A Hybrid Approach to Realizing Personalized Healthcare

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A grand challenge in the health domain is to realize the vision of personalized healthcare. Achieving this vision requires collection, integration, and analysis of vast amounts of personal health data to improve our understanding of unique behavioral and environmental factors that influence health outcomes. However, securing the right kind of data in sufficient quantity to support development of robust inference models is often a challenge. In addition, identifying the right research questions and appropriate realizations of a solution that is useful to target user groups is another challenge that is often overlooked. In response, this paper proposes: 1) a hybrid approach for sourcing personal health data to circumvent well-known limitations of self-report and manual logging, and 2) a hybrid approach for developing and evaluating artificial intelligence models to circumvent well-known challenges associated with utility and adoption in practice. As a case study, this paper will present concrete examples from the diabetes domain to ground the proposal for a hybrid approach to personalized healthcare.

CCS Concepts: • **Applied computing** → **Health informatics**.

Additional Key Words and Phrases: Personal Informatics, Artificial Intelligence

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1 INTRODUCTION

Personalized healthcare is the vision of providing the right treatment strategy for the right patient. This approach to care recognizes that *one size does not fit all*. However, attaining the vision of personalized healthcare is a grand challenge due to a combination of factors. For instance, there is a growing burden of disease in society at large, many complex health conditions are influenced by distinct behavioral and environmental factors, and there is limited resources amongst clinical care teams to navigate through so many important considerations. The effort to realize personalized healthcare now fuels greater reliance on the power and potential of: 1) ubiquitous technology (e.g., mobile and wearable systems) that is capable of continuous sensing in ambulatory settings, and 2) artificial intelligence (AI) models that can analyze and interpret large datasets to achieve and complete tasks that are usually done by humans. Sensor-rich mobile and wearable devices are an invaluable source of personal health data that provide a unique window into the lives of individual people (and/or patients), enable longitudinal surveillance, and even support population-based studies [10]. In addition, data from ubiquitous technology can also support an improved understanding of unique behavioral and environmental factors that influence health outcomes.

In spite of the potential and promise of large amounts of personal health data to support personalized healthcare, it is well-known that data alone is not sufficient [6]. There is also a critical need for intelligent "user-centered solutions" that enable data exploration, analysis and interpretation [3, 5, 13]. User-centered solutions is key because machine learning on large datasets without a clearly-defined need or direction is futile [10]. Similarly, under-utilization of large amounts of already existing personal health data due to limitations of manual analysis approaches is a missed opportunity that overlooks the benefits to be gained therein [1]. Additionally, development of high-performing AI models that never get used in practice is a waste of resources. To support realization of meaningful AI solutions to grand challenges in the health domain, it is important to optimize concurrently for performance and utility [15].

Toward the goal of realizing personalized healthcare, this paper proposes:

(1) A hybrid approach for sourcing personal health data for AI models to circumvent well-known limitations of self-report and manual logging methods.
(2) A hybrid approach for developing and evaluating AI models to circumvent well-known challenges associated with utility and adoption in practice.

As a case study, this paper will present concrete examples from the diabetes domain to ground the proposal for a hybrid approach to personalized healthcare.

2 A HYBRID APPROACH TO SOURCING PERSONAL HEALTH DATA FOR AI MODELS

A common approach in research is to start with an open problem. For example, "how can we track dietary habits in daily living?" In an effort to answer this question, we might immediately jump to building new sensing platforms for tracking dietary activities (e.g., chewing, swallowing, hand-to-mouth gesture) [2, 11]. This instinctive approach describes majority of the research in literature [12, 18]. While it is a valid approach to research and the broad problem is extremely important to advance the state-of-the-art in many health domains (e.g., obesity, diabetes, eating disorders, etc.), additional context around the specific need and target population can further guide our approach for finding and developing a meaningful solution.

For example, dietary habits are particularly important within the context of diabetes. In addition, almost 40% of patients with type 1 diabetes (and a growing number of patients with type 2 diabetes) already use continuous glucose monitors (CGMs) as a prescribed medical device for daily management of their blood glucose [8, 16]. This equates to around 640,000 with type 1 diabetes who use CGMs in the U.S alone [7, 8]. Based on today's technology, CGMs sample blood glucose every $\approx$ 5 minutes and yield around 288 samples/day. In addition, CGMs are prescribed for use day-in and day-out, and patients are expected to CGMs for months and even years, with an exception for brief periods of non-use for maintenance activities (e.g., < 1 hour every 7 - 14 days for replacing the CGM sensor) [17]. It is well-known that blood glucose is directly and significantly impacted by meals/dietary habits (as well as other factors) [4]. Hence, a potential approach to realizing a solution for dietary tracking for persons with diabetes who use CGMs could be to leverage this rich and often under-utilized data source [1]. CGM data can be used in combination with auxiliary methods for sensing other relevant dietary activities (e.g., wrist-worn approaches for detecting hand-to-mouth gestures) to provide complementary data streams for more accurate detection and understanding of the events of interest.

The proposed hybrid approach combines familiar technology (e.g., CGMs and wrist-worn devices) within a well-defined population to frame the problem "how can we track dietary habits in daily?". This approach leverages sensing platforms that are already widely used to take advantage of large and often under-utilized sources of personal health data for developing robust AI models for personalized healthcare. Additionally, the proposed hybrid approach circumvents other limitations of self-report and manual logging for personal informatics and AI including the challenges of high user burden and generation of biased and even inaccurate data for building inference models. It is no question that AI models trained on rich datasets (e.g., from continuous sensing devices) can perform significantly better than models trained on sparse datasets (e.g., from point-in-time measurements).

3 A HYBRID APPROACH TO DEVELOPING AND EVALUATING AI MODELS

Research shows that advanced AI models are capable of achieving record-breaking performance for diagnosing disease, classifying severity, and predicting treatment outcomes in several health domains. For example, deep learning models have been used to detect diabetic retinopathy with "specialty-level accuracy" of greater than 90%, and classify severity even better than trained clinicians [9, 14]. However, research also shows that accuracy alone is not sufficient for such AI models to be embedded into clinical practice [3, 15]. There are significant issues relating to utility and adoption that are hardly considered. This issue makes the case for a different approach to developing and evaluating AI models for health applications. In particular, it is important to prioritize user involvement and engagement in the process of developing and evaluating AI models for personalized healthcare. Such a hybrid approach requires collaborative and iterative partnership between model developers (e.g., data scientists) and users (e.g., patients and clinicians) for every phase of development, including problem definition and framing, data analysis, interpretation, and explanation.

An example of a hybrid approach for needfinding followed by developing and evaluating an AI model can be seen in the recent papers by Prioleau et al. [13] and Bartolome et al. [1]. In [13], the authors sought to understand open problems around routinely collected personal health data in the diabetes domain through a multi-stage user-study with patients, clinicians, and caregivers. A key finding that emerged is that users desire solutions that can "automatically extract trends/patterns" from the wealth of personal health data that is routinely collected.

In a follow-up study, Bartolome et al. [1] found that only the most recent CGM data ($\approx$ 2 weeks) is used in clinical practice to inform management strategy and future treatment plans. This norm showcases under-utilization of personal health data and leaves room for missed insights that are imperative to realize personalized healthcare. In response, the authors developed GlucoMine, an algorithm for automatically finding hidden patterns of management in extended periods of CGM data. Using an average of 3 - 6 months of CGM data from 54 subjects, they found that 96% (n=51) had clinically-significant patterns of poor management that cannot be identified with conventional tools used in practice. An evaluation study with clinicians supported the the developed solution was beneficial, however, the findings also support that there are other important metrics to consider before such a solution can be adopted. For example, majority of clinicians identified an example when they would focus on different patterns in the data that present the most pressing issue to be addressed. According to one clinician, "not all perturbations in glucose are equally injurious to health." In addition, clinicians wanted the freedom to further explore the data and results for themselves. One clinician stated "it is good that I can see all the data not just what the algorithm selects." Such insights cannot be learned and incorporated if quantitative performance was the only metric of success considered. Hence, there is an obvious need for a hybrid approach to developing and evaluating AI models in partnership with target users to realize solutions that can ultimately be adopted in practice to improve health outcomes.

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