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Making Sense of Patient-Generated Health Data for Interpretable Patient-Centered Care: The Transition from "More" to "Better"

Pei-Yun Sabrina Hsueh[a] , Sanjoy Dey[a], Subhro Das[a], Thomas Wetter[bc]

[a] *Center for Computational Health, Watson Research Center, Yorktown Heights, New York, USA*
[b] *Department of Biomedical Informatics and Medical Education, University of Washington, USA*
[c] *Institute of medical Biometry and Informatics, University of Heidelberg, Germany*

Abstract

The rise of health consumers and the accumulation of patient-generated health data (PGHD) have brought the patient to the centerstage of precision health and behavioral science. In this positional paper we outline an interpretability-aware framework of PGHD, an important but often overlooked dimension in health services. The aim is two-fold: First, it helps generate practice-based evidence for population health management; second, it improves individual care with adaptive interventions. However, how do we check if the evidence generated from PGHD is reliable? Are the evidence directly deployable in realworld applications? How to adapt behavioral interventions for each individual patient at the touchpoint given individual patients' needs? These questions commonly require better interpretability of PGHD-derived patient insights. Yet the definitions of interpretability are often underspecified. In the position paper, we outline an interpretability-aware framework to handle model properties and techniques that affect interpretability in the patient-centered care process. Throughout the positional paper, we contend that making sense of PGHD systematically in such an interpretability-aware framework is preferrable, because it improves on the trustworthiness of PGHD-derived insights and the consequent applications such as person-centered comparative effectiveness in patient-centered care.

Keywords:

Informatics; Patient-Centered Care; Machine Learning

Introduction

Owing to the trends in participation health [1] and value-based care [2], health consumer perception and adoption of direct-to-consumer devices and sensors and citizen science are at all-time high.[3] Meanwhile, more and more leading healthcare systems are evaluating the secondary use of patient-reported outcomes measures (PROM) in electronic health records (EHR).[4] A plethora of patient-centered data generating devices and care processes are producing masses of data.

The early evidence has started to emerge and stimulate the field through best practices.[5] As shown in Figure 1, many of the healthcare applications hinge on the convergence of PGHD and clinical data, as well as the clinical and patient information system. This is in line with the vision of patient-centered care as defined in a recent patient advocacy testimonial in *Health Affairs* [6] as "*the experience (to the extent the informed, individual patient desires it) of transparency, individualization, recognition, respect, dignity, and choice in all matters, without exception, related to one's person, circumstances, and relationships in health care.*"

In particular, two opportunity areas emerge. First, PGHD helps generate practice-based evidence for population health management.[7] Traditionally, clinical evidence is generated from costly randomized controlled trials (RCT) and comparative effectiveness studies in observational clinical data such as EHR, claims and administrative databases. However, as indicated in the recent Institute of Medicine (IOM) report [8], it is important to start designing clinical information systems that can help capture the patient's state such as social, behavioral and environmental determinants, while fitting situational use of PGHD-derived evidence in the clinical context.[4,6]

Second, PGHD improves individual care through adapting interventions against the incoming stream of patient observations (e.g., lifestyle and physiological measures) and outcome history. The initial results show potential in making sense of PGHD for clinicians and care coordinators [9,10] and fitting situational use of PGHD (for example, for adaptive trials of mobile app-based behavioral interventions [11]).

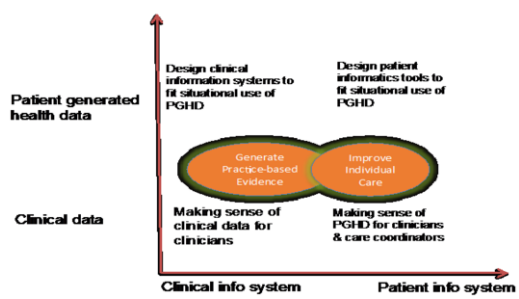

Figure 1– Convergence between PGHD and clinical data in clinical/patient information system for patient-centered care.

Both opportunity areas lead to many subsequent questions regarding the interpretability of PGHD in real-world healthcare applications. For example, how do we check if the chunks of evidence generated from PGHD are reliable? Are they directly deployable in real-world healthcare applications? How to adapt the behavioral interventions for each individual patient at the touchpoint given individual patients' needs? Despite the recent attention in developing interpretable machine learning models for healthcare applications [12,13], the definitions of interpretability are underspecified due to the many different motivations.[14]

Method

In this positional paper, we hereby first review the major dimensions underneath the interpretability mentions. Then, we address the next challenge for the development of health informatics tools to enhance the interpretability-awareness of PGHD-derived insights. We summarize the various issues and model properties that should be addressed in an interpretability-aware framework (as shown Figure 2 below). Next, we highlight the emerging practices in which the framework provides value to patients and clinicians and improves care delivery. Finally, we examine present and future challenges to incorporating PGHD-based evidence back into the care flows, and utilizing cleansed and approved data for purposes beyond their primary context and motivation of collection.

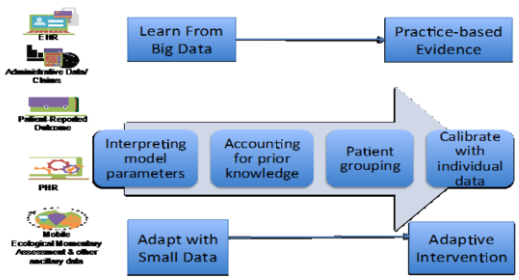

Figure 2– Interpretability-aware framework for population evidence discovery and individual intervention adaptation

Summarizing Major Dimensions of Intepretability from Patients' Perspective

To understand major dimensions behind interpretability, we need to first review the motivations of improving interpretability in different dimensions. For example, [15] explains and quantifies the intepretability metrics for decision rule-based analytics. Here are a few dimensions that we identified for applying machine learning models to generate practice-based evidence and adapt interventions for individuals.

Complexity: As noted in [16], humans are best able to reason about models that are composed of simple forms such as decision trees.[17,18] This interpretability constraint on model complexity persists when it comes to generating N-of-1 models to tailor intervention recommendations. In practice, this involves further constraining policy learner architectures to limited sets of simple rules – first at the population level, and then at the individual level. This has inspired a variety of methodological advancements recently. For example, combining reinforcement learning and regression trees can produce simpler policies for human inspection.[19] Recent results suggest that simple explainable policies could be achieved in complex problems, such as fine-tuning adaptive evaluation of behavioral intervention strategies.[11]

Knowledge Structural Similarity: The interpretability can also be defined as a distance metric based on the known domain knowledge. Intuitively, closer the concepts covered by PGHD, easier is their tnterpretion. Suppose there exist some relationships among the features defined in a hierarchical manner as represented by a tree or directed acyclic graph. The inherent hypothesis is to make sure that the similar features should have similar model co-efficients learnt by the model. One popular approach is group LASSO [20] based techniques, which can pose additional constraints on the above equation to make sure that all the nodes rooted in a particular subtree will have similar parameters during model learning.

Quality: Another major hindrance of patient interpretation of data is the quality issues of PGHD. The sources of errors in PGHD is multi-fold. For self-reported data, the baseline of patient-reported outcome and lifestyle information (for example, daily calorie intake) varies from person to person, resulting in under-reporting or over-reporting. Moreover, the measurements from health wearables and IoT (Internet-of-Things) sensors are often noise corrupted due to inappropriate placement, incorrect use, regular wear and tear of the devices. To overcome the data quality issues, the process of imputing missing values and detecting anomalies and outliers are then needed to train models; which in turn is used for forecasting.

Usability: HCI researchers conducted qualitative studies (e.g., [21]) to make sense for patients of their own data and in addition, to identify interpretability-impeding factors, including: *confounders*, *noisy on meaningful and irrelevant measures*, and *how to determine the time lag of outcome-affecting triggers at the individual level* .

Causality: To further ensure that the framework can provide statistically sound interpretation, we surveyed the causal inference research to understand the effect of following assumptions [22]: *consistency* (i.e., whether one's features and outcomes are consistently observed when the actions are taken), s*tability* (i.e., whether one's features and outcomes are affected by other subjects' actions), and *unmeasured confounders* (i.e., what is the sensitivity of conclusions with factors that influence the assignment of treatments).

The survey leads us to believe that there exist quite diverse views behind the concept of interpretability, and the field of health informatics needs to reconcile the differences by first making the previously implicit assumptions more explicit.

Developing Interpretability-Aware Framework

The development of the interpretability-aware framework is based on a two-layer approach: (1) "Learn from Big data": PGHD from heterogeneous sources are aggregated to learn practice-based evidence for optimal outcome (e.g., efficiency of patient capacity) and (2) "Adapt with Small data": interpreting evidence through comparing the effectiveness across interventions and adapting in a patient-centered way.

Learn from Big Data: PGHD to Practice-based Evidence

First, in order to learn interpretable practice-based evidence that can be conferred from the secondary use of PGHD, we need principled and scalable approaches to address the interpretability issues: model complexity and knowledge structural similarity. The goal is to minimize the model complexity during the process of interepreting model parameters, while boosting knowledge structural similarity to account for prior knowledge during model development.

Interpreting Model Parameters: Most informatics tools rely on learning a set of parameters that are associated with the features extracted from raw PGHD. In particular, an objective loss function is defined based on the original model outcomes and the predicted outcomes using the parameters of the model and then, those parameters are learnt from PGHD such that the loss function is minimized. Let X denote the original feature set, y the outcome, and W the model parameters. The loss function can be represented as below:

$$\min_{w} \; L(X, W, y)$$

Once the model parameters W have been learnt from the model, it is further analyzed to interpret the model. For example, the coefficients obtained from a logistic regression model can be converted into an odds ratio, which is easier to interpret by domain experts who prefer models of simpler forms.[16]

Another useful technique to interpret the model parameters is to impose some sparsity constraints on the model parameters. In that case, the objective function will contain both the original loss function and an additional penalty imposed on the complexity of the parameters. The function is shown in the equation below, where $\lambda(W)$ denotes the complexity of model parameter set W. One popular example of such loss function is L1-norm regularization penalty [23], since it can perform feature selection simultaneuously with model learning, and that will help reduce model complexity:

$$\min_{w} \; L(X, W, y) + \lambda(W)$$

Taking prior knowledge into account: Despite that PGHD are usually collected from heterogeneous data sources, the observational data can be interrelated by certain latent factors or well-established medical knowledge. For example, most of the interventions and care workflows are conducted using a few well-established guidelines. Such guidelines can capture the inherent relationships among observational healthcare data including both PGHD and EHR.

In addition, features obtained from observational data may be well structured with semantic relationships among them. For example, drugs, adverse reactions and diagnostic similarity each has clear role in a hierarchical organization based on how specific or generic it is in its mechanism of actions.

These pre-existing relationships are usually curated with the help of multiple domain experts and a standardized protocol.[24] In particular, the interpretability metrics is quantified as knowledge structural similarity, using a distance metric based on the distance of each pair of features in its hierarchy

$$H_{ij} = \frac{depth(LCA(X_i, X_j))}{\max\big(depth(X_i), depth(X_j)\big)}$$

Here, LCA defines lowest common ancestor of each pair of two features X_i and X_j, and depth of X_i defines length of the shortest path from the root of the tree toward X_i. Moreover, this distance metric is normalized by the maximum depth of the two features. Finally, this new metric is incorporated in the original penalty structure of the objective function as below:

$$\min_{w} \; L(X, W, y) + \lambda_1(W) - \lambda_2(H)$$

Note that similar concepts can be generalized when prior relationships exist not only among the features from one type of data, but also features coming from multiple data-sources such as the heterogeneous exogenous determinants in PGHD.

Adapt with Small Data: Interpret from Patient Perspective

Second, in order to adapt interventions on an individual basis, we include an optimal policy learning component that can tailor interventions against incoming streams of "small" data. The goal is to provide interpretable evidence that can help patients and their care teams make decisions that meet patients' individual needs. In this paper, we introduce components of patient grouping and calibration to evaluate and to inform interpretability-aware analytics.

Patient Grouping: To overcome the barrier of "one-size-fits-all" guidelines to treat all patients as an "average" patient, we apply behavior segmentation methods [25] that can identify sub-cohorts that exhibit distinctive behavioral differences and extract signature behavioral patterns. In the framework, behavioral factors are constructed as a composite of multi-source features for each subject in the cohorts. We illustrate the design of a framework able to generate, analyze and re-rank the risk factors for the behaviorally different segments (as shown in Figure 3; for a more detailed description of the key component of patient grouping, please refer to [25]).

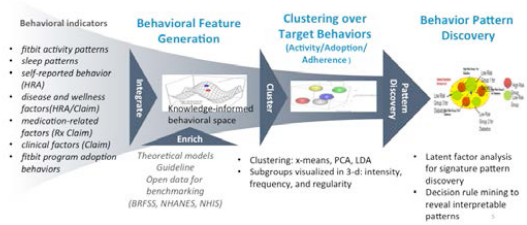

Figure 3 – Patient grouping for subcohort identification and behavioral pattern discovery

While patient grouping finds common static subcohorts directly against the incoming patient data, it has its own disadvantage. For example, it ignores the temporal relation within and among patient behaviors. The behavioral pattern discovery approach applies dynamic item response analysis to incorporate extensions to temporal patterns across multiple streams of data.[26] Such techniques are able to find patterns within groups of variables, patterns in a sequence of variables, or both. This further confirms the need to not treat all patients as an "average" patient – as defined in the guideliens.

In order to learn how confident we can be to deploy the PGHD-derived evidence in certain sub-cohorts, we need to quantify the population representativeness in each sub-cohort. This is achieved through computing an entropy-based similarity index between the sub-cohorts. Low similarity shows the separability of the population segments.

To improve the interpretability, prototypical user examples are used to provide explanations of why a certain evidence is generated for a particular sub-cohort. For each sub-cohort, we compute the prototypical core among the patients, as defined as 10% of the patients closest to the centroid in each patient group. The population means of the core and the whole sub-cohort are then compared with F-statistics. Further the features whose means are beyond two standard-deviations from the entire population means, constitute the distinctive features of that segment. These then become parts of the explanation.

Calibration against Individual Data: In addition, we further design an adaptive real-time approach to address the quality issues abovementioned and to provide intermittent feedback to individual patients.

First, in the data cleansing step, the PGHD is processed for missing values and outliers using the machine learning methods and knowledge of domain experts.

Next, the data goes through an adaptive predictive model, where the underlying data-driven phenomena are modeled as a noisy dynamical system. For each individual patient, predictions of future outcomes are compared with outcomes that are actually measured. Low covariance variables are then marked for correction. A recalibrated model is then built from the original model and the correction feedback. The correction metric for the erroneous variable is then fed back to the data processing step to calibrate the individualized systems.

Further, the system can prompt the users for labeling of inputs corresponding to the erroneous variables. This kind of dynamic feedback system will improve the data quality for analysis and improve the prediction accuracy for each person.

Discussion

In this positional paper, we summarize the major dimensions of interpretability and describe the interpretability-aware framework for further adding a patient focus into the care process. The interpretability-aware framework helps foster a continuous learning health care system as pictured in the "All of US" platform under the Precision Medicine Initiative (PMI).[27] The framework will establish prospective effectiveness based on the basic phenotypes found in mass data and new cases matching some basic phenotypes. This framework, when coupled with the best practice defined for clinical flow to increase patient understanding, is expected to further fuel the patient-centered care model for minimally disruptive medicine.[28] The framework is expected to facilitate the integration between science of data and science of care at the touchpoint. This is especially important for the complex care scenarios wherein standard guidelines and general population-based evidence fall short.

Comparing person-centered effectiveness at touchpoint

Traditionally, comparative effectiveness studies are used to provide evidence to handle "average" patients. Comparative effectiveness studies, if done with a patient focus, can empower patients to better understand and take charge of their decisions. Therefore, in the proposed framework, we further include additional patient grouping and re-calibration steps to reinforce the patient focus.

In retrospect, it can also help identify hypotheses to be verified or falsified. Although classification modeling analysis has become a routine tool in health informatics research, extracting actionable insight from such information remains a major challenge. Formalizing the interpretability metrics and framework such as the correction metrics can help pinpoint the previously unobserved inefficiency of practice and attribute it to to variables that matter to patients sub-cohorts and providers, as opposed to those that only add noise.

Putting Big Data and Small Data Together

In terms of the actual implementation, formalizing and scaling up the interpretability-aware framework means solving various practical problems. These include conducting feasibility study of monitoring devices and developing new forms of outcomes.

Take the assessment of stress-behavior relationship as an example. Traditionally, this is done with survey-based ecological momentary assessment (EMA).[29] By coupling EMA with mobile devices, we can repeatedly collect exposure data of psychosocial stressors in ecologically valid settings such as home and work, and in real time. Compared to the survey-based EMA, mobile EMA enables collecting data with the immediate context and substantially reduces recall bias.[30]

In fact, oftentimes, we would not need to develop individual models from scratch, but rather to recalibrate the existing population-based model using user's own data. The confidence level can be estimated with the sub-cohort identified from the patient grouping step. The recent trends of N-of-1 trials have started to provide evidence on the effectiveness of such approaches for adaptive design.[30,31] Currently in the field, researchers are attempting to apply N-of-1 methods to develop individualized preditive pathways that can be applied to adapt interventions at the touchpoint directly.

The societal approval and ethical issues going forward

It will also require a cultural shift from large, population-based trials to ad-hoc, post-trial analyses that aim to interpret the factors that cause some patients to be responsive. We have to meet such challenges as balancing the economic power of holding the data against the moral maxim of equitable access for citizens to individualized recommendations. Since the data themselves often are public domain there is a moral obligation to make them available free of charge. Since the aggregation of the data requires proprietory technology, there is equal legitimacy to charge market prices for such recommendations.

This compares to the question whether medical advice is a commodity or a merchandise. We have to find answers for patients who find themselves in a Gestalt whose treatment by far exceeds their individual economic reach. We have to find agreement, world wide—since the origin of data is world wide—how to handle the detection in passing of alarming conditions: are we entitled to know the name of data source and its identity and to take action? May we, who detect a risk, even be obliged to take action or else be taken accountable for nonfeasance, as physicians would be? Therefore, do we, as informaticians who are engineers in a wide sense, assume the role of physicians and hence inherit the moral standards that physicians have to uphold? Does such an obligation differ between individual risks and societal risks such as epidemics?

Today, we are far from answers. We will, however, demonstrate how principles and maxims from ethics can be used as tools to address these and more question.[32]

Conclusion

The advent of large-scale PGHD collected from diverse sources poses unique opportunities to harvest insights about patients' behavior and response to a particular treatment, which can ultimately be used to derive knowledge for making better clinical and self-care decisions. Given the prevalent adoption of EHR and the shift to value-based care, many leading healthcare systems are now evaluating the value of PGHD generated from care processes, which can be either used directly to enhance care processes, or aggregated in big data to derive practice-based evidence.

Traditionally, the generation of clinical evidence relies on RCT and comparative effectiveness studies, which employ costly clinical trial research design and observational data sources such as EHR, claims and administrative data. While these data sources reveal valuable information about treatment effect and healthcare utilization, individual patient data are still needed to identify individually outcome-differential health determinants such as in their social, behavioral, environmental, and psychological factors.

However, the current interpretability of PGHD-driven insights is still questionable when applied to real world applications. In addition, the interpretation of such insights often hinges on experienced healthcare professionals (e.g., care managers). By applying the framework to communicate, it is easier to advocate for post-statistics decision models, which often incur new forms of outcomes and social desirability bias.

This inevitably incorporates humans in the loop during the process of transforming big data to practice-based knowledge and deploying such evidence at the touchpoint for individuals.

In this positional paper, we first identify the major dimensions of interpretability. Then, we depict our intepretability-aware framework in which interpretable analytics are enhanced to better incorporate PGHD insights back to the care flow. The aim is two-fold.

First, the proposed framework gives care team tools to address two major challenges: (1) Enable the generation of practice-based evidence from aggregating "big data" from heterogeneous PGHD sources, especially useful for complex care scenarios wherein no clear evidence or guidelines are applicable; (2) Learn to further adapt population health-based recommendation with "small data" from individuals or sub-cohorts for self-care and experimentation.

Second, the framework aims to make personalized recommendations on *what to intervene on* at the touchpoint. However, oftentimes the human opinions are subjective and highly depend on their prior expertise and training, which lead to underlying bias and noise factors and decrease the generalizability of the model. Therefore, how to extract best practice and make it scalable throughout organizations and in real world applications is the key for future uptake in practice.

These issues can be mitigated to some extent by taking human knowledge into account in an earlier stage of model development rather than during the model validation step. Therefore, the proposed interpretability-aware framework can help pinpoint more relevant yet explainable risk factors along with their relationships with disease outcome. The bottom line is that these methodological advances should be used to augment, but not to replace the central role of human insights in predicting behavior that can be intervened on.

Using the interpretability aware framework, we can also establish prospective effectiveness of interventions based on more interpretable basic phenotypes found by the patient similarity in mass data. This is important to identify evidence deployable for individuals with uncommon characteristics rather than hiding the apparent noise they contribute as variance and noise.

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Address for correspondence

Corresponding author: Pei-Yun Sabrina Hsueh

Email: pyhsueh@gmail.com