Personalized Machine Learning using Passive Sensing and Ecological Momentary Assessments for Meth Users in Hawaii: A Research Protocol

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Abstract

Background: Artificial intelligence (AI)-powered digital therapies which detect meth cravings delivered on consumer devices have the potential to reduce these disparities by providing remote and accessible care solutions to Native Hawaiians, Filipinos, and Pacific Islanders (NHFPI) communities with limited care solutions. However, NHFPI are fully understudied with respect to digital therapeutics and AI health sensing despite using technology at the same rates as other races.
Objective: We seek to fulfill two research aims: (1) Understand the feasibility of continuous remote digital monitoring and ecological momentary assessments (EMAs) in NHFPI in Hawaii by curating a novel dataset of longitudinal FitBit biosignals with corresponding craving and substance use labels. (2) Develop personalized AI models which predict meth craving events in real time using wearable sensor data.
Methods: We will develop personalized AI/ML (artificial intelligence/machine learning) models for meth use and craving prediction in 40 NHFPI individuals by curating a novel dataset of real-time FitBit biosensor readings and corresponding participant annotations (i.e., raw self-reported substance use data) of their meth use and cravings. In the process of collecting this dataset, we will glean insights about cultural and other human factors which can challenge the proper acquisition of precise annotations. With the resulting dataset, we will employ self-supervised learning (SSL) AI approaches, which are a new family of ML methods that allow a neural network to be trained without labels by being optimized to make predictions about the data itself. The inputs to the proposed AI models are FitBit biosensor readings and the outputs are predictions of meth use or craving. This paradigm is gaining increased attention in AI for healthcare.
Conclusions: We expect to develop models which significantly outperform traditional supervised methods by fine-tuning to an individual subject's data. Such methods will enable AI solutions which work with the limited data available from NHFPI populations and which are inherently unbiased due to their personalized nature. Such models can support future AI-powered digital therapeutics for substance abuse.

Keywords: machine learning; precision health; Indigenous data sovereignty; substance use; personalized artificial intelligence; wearables; ecological momentary assessments; passive sensing

Introduction

Significance

Methamphetamine (meth) abuse is highly prevalent in Hawaii, especially among Indigenous Pacific People (IPP) [1]. Since the 1980s, Hawaii has been considered as the meth capitol of the U.S. Data from the Pacific Health Analytics Collaborative shows that from 2015-2018, 1.5% of Hawaii residents used meth annually [2]. This is more than twice the national rate of 0.6%. According to the Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF), 71% of all drug cases in Hawaii were related to meth [3]. There are major meth-related disparities between NHFPI and other races in Hawaii, with NHFPI exhibiting elevated rates of illicit substance abuse [4]. According to the CDC, NHPI high school students exhibited lifetime meth use of 7.7%, versus 3.7% in White students, 2.7% in Black students, 3.1% in Asian students, and 5.7% in Hispanic and Latino students5 and these disparities continue into adulthood [5]. Digital interventions powered by AI have the potential to reduce these disparities by aiding clinicians in remotely providing care and monitoring patients between visits, especially populations living in rural areas in Hawaii. Furthermore, such technology could be useful in relapse prevention for those hoping to maintain abstinence. Native Hawaiians have home Internet access at comparable rates to non-Native Hawaiians (58% for Native Hawaiians vs. 55% for non-Native Hawaiians in 2022) [6].

The field of AI-based detection of substance abuse using biometric signals measured by wearables is an active field of research across several research labs globally, as documented in a 2022 review paper by Rumbut et al. [7]. Studies in this field tend to collect prediction labels through remote administration of an ecological momentary assessment (EMA), a methodology where participants are periodically asked to answer questions about their psychiatric or behavioral state while living as usual [8-10]. Unfortunately, prior AI models suffer from clinically unacceptable performance. The primary reason for this lackluster performance is because prior methods attempt to train models using data from many patients, which is the status quo in deep learning due to the requirement of massive datasets to for successful training. In contrast to these prior works, we will develop personalized AI models using a method developed by Dr. Washington's lab which is capable of learning baseline patterns of human behavior and transferring this knowledge to prediction tasks with very few labeled examples to learn from.

My research lab is particularly qualified to carry out this project, as we are already developing computer science methods to support the personalization of AI models for large and mostly unlabeled data streams, with promising preliminary data and publications in preparation supporting this methodology. As a T1/T2 project (i.e., covering basic discovery and initial human trials), my proposed work is significant both in terms of equitable substance abuse therapeutics but also as a general methodology for clinical and translational research (CTR) in other domains. There are countless situations in healthcare where vast amounts of unlabeled data are collected from a single patient. Annotations for the event of interest (e.g., substance abuse) are frequently sparsely dispersed. The development of predictive supervised models is infeasible in such circumstances, as classical approaches cannot handle the complexity of the data and modern deep learning approaches require vast amounts of data.

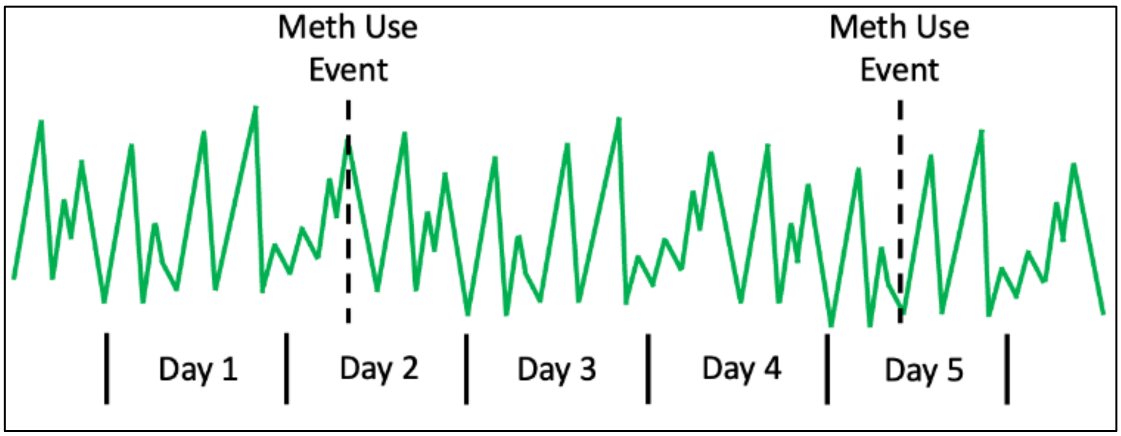

Figure 1. In many biomedical domains, there exist large datasets with sparse annotations of health events. We propose a "personalized self-supervised learning" method which can support training of deep neural networks in such scenarios. We will evaluate our method primarily on the prediction of meth use events using biosignals data from a FitBit.

Innovation

To support ML development in situations where vast longitudinal data are collected with minimal human-provided annotations, we propose the development of personalized ML models which are trained solely on an individual's unlabeled data to learn feature representations which are specific to their baseline temporal dynamics. We are creating a novel method and framework which has never been explored in healthcare, consisting of pre-training neural networks to learn the temporal dynamics of a patient's biosignals. This method will enable deep networks to be trained using relatively small datasets which would not be possible without the self-supervised approach proposed here. This technique is particularly well-suited for massive datasets with few labels.

The application of personalized AI with a diverse population of persons using substances is unique. NHFPI have been understudied and could benefit from novel treatments to address meth use. While we will apply this technological innovation towards the prediction of meth use, multimodal time-series personalization can be applied to a variety of other biology and health problems where (1) multiple signals are sparsely emitted, (2) the baseline signal patterns are specific to each individual, and (3) it is infeasible to acquire the vast amounts of labels required to train a supervised deep learning model.

This method has the potential to dramatically advance the field of precision healthcare by enabling reliable AI/ML predictions from massive but mostly unlabeled datasets which are trained in a self-supervised manner on data from a single user. This setting of large unlabeled datasets with sparse supervision appears frequently in the field of digital healthcare. Notable examples include passive mobile sensing studies for mental health and wellbeing [11-20], digital therapeutics for children with autism spectrum disorder which record video of the child [21-37], and passive brain sensors for brain-computer interfaces [38-46]. As such, this research protocol can be considered as one of the first tests of a broader emerging paradigm in precision health.

Methods

Overview

This protocol was approved by the University of Hawaii Institutional Review Board (IRB) under protocol #2022-01030. Additionally, this study has received further scrutiny and approval via the University of Hawaii's Data Governance Process under request #230410-3.

The long-term methodological goal of the proposed work is to develop novel AI methodologies for predicting health events (e.g., meth use and cravings) from biosensors in a personalized manner. This technical innovation will be applied towards the detection of drug use events from wearable device sensors. The inputs to the proposed AI models are FitBit biosensor readings and the outputs are predictions of meth use or craving (Figure 1). The developed methods developed can pertain to a variety of biomedical domain areas.

Diagnostic ML models are typically trained and deployed at a population level. In this traditional scenario, a single model is developed which makes predictions for all individuals within a population. In several health contexts, however, an event of interest occurs repeatedly for an individual. For example, diabetes patients have repeated blood glucose spikes and chronically stressed individuals might have repeated blood pressure spikes. In these cases, ML models can be developed by conducting supervised training on the individual's data only, resulting in a separate personalized model per individual. While deep learning models have achieved state-of-the-art performance in a variety of health contexts, neural networks require massive datasets which are infeasible to collect for a single individual. However, recent advances in self-supervised learning (SSL), or the subfield of ML focusing on pre-training models without any human-provided labels, are making it possible to realize the personalized ML diagnostics paradigm using deep learning by pre-training the weights of a neural network such that it can learn the baseline temporal dynamics without any labels. The pre-trained model can then transfer learn using relatively few labels that are acquired solely from the individual in question. This methodology can work especially well in scenarios where massive amounts of unlabeled data are collected, such as with continuously worn devices.

Aim 1: Understand the feasibility of continuous remote digital monitoring and ecological momentary assessments (EMAs) in NHFPI in Hawaii by curating a novel dataset of longitudinal FitBit biosignals with corresponding craving and substance use labels.

Description

We will recruit 40 carefully selected NHFPI participants, who are either in treatment or have received services from one of our community partners, to each participate in a 4-week remote FitBit data collection and concurrent ecological momentary assessment (EMA) study. EMA studies, which involve periodic digital self-reports about psychiatric and behavioral outcomes "in the wild", have often been used to understand substance abuse [47], including for meth users [48]. We expect >=80% complete data from roughly 25% of the participants (or 10 participants total; see Recruitment section below for justification). Each participant will wear a study-provided FitBit Luxe watch during all waking hours for at least 15 hours each day. Apart from wearing the devices and periodically proving an EMA about their meth use, participants will be asked to follow their normal routine throughout the study.

Participant Recruitment and Management

We will recruit participants from a combination of sites, including the Hawai'i Health & Harm Reduction Center (HHHRC) and other sites that the clinical collaborators have connections with (i.e., Hina Mauka). Potential participants will be eligible for the study if they: 1) are 18 years of age or older, 2) self-report consumption of meth on two or more different days per week on average, 3) have no plans to leave Oahu for at least one month, and 4) own a smartphone with either a data plan or regular access to a WiFi connection. Potential participants will be excluded if they: 1) are currently homicidal or suicidal, 2) cannot provide informed consent, 3) are not able to complete interviews in English, 4) expecting incarceration or plan to leave Oahu within the next month, or 5) are unable to provide names and contact information for at least two verifiable locator persons for retention purposes.

We will onboard 40 total participants. A secondary analysis on EMAs for meth abuse monitoring measured the percentage of participants who reached >=80% compliance at different frequencies of meth use, finding that roughly 50% of meth users using 1-3 times per month met this 80% compliance bar, 40% of users using 1-2 days per week met the bar, and 25% of users using 3-4 days per week met the bar [49]. We therefore anticipate a roughly similar compliance rate of around 10 participants (25%) at >=80% compliance, which is sufficient to demonstrate the feasibility of our AI method, as a separate analysis will be conducted for each participant (i.e., 1 model per participant).

Data Collection

We will leverage the existing application programming interface (API) provided by FitBit to record the user's watch sensor readings and upload the data to the cloud. The FitBit API provides access to heart rate (HR), gyroscope, accelerometer, breathing rate, blood oxygen levels (SpO2), and skin temperature sensor readings. These biosensors have previously been used to predict substance abuse and cravings using AI [50-54]. The data will be managed on each participant's smartphone device through an application, implemented for both iOS and Android, that we are already actively developing. The study team will install the application on the user's smartphone and configure the FitBit device during study onboarding.

Measure/Domain (Time of Administration)	Question
Background characteristics (Intake)	To better describe the sample, participants will be asked about their sex, gender/sexual orientation, age, race/ethnicity, marital status, education, income, employment, housing, and health insurance status.
Substance use and treatment history (Intake)	Questions will be developed to assess current and history of substance use and participation in treatment services.
Tolerability (Study conclusion)	How comfortable was the device?
Obtrusiveness (Study conclusion)	Did the device change your daily routine? Do you have any concerns with continuously FitBit usage?
Meth use (EMA)	Have you used meth since the last time we contacted you? [a]Approximately what time did you LAST use meth? [a]How did you use meth the last time you used?
Craving (EMA)	Please rate your current craving or desire to use meth at this exact moment on a scale of 0-10, with 0 being "no cravings" and 10 being "extremely intense cravings."

Table 2. Study intake/outtake measures and EMA* Questions (adesignates skip logic) collected for each participant.

We will run the study with 8 participants at a time, as we have 8 total FitBit Luxe devices, resulting in 5 batches of data collection periods. We will record background characteristics and substance use and treatment history during study intake; we will record questions pertaining to tolerability and obtrusiveness of the app during study outtake (Table 1). The smartphone app will record EMA responses from participants throughout the one-month study period (Table 1). At each EMA, we will ask participants to list approximate times (date, hour, and minute) of their meth intake in the past 24 hours via a user interface on the smartphone app. Participants will be asked to do the same for cravings. Participants will be prompted to provide EMA responses both when drastic signal changes are detected (event-triggered EMA) and every 24 hours (fixed-interval EMA).

We will institute procedures to reduce burden associated with EMA and increase compliance, as suggested by Burke et al [55]. To reduce burden related to the time commitment, we are compensating for every signal-contingent response and providing additional compensation when participants respond to greater than 80% of prompts. Participants will be trained extensively on the EMA protocol during baseline and if they experience any technology-related issues, my research assistants will help troubleshoot remotely. Participants who experience technology-related problems will not have their compensation decreased due to missing prompts.

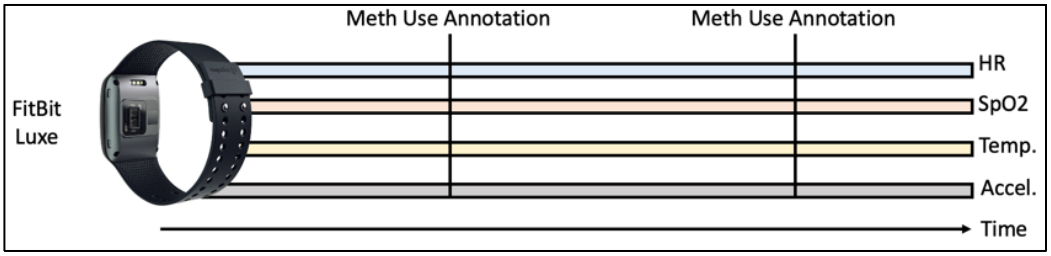

Figure 2. Depiction of the proposed dataset, consisting of continuous FitBit Luxe sensor readings and corresponding meth use and craving annotations from 20 participants collected over a 4-week period.

We will store the curated data from each participant (Figure 2) on a centralized server hosted on Amazon Web Services (AWS). Data uploaded from both wearable systems and the smartphone will first run through a preprocessing server hosted on an Elastic Cloud Compute (EC2) instance with data stored on DynamoDB. Each table will have columns for the participant ID and the timestamp. To ensure privacy and HIPAA compliance, we will encrypt all server-side data and require secret access keys for data access. DynamoDB tables are automatically encrypted on the server side. To add an additional layer of security, we will implement client-side encryption on the mobile application, ensuring encrypted data transmission over an HTTPS connection to move data between the devices and AWS. The data will not be accessible without a secret access key. All data will be anonymized.

An anonymized version of participant data will be made available to other computational researchers as a publicly available dataset. This dataset will be stored on Amazon Web Services on a HIPAA-compliant server and will be password protected. Researchers will only gain access to this dataset by signing a Data Use Agreement. Such datasets exist for activity and emotion recognition from wearable data, but prediction of meth use from these measurements will be a challenging task, and other ML practitioners can improve upon our initial AI models with the release of the de-identified dataset. This will be the first publicly available dataset which includes substance use self-reports alongside wearable sensor readings.

Data Analysis and Interpretation

We will measure the success rate of remote data collection procedure, as measured by the response rate to EMA notifications. We hypothesize that we will observe higher compliance rates with event-triggered EMAs over fixed interval EMAs. We will also document qualitative challenges with the data collection process, tolerability, and unobtrusiveness (Table 1). We will conduct an interview with participants at the study conclusion when devices are returned. The research team will qualitatively code interview responses to derive recurring themes and design insights.

Potential Pitfalls and Mitigation Strategies

This analysis plan is uniquely robust to incomplete data collection because a separate AI model will be trained and evaluated for each participant. There is no requirement for equivalent data streams between participants nor will the analysis be prevented if the full 28-day data collection period is not achieved. The ML strategy can work with only a few logged meth use events. We expect roughly 25% of participants to complete the study at a sufficient level of compliance to support personalized ML analysis. This will provide sufficient data to demonstrate the feasibility of personalized ML analysis.

We have budgeted a 4-month buffer period beyond the 5 months required for complete data collection to account for participants delays and no-shows. Because participant data will be uploaded to AWS daily, we will remotely monitor participants through an automated tracking system already developed by my research lab and will cease the study if compliance is not logged after 4 days. Another possible issue is FitBit theft or loss. To minimize this risk, we will compensate participants $135 for study completion, paid when they return the FitBit. In the case of FitBit device breakage or loss, my lab will purchase additional devices with funds separate from PIKO, up to a limit of 6 additional devices over the course of the study period.

Aim 2: Develop personalized AI models which predict meth craving events in real time using FitBit sensor data as the model input.

Description

Based on extensive support from prior literature, we hypothesize that AI solutions can detect periods of both meth use and cravings with high sensitivity through personalization of machine learning models. Such models will achieve high performance on a single individual through the fine tuning of each model using only the person of interest's data for model training. These personalized predictions can trigger the onset of a digital therapy. We will develop two separate AI models per participant: (1) a model which detects meth use in real time, and (2) a model which predicts meth craving in real time. We hypothesize that model personalization using novel self-supervised pre-training strategies will outperform traditional state-of-the-art AI techniques with <5% of the required label data.

ML Model Training

The inputs to the models will consist of a separate 1D convolutional backbone pre-trained for each biometric modality. The convolutional features will be fused upstream into a shared joint dense representation space and finally a dense prediction layer with linear activation for regression prediction (Figure 3). We will implement all models using TensorFlow [56].

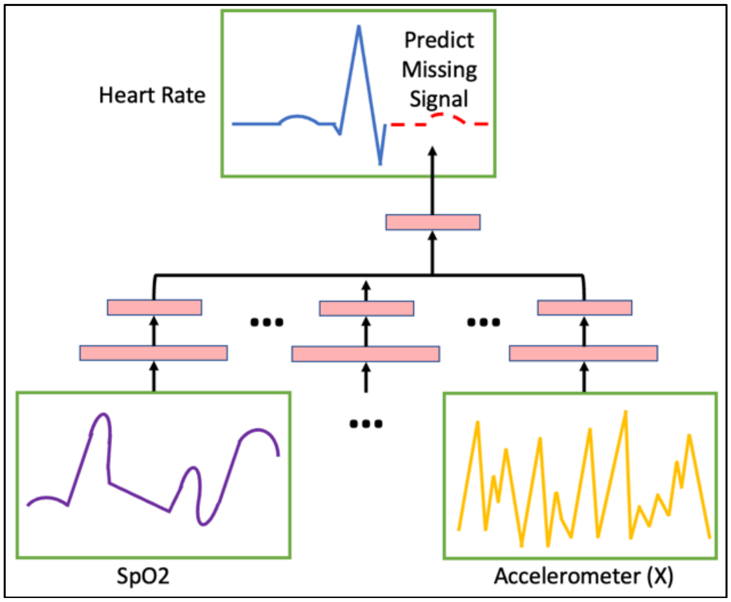

Figure 3. The key methodological computer science innovation of this proposal is the personalization of ML models which make predictions from biosignals time-series data without user-provided labels. Here, we depict a neural network which is trained to predict a heart rate signal given SpO2 and accelerometer signals from a single participant.

The data augmentation techniques that we apply to the signals will be domain-specific, keeping in mind the inherent dynamics of each sensor. For example, for accelerometer data, rotations simulate different sensor placements and cropping is used to diminish the dependency of event locations [57]. Across several modalities, sensor noise can be simulated through scaling, magnitude-warping, and jittering [57]. We will be careful to not apply augmentation strategies which might change the meaning of the underlying signal.

Model Personalization

SSL is usually used to pre-train an entire dataset with no explicit labeling by humans to guide the supervision task. We propose to redesign the SSL paradigm towards the task of model personalization. By pre-training a model only on the vast amounts of data curated from a single individual, the weights of the neural network will learn to make predictions using the inherent structure of each participant's biosignals. This is essential because baseline HR, SpO2, skin temperature, and movement patterns, regardless of stress, will vary drastically across individuals, limiting the performance of general-purpose ML models.

We plan to exploit the multimodal time-series nature of the collected data to perform novel SSL pre-training. We will use one or more signals to predict the value of another signal source (Figure 3). The motivation for this approach is that the biometrics of interest recorded by FitBit are correlated [58-61].

Data Analysis and Interpretation

We will train the model on the first 75% of data (by time) and calculate the balanced accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (AUROC) curve on the final 25%. This evaluation pattern mimics real-world use, where a model will be calibrated by a user prior to real-world deployment. It is important to emphasize that we will train and test a separate personalized ML model for each individual (up to 40 separate models).

In a similar nature to our preliminary data, we will evaluate the models by comparing the performance with respect to the number of labeled examples used for supervised fine-tuning. A plot of this comparison will elucidate the number of meth annotations required for model calibration to a single individual. We will create a separate plot for each study participant, as the ML portion of this proposal is testing the personalization of ML models rather than a general-purpose one-size-fits-all ML model which is more typical in ML evaluations.

Feasibility

Self-supervised pre-training has been successfully demonstrated in several contexts in computer science and even healthcare [58, 62-63], although never in the personalized context which we will explore except for preliminary results which we have recently published. Multimodal SSL has demonstrated success in prior literature [64-67], although not in the personalized manner in which we will innovate in.

Conflicts of Interest

None declared.

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