making a case to move to complex machine learning algorithms.

Plan, design, and develop systematic experiments to test and learn from interventions. Use this data as an asset for future studies.

Leverage artificial intelligence techniques to scale and automate solutions.

It's time to reduce unnecessary ER visits and deliver impactful interventions to prevent them from occuring in the future. An analytics-powered approach, delivered in an agile manner, can help organizations deliver on this opportunity.

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Fractal Analytics is a strategic analytics partner to the most admired Fortune 500 companies globally and helps them power every human decision in the enterprise by bringing analytics & AI.

Fractal Analytics has presence across 12 global locations including the United States, UK, and India and has been recently featured as a leader on Forrester Wave™: Customer Analytics Service Providers, 2017. Fractal has also been recognized as a “Hot Artificial Intelligence (AI)” company by Forbes and a “Cool Vendor” and a “Vendor to watch” by Gartner.

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