HEALTH OUTCOMES CHALLENGE

The CMS Artificial Intelligence (AI) Health Outcomes Challenge

APPLICATION FORM

The CMS AI Health Outcomes Challenge invites you to submit innovative AI solutions that accurately predict health outcomes while enabling Human-AI collaboration. This is a multi-stage competition that will award up to $1,650,000. Enter the competition by completing this application form online at cmschallenge.ai by June 18, 2019, 5:00 p.m. ET. Applications must be submitted on the online platform to be considered eligible. Emailed applications will not be accepted. Multiple submissions are allowed, but each one must be a unique approach, sufficiently differentiated, and in compliance with the Challenge Requirements.

PARTICIPANT INFORMATION

Please provide the following information for the individual or organization being entered into the Challenge.

1. Submission Title : Health Care in 3 Dimensions
2. First Name : Robert
3. Last Name : Ripley MD
4. Job Title : CEO and founder of Ripley and Associates
5. Participant Contact Information
    a. Address (Street, City, State, Zip)
    397 Wallace Rd. #216, Nashville TN 37211
    b. Phone : 615.347.8363
    c. Email : rcripley@ripleyandassociates.com
    Note: Emails should also be sent to Team Logistics Lead: Allen Hall (ahall4@isdn.net)
6. If you are submitting as part of a team or on behalf of an organization, please provide the following:
    a. Registered name of your organization (if applicable) : Ripley and Associates
    b. Registered address of your organization (Street, City, State, Zip)
    397 Wallace Rd. #216, Nashville TN 37211
    c. Which of the following best characterizes your organization? [Multiple Choice]
        i. Not-for-profit organization (non-academic)
        ii. Not-for-profit academic or research institution
        iii. Medium sized or large sized business
        iv. Start-up
        v. Other (explain)

d. Provide full names and associated organizations of all team members
   i. Robert Ripley MD, CEO, Ripley and Associates
   ii. Donna Abercrombie, Project Manager, Ripley and Associates
   iii. Allen Hall (Team Logistics Lead), Consultant, The Sero Group
   iv. David Langer, Data Scientist

e. Is your organization partnering with other organizations on this challenge? If Yes, please provide the following details: No

BACKGROUND & PRIOR EXPERIENCE

1. Briefly describe yourself and your team's professional background. (word count: 500 max)
   a. Robert Ripley MD, CEO

      Is the CEO and founder of Ripley and Associates, brings his interest and medical expertise in data management to promoting cost effective health care. This interest is founded on a multi-decade practice in cardiology where it has become clear that wise decisions on patient's behalf must be disseminated among provider networks to achieve desired outcomes.

      Dr. Ripley's background includes membership in the American Heart Associates Health Services section, Board Certification in Nuclear Cardiology and General Cardiology, membership in Health Care Insurance Companies Advisory Panels, a 10 year appointment to the Tennessee State Medical Board, and cardiology program development in rural and suburban hospitals. Ripley and Associates' system, Health Care in 3 Dimensions, optimizes and assesses the delivery of healthcare using counterfactual analysis of care paths, translating patient level decisions to population level outcomes, which manages costs without sacrificing the individuality of the patient.

   b. Donna Abercrombie, Project Manager

      Is the Project Manager at Ripley and Associates since 2001. Coordinating Backroom operations for as many as 15 physicians. Manages staff outcomes reporting. MIPS (Merit-based Incentive Payment System) Implementation.

      She is a seasoned medical practice executive with nearly a quarter century of experience in the health care industry. She has extensive knowledge in specialty based operations, revenue cycle management, value based care, patient centered medical home, patient centered specialty practice, EHR implementation, medical record management, PQRS implementation, coding and compliance, and ICD-10 transition; having worked with local specialist in cardiology, gastroenterology, pulmonology, orthopedics, and internal medicine; and with surgery centers and dialysis clinics in Georgia and New York. She is also an active member of the Medical Group Management Association.

c. Allen Hall MCDBA, MCSD, MCSE, MCT Alumni

Has been a team member since 2013, providing Information Technology support and creative assistance in multiple areas of specialty including database systems design and infrastructure, website, documentation, illustration, and proof-of-concepts.

He has over 3 decades of IT experience specializing in system architecture on Microsoft platforms and technologies including SQL Server, Power BI, and Visual Studio. He has extensive experience as a consultant and trainer in both the private and public sectors over the last quarter century.

d. David Langer, MS Computer Science & Software Engineering

Is a recent addition to the team, providing expertise in analytics, data science, and artificial intelligence. Dave has over 2 decades of experience in technology and analytics, including hands-on work applying Artificial Intelligence for companies like Microsoft, Data Science Dojo, and Schedulicity.

2. Describe your experience in Artificial Intelligence/deep learning with complex data sets. (word count: 500 max)
   a. The Team has collective experience working with a broad range of data, including (but not limited to):
      i. Device-level telemetry data (since 2013).
      ii. Natural language text data such as warranty claims, customer trouble tickets, and customer support conversation (since 2011).
      iii. Complex website navigation path data (since 2017).
      iv. Customer behavioral & marketing data (since 2012).
   b. The team has collective experience applying Artificial Intelligence, using the above data sets, for prediction including (but not limited to):
      i. Warranty claims.
      ii. Customer churn/dissatisfaction.
      iii. Customer abandonment.
      iv. Customer conversion.
3. Describe your experience with health care-specific data, including experiences with and knowledge in hospital admissions data and measures of clinical quality. (word count: 500 max)
   a. The Team's collective experience with healthcare data is extensive, encompassing many aspects of Healthcare system's design and use over several decades, including, but not limited to:
      i. Outcomes based, outpatient health record, developed in house by Ripley and Associates, (since 2009).

ii. Detailed analysis of the TennCare Beneficiary Data Dictionaries and Claims Analysis Schema for use in HCn3D, (since 2018).

iii. Participation in Tenncare (Tennessee Medicaid) Technical Advisory Group for review of Episode of Care, (since 2016).

iv. Presentation to Tenncare management of Artificial Intelligence tool, counterfactual analysis of population data to apply to population scale cost reduction, (May 2016).

v. Presentation to the Cardiac Catheterization guidelines writing group of the American Heart Association reviewing 5000 patients who underwent cardiac catheterization in a mobile lab at community and rural hospitals.

vi. Community based angioplasty safety data for intracoronary interventions in hospitals without surgical standby, (since 1996).

vii. Member Tennessee Board of Medical Examiners which included regular review of DEA drug distribution data, and other health information, (1996 to 2006).

viii. Market analysis reporting solution for the Tennessee Hospital Association, (2002 to 2003).

ix. Data collection and analysis (for safety and outcomes) of the thrombolytic management of acute myocardial infarction in rural and community hospitals, (1983 to 1996).

x. Advisory group Blue Cross Blue Shield of Tennessee; analysis of MI data, regular review of plan data.

xi. EHR conversion from Emedsys to AdvancedMD , which included implementation of new cardiology templates, master files, and utilities; CPT, ICD-9/ICD-10, charge master, billing rules, electronic billing, scheduling, and super bills, (2011)

xii. Surgery center software conversion from Med Occur to Advantx, (1998)

xiii. Preparations for Version 5010. The revised set of HIPAA electronic transaction standards adopted to replace version 4010/4010A standards. (5010A1 current version)

xiv. Cardiology Practice implementation of ICD-10. Including practice assessment, coding, clinical documentation, software readiness/transition for pre and post go live date, (2015)

xv. Data conversion to Practice Fusion from AdvancedMD, (2015).

xvi. Implementation of Transitional Care Management operations within cardiology practice, (2017).

xvii. PQRS (Physician Quality Reporting System) implementation with monitoring of measures and clinical data reporting criteria, (2013 to 2015)

xviii. Quality reporting via Qualified Clinical Data Registry (QCDR), Clinic Spectrum, Inc., (2016 to 2017).

xix. Quality Payment Program (QPP), implementing the Merit-based Incentive Payment System (MIPS). Oversight of MIPS measures and clinical data reporting criteria, (since 2016)

xx. Merit-based Incentive Payment System (MIPS) reporting via the Quality Payment Program (QPP) website, (since 2018).

xxi. EMR/EHR software and related (including but not limited to): AdvancedMD, Meditech, Emedsys, Advantx, Vidistar

4. Describe your experience, if any, with administrative claims data from CMS or other payers/plans. (word count: 500 max)

   a. Detailed analysis of the TennCare Beneficiary Data Dictionaries and Claims Analysis Schema for use by HCn3D.

   b. 1 Million claims over the past few decades:

      i. Direct data entry (DDE) of institutional submissions, 10,000+ claims
      ii. Submission of professional HCFA 1500/837P, 700,000+ claims
      iii. Submission of institutional UB-04/837I, 200,000+ claims

PROPOSAL & METHODOLOGY

1. Describe your proposed solution, such as an AI model that uses deep learning techniques and neural networks, to achieve the following:

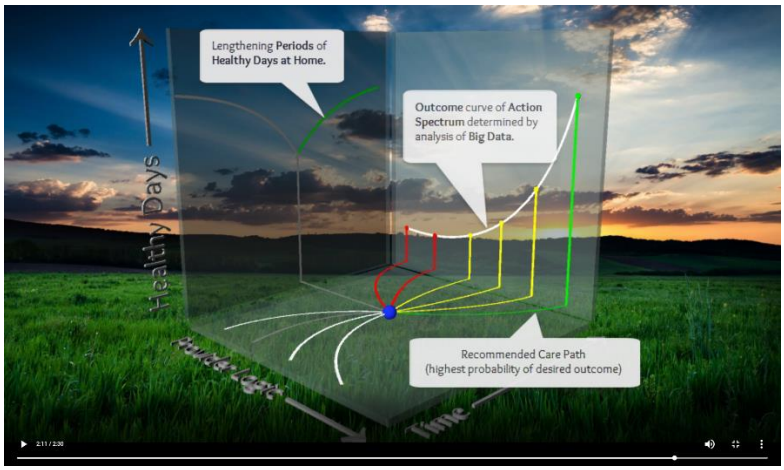
   a. To predict unplanned hospital and skilled nursing facility (SNF) admission and adverse events within 30 days for Medicare beneficiaries, based on a data set of Medicare administrative claims data, including Medicare Part A (hospital) and Medicare Part B (professional services). (word count: 750 max)

      The ranking of Future Value Outcomes determined via counterfactual analysis. Future Value Outcomes are simply the result of possible decision or actions the provider and/or patient may execute that have the greatest potential to result in the desired outcome.

      Counterfactual analysis allows one to distinguish single entities such as individual patients in the context of a variety of defined populations. A counterfactual is the result of a single action given specific context; the same event or need for action can elicit different effects on the individual given different extrinsic (or intrinsic) conditions.

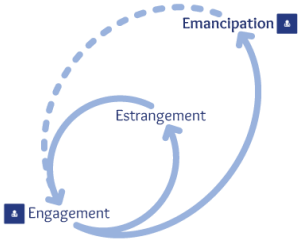
      This is a basis for realizing preferences of primary care physicians. They wish to be holistic, accounting for all factors relevant for the patient. And when they do so they avoid certain unwanted outcomes (e.g. unplanned hospital admissions), or move through the patient's path more efficiently. And they want to do this for a single patient, not to conform to population averages as a purely statistical approach would require.

The following video conceptualizes how HCn3D can not only predict unplanned hospital stays along a patient journey, but any scenario/question it's configured and trained for. https://youtu.be/cMlbTdbNRZg

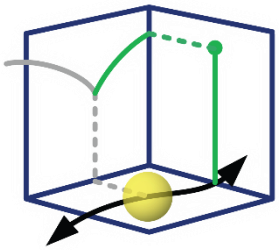


b. To develop innovative strategies and methodologies to: explain the AI-derived predictions to front-line clinicians and patients to aid in providing appropriate clinical resources to model participants; and increase use of AI-enhanced data feedback for quality improvement activities among model participants. (word count: 750 max)

For the last few years the HCn3D team has approached this conceptually in two distinct ways, with plans to implement user interface and business intelligence tools, some of which will deliver AI driven solutions directly to the clinician (and patient) at the point of service.

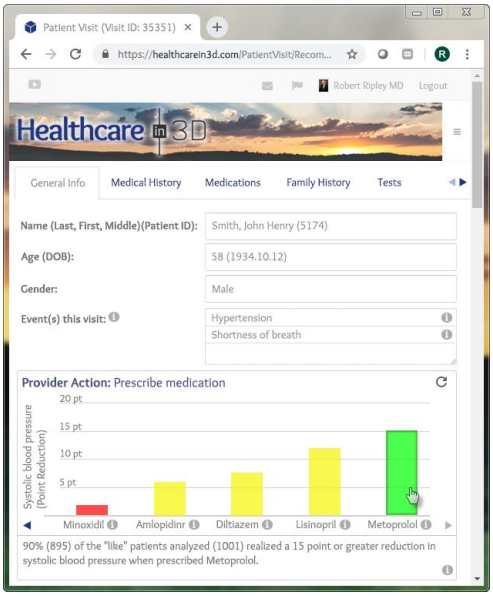


The first is via Provider Engagement. Any and all discussions of improving outcomes via technology, require an alert and attentive provider community. Physician burnout is clearly an impediment to this attention. It is estimated that 50% of physicians either have, or are at risk for burnout. Adding complexity in the form of new systems and/or programs will only exacerbate the problem unless they deliver tangible value that serves to emancipate. Perhaps no one understands this cycle of engagement, estrangement, and emancipation better than the HCn3D team led by Robert Ripley, MD a 42 year veteran of cardiology practice. HCn3D Blog: "*A pathway for burnout: From physician engagement to Emancipation or Estrangement*"



The second via a metaphorical construct "The Cube". Understanding the challenges faced by providers combating burnout is not enough. Understandable explanations of the technology are still required if the physician (and patient) is going believe that the technology can in fact emancipate, making their jobs easier not more difficult. For this facet the HCn3D team has turned to the analogy of "The Cube". It has been extremely effective because it can be sited figuratively, literally, and most importantly visually in the context of the patient journey, incorporating as little or as much complexity as desired to explain and model how HCn3D works.

User Interface and Business Intelligence Tools. Mobile (and desktop) applications where the clinician and/or patient is presented with possible actions/decisions. These potential decisions are supported with the most relevant variables or dimensions analyzed.



For instance a clinician would be presented with top 5 (option to see more) desired outcomes and the decision(s) that would have be made to result. Supporting information would include readily understood natural language explanations. (e.g. 90% (895) of the "like" patients analyzed (1001) realized a 15 point or greater reduction in systolic blood pressure when prescribed Metoprolol). Clinician would have the option to review more detail, like the total number of patients analyzed for "likeness" and ranking of what made them most like their subject patient. So AI is not only used to identify the potential outcomes, but also describe them to the clinician or patient.

Future versions of the UI and Tools will included virtual and augmented reality technologies allowing the clinician and patients to step through the Cubes of Patient Journey much like one would walk from room to room. This would allow for seamless integration with other healthcare reality technologies being used for training, diagnostics, and surgery.

2. Describe the AI algorithm(s), framework(s), and technique(s) you plan to use. (word count: 750 max)

   The solution employs counterfactual analysis as the main AI engine. As such, the selection of tooling, frameworks, techniques, and algorithms are driven by the construction of counterfactual analysis automation.

   Data analysis tooling/techniques will center on the use of the relational database paradigm, including the use of relational databases (e.g., Microsoft SQL Server) and/or SQL-like technologies (e.g., Apache Hive) where appropriate.

   Where more advanced capabilities are needed, the open source R language – and associated libraries/frameworks (e.g., the R counterfactual library) shall be employed.

3. Describe your approach to verify, validate, secure and control the proposed AI model. (word count: 750 max)

   The Team will implement the latest in software engineering practices with respect to source code control. This will include both model binaries (e.g., an .RData file) and the source code and data sets used to train the model. The team shall leverage source code control (e.g., Git) to enforce access control to data, source code, and model binaries. Additionally, the team shall implement code review tollgates before new assets are added to the source code repository.

   For verification/control the Team will leverage a training protocol consisting of a 3-way split of the Limited Data Sets provided by CMS in both Stage1 and Stage 2 of the Challenge: Training, Validation, and Test data. These splits will be disjoint subsets of the original data. The Test data shall be held until the end of each Stage and will be used in any final evaluation of model efficacy. The validation set shall be used only at major project milestones to ensure model efficacy is improving throughout the project.

4. What data would your model consume and what information or decisions would it produce? (word count: 750 max)

   Of course the Limited Data Sets provided by CMS. Additionally HCn3D may also consume other publically available de-identified data from state beneficiary databases (e.g. TennCare) (other sources) and of course census data.

   The information HCn3D produces are potential outcomes from an array of actions/decision along with supporting information for those outcomes. For the purposes of this Challenge the outcomes can be filtered or flagged for unplanned admissions and/or adverse events. For more explanation regarding how that information is presented to the clinician please refer to question #6 and/or the presentation Brief.

5. Describe how the proposed model will learn and improve over time. (word count: 750 max)

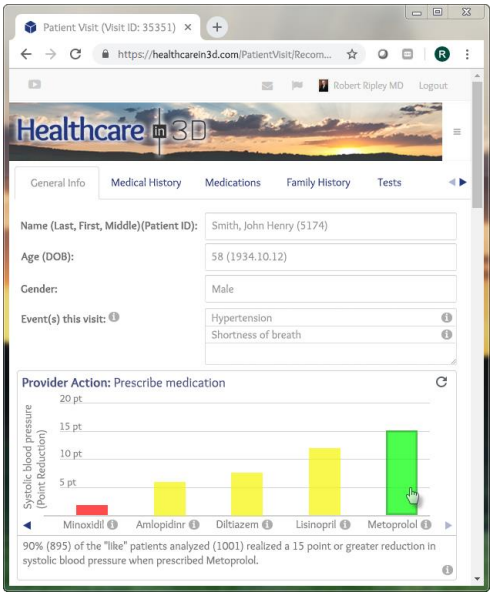
   The Team's use of counterfactual analysis as the main AI engine differentiates our solution. Specifically, our solution will not have a "model" as one would expect from a trained random forest or deep neural network. In machine learning terms, the counterfactual analysis AI engine (CAE) is akin to the k-nearest neighbors (kNN) algorithm. As with kNN, the CAE provides predictions/guidance to the provider via application of the algorithm(s) to the data at the time of prediction/guidance request. As such, the CAE (as with kNN) learns and improves over time as additional high-quality data is added to the algorithm's search space.

   This additional high-quality data will be the key for model improvement over time. Firstly, the model will improve simply from an ever-increasing database of patient data. Secondly, the Team will leverage additional data sources (e.g., U.S. Census socioeconomic data) to augment/enrich patient data as part of initial development.

   For example, inclusion of location data as it relates urban residences and falls. Does living in urban setting result in more falls where geriatric individuals are more likely to break a hip and result in an unplanned hospital stay. Maybe, but knowing absolutely whether the patient lives in a 6th Floor Walk-up is a far more reliable marker, and inclusion of it in analysis makes HCn3D Smarter.

   Lastly, the Team shall implement a continuous process of data investigation to identify and curate new data sources beyond initial launch to enhance our solution's efficacy.

6. Describe to what extent the proposed model will work with clinicians and patients to explain AI-derived predictions in comprehensible and interpretable formats. (word count: 750 max)



   Chiefly through mobile (and desktop) applications where the clinician and/or patient is presented with possible actions/decisions. These potential decisions are supported with the most relevant variables or dimensions analyzed. For instance a clinician would be presented with top 5 (option to see more) desired outcomes and the decision(s) that would have be made to result. Supporting information would include readily understood natural language explanations. (e.g. *90% (895) of the "like" patients analyzed (1001) realized a 15 point or greater reduction in systolic blood pressure when prescribed Metoprolol*). Clinician would have the option to review more detail, like the total number of patients analyzed for

"likeness" and ranking of what made them most like their subject patient. So AI is not only be used to identify the potential outcomes, but also describe them to the clinician or patient.

7. Describe your strategies to build trust and transparency with stakeholders to use the AI model. (word count: 750 max)

   Unfortunately there is little interest in the use of data science and related technologies by the provider community. The reasons vary, but as soon as you use terms like AI, Machine learning, etc… most physician and clinicians simply glaze over. As the CMS Challenge has recognized, convincing those closest to the patient that AI has a role is crucial to providing value in the healthcare system. The HCn3D team has been out front proselytizing for the adoption of date science concepts for the last few years. During that period it has become obvious that simply convincing providers the technology works is not enough. The physician must also be "emaciated" by the use of the technology otherwise they will simply perceive it as one more thing hampering delivery of healthcare to their patients.

   Dr. Ripley and the HCn3D team has seen some success generating interest with physicians and others in the healthcare community using the "Pyramid" metaphor and its inversion to describe what must be done to engage physicians and emancipate them. HCn3D is integral to fixing issues at all levels of the Pyramid. HCn3D Blog: "*A pathway for burnout: From physician engagement to Emancipation or Estrangement*"

8. Describe (if any) the intended impact your solution will have to current health care practices and delivery methods, especially to Medicare beneficiaries. (word count: 750 max)

   It is understood by many that impediments to effective and sustainable health care reform result from barriers of many types. The most important barrier arises from physicians. Rather than being engaged in important goals of CMS, primarily cost reduction, physicians feel estranged from the complex health care system as a whole. The thrust of CMS policy is to require 100% downside risk through mandatory accountable care organizations and BPCI by 2025. These requirements are driven by financial goals. The clinical processes to support these goals are left up to the providers, who lack the systems and access to data to feel confident they can accept risk.

   HCn3D on many platforms both online and offline will assist in this transition to total accountability. The first and most obvious barrier is the lack of interoperability of health records. HCn3D is designed to evolve, first as a parallel system that exists as a complement to detailed transactional health data that adds value through analytics and metadata relevant to real time clinical decisions. The next important barrier is lack of awareness of outcomes in the patient centered provider network. There can be a sense that a decisions today can lead to a beneficial outcome in the future, and this will be communicated to the provider network. This functionality exists in HCn3D,

and will be an important stimulus to the critical goal of care coordination and collaboration. An emerging understanding of the importance of transparency of cost data is evolving through the ACOs, and this information can be located in the health record from more levels than just the patient or provider level. CMS is able, and probably willing, to provide population scale data in a context useful to providers to have deeper insight into patient centered decisions. The translation from population scale to individual patient scale is a core function of the unique analytics of HCn3D and draws on many facets of AI.

Meaningfulness for providers is the antidote to estrangement and requires an intimate association of physicians with the health record, designed with meaningfulness in mind. The stance of primary care physicians as a totalizing presence for the patient makes the providers intuitively holistic. The health record is now transactional and reductionist and designed to communicate with insurance plans, and does not capture features of coordination or extended patient journeys. A holistically minded clinician will be aware of many patient factors that will not end up in the health record, factors such as social determinants of health, transportation, poverty, and many others. Primary care physicians will quickly perceive meaning when the health record captures these factors and will allow the primary care physicians to show the broad provider networks their contribution holistically in a transactional health care world.

9. Describe how the solution will manage potential adverse effects of automation and AI. (word count: 750 max)

   The most significant effect of automation is the propensity to foster "checkbox medicine", and thereby contribute to physician burnout. Can the "checkbox" be eliminated? No, but it can be designed into the medical record as background for physician workflow, with more important patient centered, meaningful tasks captured dynamically where context of the information is framed as decision support, which would be of great interest to clinicians. This is the value of the HCn3D Inflection Point / Cube metaphor, where the difference of context and actionable information is automated with guidance from AI. The user interface mockup illustrated in this document (and the brief) is a simple, but tangible example of presenting context relevant information to the clinician.

10. Describe the metrics you propose to measure and forecast both the economic and technical success of the proposed AI model to predict and reduce unplanned hospital admissions and adverse events. (word count: 750 max)

    Reduction of unplanned hospital admissions is a complicated objective and requires recognition of health care as complex and stratified. AI can move the needle forward in clarifying the complexity, but the limitations of AI reside in its inability to name the dimensional layer or strata in which the metrics or measures reside. For large datasets within a single strata, such as pattern recognition of radiology images and

pathology slides, machine learning is essential. This strata contains all the known data, at least the data to provide the diagnosis, not necessarily the data to provide the prognosis, and is static. An image does not change once it is captured.

The strata specific metrics will support a wise clinician who makes decisions with incomplete information along the progressing patient journey. In addition the outcomes of beneficial decisions, are often the absence of an event (e.g. hospital admission). This absence can only be measured with data that spans different strata, each with its own complexity. Recognizing the relevance of multiple strata (dimensional sets) is what holism is all about.

The different strata and a few relevant features of each, for unplanned admissions, are described below. First from the smallest to the largest strata by population and then by complexity least to most. Each strata will have its own metrics pertaining to unplanned admissions.

Strata 1. Patient Centered/Primary Chronic Care, physician holistic Strata – Diversity of providers, diversity of diagnoses for known CMS data. For data known to the provider, but not CMS, health record data is a metric, a completeness metric if you will. For unknown data to providers and CMS that may be relevant to drive unplanned admissions, the metrics are transfactual data that may be available in the future. Machine learning can search for patterns that suggest the existence of the transfactual data.

Strata 2. Patient Centered Provider Network/ACO Strata – Evolution of patient journeys, patient level; specialty mix index provider level; network linkages and hub linkages to determine patient quarterback to influence care and cost metrics

Strata 3. Regional Population Strata – Benchmarks for ACOs, expected costs versus benchmarks are metrics

Strata 4. CMS Population Strata – Policy metrics, origin of determining opportunities for cost saving such as avoidance of admissions, ER visits, unnecessary imaging and procedures.

…and then by complexity are essentially reversed, less complex the larger the population. This is essentially so, because the complexity and uniqueness of the patient is lost in aggregation.

Strata 4. CMS Population Strata – Admission rates

Strata 3. Regional Population Strata – Metrics for regional integrated provider benchmark comparisons.

Strata 2. Patient Centered Provider Network/ACO Strata – Admission rate conditioned on provider factors such as provider access, care transitions from acute to chronic for readmission rate, care transitions from chronic to acute conditioned on provider factors and patient factors such as risk level and chronic disease.

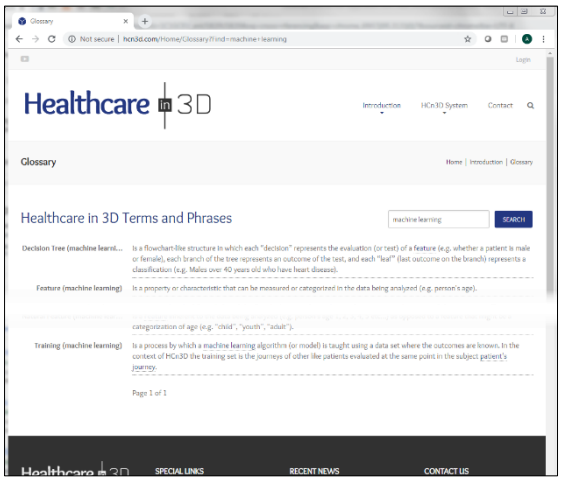
Strata 1. Patient Centered – Captured admission event, the context for the event spans all strata allowing multiple metrics from each strata to clarify policy from CMS to lower unnecessary admission rate. The destination of the complex assembly of metrics is the wise clinician. AI can function in its realist color at the single patient strata by using counterfactual analysis to show the metrics of what did not occur, and why, by reference to other metrics.

11. Describe what other data sets and/or types of information that would be useful to further refine the model following the competition. (word count: 750 max)

Each of the Strata above could include many other datasets. For example the population strata could include census data for rural/urban residence, poverty pockets by MSAs, and georeferenced death rates as a surrogate for population health status. The Provider Network strata can include Professional Society best practice guidelines, local data to define provider hubs based on degree of connectivity with other providers as an index of collaboration, public health data such as disease prevalence associated with water quality. Patient centered data could include effects on local health status of consumer directed health care. The HCn3D platform allows inclusions of any potential dataset. Any conceivable dataset can be framed as context for the patient strata via the flexibility of the cube of HCn3D

12. If selected for subsequent stages of the competition, how will you make the results of the research derived from CMS data publicly available? (word count: 500 max)

Through a web based demonstration application and knowledge base, and highlighted in blogs via the existing HCn3D website. The predecessor to the Knowledge Base has already been implemented in the form of a glossary, with cross-referenced links, on the HCn3D website. http://hcn3d.com/Home/Glossary



13. What interest prompted you to participate in the Artificial Intelligence Health Outcomes Challenge? (word count: 500 max)

Robert Ripley, MD and his team have been working towards healthcare value solutions using AI for the past few years. The goals of Health Care in 3 Dimensions align with those of the AI Health Outcomes Challenge. Participating affords both the opportunity to contribute, and apply concepts and technologies that will reduce cost and increase value.

APPENDIX

Video: *The Patient Journey Through HCn3D*, https://youtu.be/cMlbTdbNRZg

Blog: *A pathway for burnout: From physician engagement to Emancipation or Estrangement*, https://bit.ly/2H7bNIf

Website: HCn3D Glossary, http://hcn3d.com/Home/Glossary

Brief: *CMS AI Health Outcome Challenge*, https://prezi.com/view/W47fEAarBtQKQTmY74zh/