Understanding Barriers to Diabetes Self-Management Using Momentary Assessment and Machine Learning

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Abstract

Persons with diabetes must per- form many self-management tasks each day to obtain optimal control of blood glucose. Psychosocial and contextual factors impact the ability to perform those tasks. Ecological momentary assessment (EMA) uses technology-mediated approaches to monitor and assess psychosocial and contextual variables that may impact self-management. To utilize EMA data in applied settings, however, feasible methods are needed to automate prioritization of the many factors that can impact health behaviors.

This study uniquely applies machine learning algorithms to demographic and EMA-generated psychosocial data to predict self-management in adolescents with type 1 diabetes (T1D). The results suggest certain domains of factors more accurately predict on self-management than others and have promise for prioritization in future research. Results have implications for scaling up this combination of assessment and analytic approaches in population health.

Keywords: Precision Behavioral Medicine, Self-Management, Machine learning, Type 1 Diabetes, Ecological Momentary Assessment

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1. Introduction

Type 1 diabetes (T1D) is a prevalent chronic illness with increasing incidence rates reported worldwide [1, 2]. It is an autoimmune disorder where the body does not produce insulin and requires patients to perform critical self-management tasks multiple times per day [3]. Two key self-management tasks in T1D involve frequent monitoring of blood glucose and administering insulin. These tasks help manage glycemic control to avoid or delay serious short- and long- term consequences, such as retinopathy, neuropathy, and mortality [4, 5, 6].

Adolescents and young adults have the worst glycemic control of any age groups [4]. For young people with diabetes, living successfully with T1D is particularly hard due to many potential psychosocial and contextual barriers to self-management [7, 8, 9]. Mealtimes are a critical time for diabetes self-management.

A recommended approach used to improve self-management of diabetes involves promoting and supporting problem solving skills to reduce barriers [10]. To identify problems related to self-management, patients, caregivers, and clinicians must rely on blood glucose and insulin administration data from devices along with a patient-generated recall of potentially relevant behavioral, emotional, and/or contextual events that could pose barriers to self-management. However, utilizing retrospective memory or recall for events that are days or weeks in the past has been identified as generally unreliable and potentially biased in nature [11]. Unreliable recall of events in diabetes problem solving could result in modifications to the insulin regimen that are not based on reliable information.

To address the limitations of human recall and bias in health behavior research, ecological momentary assessment (EMA) methods have been developed and successfully utilized in a range of health conditions. EMA methods provide a more proximal (and often more accurate) technology-mediated method to monitor and assess the contexts, subjective experiences, and processes that surround health decisions in daily life [12, 13]. In contrast to traditional assessment methods, EMA utilizes more frequent and in-vivo ambulatory assessment of factors that impact health behaviors and decision-making. This approach provides more relevant, proximal, and frequent observations per patient, EMA (also known as experience sampling) methods generate rich data to more accurately assess previously identified correlates of health behavior and identify novel correlates for intervention [14].

Many studies in the EMA literature have used hierarchical linear modeling (HLM) or other similar analytic approaches. These studyes, however, have not identified a model for prioritizing variables or automating analyses. Machine learning (ML) has promise for integration with EMA for those purposes.

The goal of the study reported in this paper was to use ML to identify patterns of psychosocial and contextual factors that may impact diabetes self-management assessed by EMA. To achive this goal, we devised a learned filtering architecture (LFA) to identify phenotype groups that are related to two self-management behaviors: insulin administration (IA) and self-monitoring of blood glucose (SMBG).

The data generated from EMA systems is well suited to analytic techniques that identify patterns. In particular, ML methods have been employed to detect type 2 diabetes and identify targets for improvement in diabetes management and outcomes [15, 16, 17]. These advanced ML methods, however, have *not* been used to examine patient-generated data, behavioral patterns, and self-management in diabetes. Research indicates that ML methods have the potential to efficiently and effectively identify meaningful sub-groups of self-management styles and phenotypes upon which to base personalized behavioral treatments [18].

The remainder of this paper is organized as follows: Section 2 summarizes the background of our research, focusing on the use of EMA methods, our rationale behind the construction of the LFA, and a comparison with related work; Section 3 describes the design and methods we employed in this study; Section 4 analyzes the results obtained from the LFA we constructed; Section 5 discusses our main findings and analyzes limitations regarding our work; and

Section ?? presents concluding remarks and outlines future work.

2. Background and Related Work

Much prior research using traditional retrospective questionnaire methods has focused on identifying psychosocial correlates and predictors of self-management in chronic illness in general and specifically in diabetes [9]. With few exceptions, little research using EMA has been conducted in diabetes. The few studies conducted have uniquely identified time-based factors such as time of day and momentary negative emotions as related to self-management behaviors [19, 20, 21].

Our study focuses on advancing assessment for factors that have been previously associated with self-management, such as stress [22], mood [23, 24], stigma [9, 25] and social context [8, 12]. We also uniquely assess novel factors not previously studied in this population, such as fatigue [26], location [27], social contexts [8], contextual factors such as rushing and traveling.

Machine learning (ML) analyses have been applied in various studies focusing on the improvement of diabetes management and control. Studies constructed and fine-tuned different ML models to predict future blood glucose levels based on historical physiological data, [28, 29, 30], detect incorrect blood glucose measurements in [31], predict hypoglycemia [32, 33], manage insulin dosing [34], and applied to provide lifestyle support integrating food recognition, and energy expenditures [35, 36].

In this study, we apply a learned filter algorithm (LFA) to psychosocial EMA data to predict self-management behaviors. Our application of predictive analytics differs from other studies outlined above. Previous studies focused primarily on how accurately a model can predict a specific outcome such as glucose values or hypoglycemia. In contrast, our study focuses on understanding what types or group(s) of factors have the greatest relative accuracy in predicting the presence or absence of an event.

Our study focuses on reducing the amount of variables used to predict an outcome by filtering one or more domains of variables with the LFA, yet still extracting the necessary behavioral insight(s).

3. Materials and Methods

This study analyzed data from a feasibility trial of the mobile EMA and feedback app called MyDay, which is an IoT-based, multi-faceted self-management problem solving tool for pediatric T1D patients, using a 30-day assessment period [37]. Youth from the Vanderbilt Eskind Pediatrics Diabetes Clinic were invited to participate if they were between the age of 13 and 19, had been diagnosed of T1D for at least 6 months, owned a smartphone, understood and spoke English, and were willing to use a Bluetooth meter during the study.

A total of 48 participants were recruited for the pilot study. Three participants dropped out of the study noting competing demands, and one was eliminated due to lack of data, leaving 44 for our analyses. Subjects were randomized on a 2:1 ratio to the app + Bluetooth blood glucose meter group (n=31) and a control group (n=14) who provided BG data only using Bluetooth BG meters. Design processes [38] and feasibility/engagement results for MyDay were previously published [39].

3.1. Momentary Assessments and Glucose Meter Data

All SMBG data was objectively assessed using iHealth [40] Bluetooth meters that uploaded data automatically to the iHealth server. App condition participants were instructed to use MyDay at each mealtime and bedtime to answer questions focused on factors likely to impact diabetes self-management, including stress, fatigue, mood, social context, and contextual barriers to self-care [37]. Mealtime BG monitoring was assessed objectively via data transfer from the Bluetooth meters. Likewise, mealtime IA was self-reported into MyDay.

MyDay provided notifications to complete the EMA assessment personalized to typical mealtimes identified by participants as a reminder to complete EMA.

Timestamps were associated with all data entries. Bedtime EMA was not included in analyses since self-management tasks could not be reliably expected at that specific time. Only mealtime EMA were used in analyses.

Variables analyzed in relation to self-management outcomes were organized into the following subsets. The first two domains of variables were collected for all participants: (1) Demographics obtained at baseline (gender, age, fathers education, mothers education, family income, and race) and (2) Time variables that were passively coded: weekday, weekend, and mealtime (breakfast, lunch, dinner).

The next three domains of EMA data were available only for the MyDay app group: (3) Context related to who was with the youth at time of self-management (parent, sibling, alone, casual friend, close friend, other family, other person, strangers, and boyfriend/girlfriend) and location (home, school, work, restaurant, friends house, or on the road), (4) Stress, fatigue, mood: scored as 0-100 with higher scores indicating greater stress, more fatigue, and worse negative mood, and (5) Situational barriers (including rushing, sick, on the road, hungry, wanting privacy, busy, without supplies, having fun).

3.2. Outcomes

We examined three self-management behavioral outcomes:

- Daily SMBG Frequency of "less than 4" or "4 or more" times a day. Four glucose checks per day is generally considered the minimum recommended [**?**],
- Missed SMBG at mealtimes,
- Missed insulin administration (IA) at mealtimes

Data from all subjects were available (n=44) for analyses examining daily number of SMBG from meters. The data that was available for all subjects were demographic and time variables. Analyses examining outcomes 2 and 3 used data from participants who used the MyDay EMA app (n=31) which obtained mealtimes.

3.3. The Learned Filtering Architecture (LFA)

For this study we devised a learned filtering architecture (LFA) using a Random Forest (RF) [41] classifier. We applied this classifier to extract domains of variables to predict IA and SMBG self-management behaviors. Figure 1 presents the workflow of our learned filtering architecture (LFA) [42]. As shown

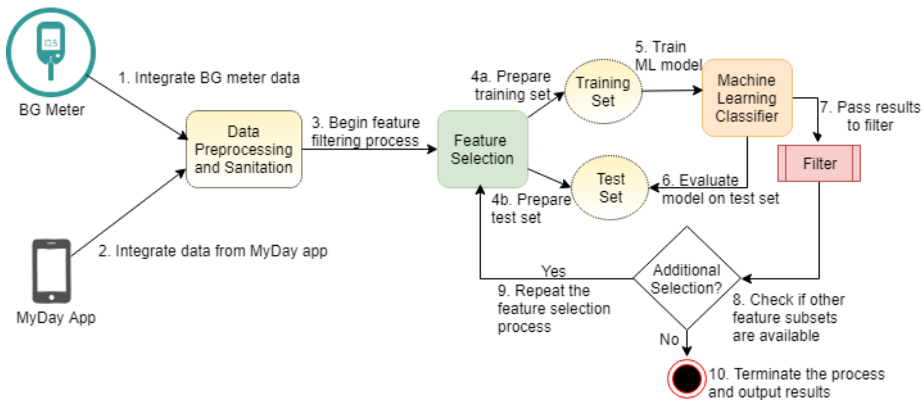

Figure 1: Iterative Process of Our Learned Filtering Architecture (LFA).

in the figure, SMBG data and the EMA data collected from the MyDay app were integrated as a complete dataset fed into the LFA (steps 1 and 2). The LFA then performed necessary pre-processing and data sanitation, such as normalizing numeric values and removing empty entries (step 3). After this step, data filtering process began where subsets of variables were extracted from the cleaned data either based on configurable human input or automatic selection.

The variables were grouped as described above to create multiple data subsets that were then split for training and testing (steps 4a and 4b). The training set was used to train an ML classifier i.e., RF in this study (step 5), and the test set is used to evaluate the trained model (step 6).

Specifically, we used the following metrics to assess our models: (1) accuracy, which is the of correct predictions and all predictions, (2) precision, which is the ratio of true positive and all predicted positive that evaluates if a model can discriminate only the related data, (3) recall, which is the ratio of true positive and all positive data that evaluates if a model is able to find all related data, and (4) F1 score, which evenly weights precision and recall.

Figure 1 presents the workflow of our learned filtering architecture (LFA) for processing, analyzing, and extracting insights from the data collection. The classification results obtained from the current feature subset were then sent to the Filter component, which compared them with other feature subsets (step 7). The filter component has a configurable tolerance value, which was used to select feature subset(s) that have relatively good classification results compared to the best performing model(s) or other benchmark(s).

Next, the LFA checked whether other variable groups were available for processing (step 8). If so, the Feature Selection process was repeated to create the next subset (step 9). Otherwise, the filtering process terminated and output the filtered results, i.e., variable groups with relatively strong predictive power of the target outcomes (step 10).

A large portion (75%) of the combined input data formed a structured training set used to construct a classifier. The remaining data was a hold-out test set for evaluating the classifier. The classification results then went through a filter that extracted the best predictor group(s) of the target class variable. For example, if the performance metrics exceed their threshold values, the predictor group was added to the final output queue. When all variable groups were evaluated, LFA returned the final insights obtained from the input.

Although the number of observations per participant was substantial, the overall number of participants was relatively small. As a result, the collected data had some imbalance in the distribution of the outcomes, with missed mealtime insulin being a relatively less frequent event. Classification models constructed using imbalanced datasets may result in the minority class being neglected [43]. To avoid this problem, we applied an imbalanced learning algorithm that combined the Synthetic Minority Oversampling Technique (SMOTE) [44] and Tomek link (T-link) [45] Both techniques have been used effectively for training imbalanced data, especially for small datasets [46, 47, 48].

We employed SMOTE to enrich the minority class by creating artificial examples in the minority class rather than replicating existing samples to prevent overfitting. SMOTE creates new samples from linear combinations of two or more similar samples selected from the minority class using a distance measure. Each instance was created by perturbing the original sample's attributes one at a time at a random amount within the difference to the neighbouring instances.

We applied T-link to remove noisy data (which may have been introduced by SMOTE) from the majority class. Potential noisy data was detected by comparing the distances between any two samples from different classes and the distances between an arbitrary sample and one of the two samples [45]. If the distance between the former pair is smaller, then either sample in that pair is a noise or both are border-line instances [49]. SMOTE and T-link were applied *only to the training set* to ensure integrity of the test set.

4. Results

This section analyzes the results obtained from the LFA we constructed using the method described in Section 3.

4.1. Descriptive Statistics of the Sample

The sample of n=44 participants were on average 15.33 years of age (SD 1.67), were 53.33% female, 86.67% White, 68.80% used an insulin pump and had a mean HbA1c (indicating overall glycemic control) of 8.56% (SD 1.88).

4.1.1. Daily SMBG Frequency

We obtained 6,524 blood glucose (BG) measurements from Bluetooth meters from all participants (n=44)For this analysis we related the demographic and time variables to the outcome of SMBG frequency per day. SMBG frequency ranged between 0-12 measurements per day. We aggregated the measurements on a daily basis to obtain a new dataset of 1,244 entries, with each entry per participant being the total number of measurements an individual had each day during the study period.

We observed the following distributions of SMBG daily frequency: there were 595 days with "Below 4" frequency and 649 day with "4 or Above". We trained a Random Forest classifier (the best performing model compared to several other classifiers we chose, such as Support Vector Machine and Naive Bayes) with a 10-fold cross validation and obtained the classification results using the test data.

The results of our analysis are shown in Table 1 for SMBG frequency *Below 4* or *4 and Above*. The filter then compared the benchmark value with the

Table 1: SMBG Classification of "Below 4" or "4 and Above" Performance Metrics

Feature Group	Accuracy	Precision	Recall	F1 Score
Demographics	75.2%	0.75	0.75	0.75
Time variables	48.2%	0.48	0.48	0.47
All	67.5%	0.68	0.68	0.68

outcome classification results obtained from each variable group. We configured a tolerance value of 15% for the filter to select subsets with significant predictive power. As shown, the demographics variable group for SMBG frequency resulted in a better performance than time variables and all variables.

4.2. Missed Mealtime SMBG and Insulin Administration

From the app group (n=31), we had 1,855 entries that were associated with breakfast, lunch, or dinner to analyze factor(s) that could impact SMBG and IA. Missed IA had a distribution of 1:6 for True (missed) vs False (administered) outcomes; whereas the outcome missed SMBG had a class distribution of 1:5 for True (missed) vs False (completed). LFA created classification models for each variable group (demographic, time, social context, psychosocial) using the 75%/25% split for training and testing.

An RF classifier with a 10-fold cross validation was the best performing model. Tables 2 and 3 present the classification results of missed SMBG and missed IA. The RF filter selected demographics as the variable group that most accurately predicted missed SMBG. Stress/fatigue/mood and social contexts

Table 2: Missed SMBG Classification Performance Metrics

Feature Group	Accuracy	Precision	Recall	F1 Score
Demographics	85.5%	0.85	0.85	0.85
Time Variables	71.8%	0.61	0.72	0.64
Social Context	71.3%	0.73	0.71	0.72
Stress, Fatigue, Mood	73.1%	0.71	0.73	0.71
Contextual Barriers	75.4%	0.70	0.75	0.68
All	86.7%	0.87	0.87	0.87

Table 3: Missed Mealtime Insulin Administration (IA) Classification Performance Metrics

Feature Group	Accuracy	Precision	Recall	F1 Score
Demographics	65.9%	0.84	0.66	0.71
Time Variables	56.7%	0.79	0.57	0.63
Social Context	62.1%	0.78	0.62	0.67
Stress, Fatigue, Mood	72.5%	0.78	0.73	0.75
Contextual Barriers	75.6%	0.77	0.76	0.76
All	80.1%	0.84	0.80	0.82

were the next best sets of variables associated with Missed SMBG. Table 3 shows that the variable group with contextual barriers had the greatest accuracy in predicting IA and stress/fatigue/mood was the variable group with the next best accuracy for predicting IA.

5. Discussion

This section discusses our main findings and analyzes limitations regarding our work.

5.1. Main Findings

To better understand the factors impacting self-management behavior of adolescents with T1D, our study applied ML analyses to construct a learning filter architecture (LFA) using demographic, novel momentary psychosocial data and self-management data. We compared the relative association of five domains of variables for predictability of self-management behaviors using all the variables collectively as the benchmark.

The results indicated that demographic variables were most associated with average daily SMBG frequency. These were the only non-EMA variables included in the study. The results highlight the value of social determinants of health, as defined by demographics. While demographic factors are generally not modifiable, social determinants of health are increasingly used to adapt care to for those who are most vulnerable and may not receive the full benefit of current approaches to healthcare [50, 51].

A limitation of our results is that only demographic and time-related variables were available for analyses of the SMBG frequency outcome. Demographic variables were not directly tested against the other EMA variables. Future research is needed to contrast all of the current variable domains within one sample.

Our results support the feasibility and value of integrating EMA and ML to improve behavioral assessment and automate behavioral pattern recognition in healthcare [52]. Our methods show promise to quantify the impact of psychosocial factors on self-management. In previous studies [53, 54] using behavioral observation in the context of identifying patterns of hand hygiene compliance monitoring, from which we obtained very useful initial insights into which domains of variables had the most impact on compliance behavior. Based on the current findings, similar experiments are needed with larger samples to prioritize multiple potential domains of influence on health behaviors, and advance the assessment and analytic approaches utilized here.

For small datasets that have disparities in the frequencies of observed classes or outcomes, applying an over-sampling technique is a strategy to mitigate the negative impact this imbalance has on model fitting. Nevertheless, synthetic sampling (under-sampling or over-sampling) methods may overestimate performance. The trained model with synthetic samples may not reflect the class imbalance future studies may encounter, potentially leading to overly optimistic estimates performance. Relatedly, synthetic samples could induce model uncertainty. Depending on how accurately the synthesized samples represent the actual samples, the prediction outcomes may be better or worse, so the model could appear more or less effective than it actually is.

The use of primarily passive psychosocial and behavioral data streams combined with ML moving forward will provide the basis for a population-based monitoring system that can help guide automated pattern detection for clinical management. For example, experimental unobtrusive indicators of mealtimes are in development [55] and insulin administration is available via pumps but not in real time [55]. If successful, additional passive data streams would greatly improve our methodological rigor and reach [56].

Finally, the LFA machine learning methods employed here should be applied to a large diverse sample of patients to confirm and expand results reported in this paper. Although passive methods are increasingly used to infer behavior and psychosocial status [57, 58], there are important subjective experiences, such as mood, which may continue to require self-report. For the foreseeable future, both self-reported real-time data and passive data, such as social networking [59], may be integrated to optimize insights for healthcare.

6. Concluding Remarks

This paper reported the results of a study that applied EMA and ML methods to better understand psychosocial and contextual aspects of self-management behavior in adolescents with T1D. Combining EMA data with ML methods may result in enhanced identification of barriers or facilitators or health behaviors and automated identification and prioritization of relevant factors [60]. Using LFA, we systematically identified relevant variables by filtering out data with relatively less impact on the outcomes.

The results of our study suggested that LFA can reduce the scale and complexity of EMA datasets. As EMA is used to collect larger-scale data in public health settings, the filtering capability will be useful to reduce complexity yet guarantee relatively accurate insights![54]. The trade-off in reducing complexity in this case, is a reduction in specificity for individual variables as targets for intervention. Future systems will benefit from combining self-report of subjective human experiences along with passive indicators of factors that impact health behavior decision-making in daily life.

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