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

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Abstract

Persons with diabetes must perform many self-management tasks each day to obtain optimal control of their 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]. Mealtimes are a critical time for diabetes self-management.

Adolescents and young adults have the worst glycemic control of any age group [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]. A recommended approach used to improve self-management 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 recall of 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 person, and generates rich data to assess correlates of health behavior more accurately and identify novel correlates for intervention [14].

Many studies in the EMA literature have used hierarchical linear modeling (HLM) or other similar analytic approaches [15, 16]. These studies, however, have not identified a model for prioritizing variables or automating analyses. A promising approach for identifying such a model involves integrating EMA with techniques and tools associated with machine learning (ML), which is a data analysis method that automates statistical model building by identifying patterns and making decisions with minimal human intervention [17].

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 achieve 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).

2. Background and Comparison with Related Work

Prior research using traditional retrospective questionnaire methods has focused largely 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 [18, 19, 20].

The current study focuses on advancing assessment for factors that have been previously associated with self-management. These factors include stress [21], mood [22, 23], stigma [9, 24], and social contexts [8, 12]. This study also uniquely assesses novel factors not previously studied in the T1D population, such as fatigue [25], location [26], social contexts [8], and contextual factors, such as rushing and traveling.

Machine learning (ML) analyses have been applied in various studies, focusing largely on the improvement of diabetes management and control. Earlier studies have constructed and fine-tuned different ML models to predict future blood glucose levels based on historical physiological data, [27, 28, 29], detect incorrect blood glucose measurements in [30], predict hypoglycemia [31, 32], manage insulin dosing [33], and applied to provide lifestyle support integrating food recognition, and energy expenditures [34, 35].

This current study applies a learned filter algorithm (LFA) to psychosocial EMA data to predict self-management behaviors. This application of predictive analytics differs from other studies outlined above. In particular, previous studies focused primarily on how accurately a model could predict a specific outcome, such as glucose values or hypoglycemia. Conversely, this 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. This study also 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 designed for pediatric T1D patients [36]. Youth from the Vanderbilt Eskind Pediatrics Diabetes Clinic were invited to participate in a 30-day assessment period if (1) they were between the age of 13 and 19, (2) had been diagnosed of T1D for at least 6 months, (3) owned either an Android or iPhone smartphone, (4) understood and spoke English, and (5) were willing to use a Bluetooth blood glucose 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, leaving 45 for our analyses. Subjects were randomized on a 2:1 ratio to the MyDay app + Bluetooth blood glucose meter group (n=31) and a control group (n=14) who provided BG data only using Bluetooth BG meters, but no Myday app. Design processes [37] and feasibility/engagement results for MyDay were previously published [38].

3.1. Momentary Assessments and Glucose Meter Data

All SMBG data was objectively assessed using iHealth [39] BG5 glucometers. BG5 is a commercially available Bluetooth Low-Energy meter that can upload data automatically to the iHealth secure cloud server via their open API. Thirty-one participants were instructed to use the MyDay app at each mealtime and bedtime to answer questions that focused on factors likely to impact diabetes self-management.

MyDay provided notifications to complete the EMA assessment personalized to typical mealtimes identified by participants. 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, e.g., weekday, weekend, and mealtime (breakfast, lunch, dinner).

The next three domains of EMA data were available only for the thirty-one participants using the MyDay app: (3) context related to who was with the youth at time of self-management (e.g., parent, sibling, alone, casual friend, close friend, other family, other person, strangers, and boyfriend/girlfriend) and location (e.g., 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 (e.g., rushing, sick, on the road, hungry, wanting privacy, busy, without supplies, and having fun).

3.2. Outcomes

We examined three self-management behavioral outcomes:

1. 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 [40],
2. Missed SMBG at mealtimes,
3. Missed insulin administration (IA) at mealtimes

Data from all subjects were available (n=45) for analyses examining daily number of SMBG from meters. The data that was available for all subjects were demographic and time variables. Analyses for outcomes 2 and 3 examined data from participants who used the MyDay EMA app (n=31), which obtained mealtimes.

3.3. The Learned Filtering Architecture

To extract domains of variables to predict IA and SMBG self-management behaviors, a learned filtering architecture (LFA) [41] was created in this study using a Random Forest classifier [42], which is a popular ensemble learning method that trains multiple decision trees on different parts of the dataset and then averages the results to improve classification accuracy.

Figure 1 presents the workflow of this LFA. This figure shows that SMBG data and 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, such as normalizing numeric values and removing empty entries (step 3).

After step 3, a data filtering process began, where subsets of variables were extracted from the cleaned data either based on configurable human input or automatic selection. These variables were grouped as described above to create multiple data subsets that were split for training and testing (steps 4a and 4b). The training set was used to train an ML classifier via the Random Forest method (step 5) and the test set was then used to evaluate the trained model (step 6).

Specifically, we used the following metrics to assess our models: (1) *accuracy*, which is the percentage of correct predictions, (2) *precision*, which is the ratio of true positives and all predicted positives that evaluates what proportion of predicted positives was actually correct, (3) *recall*, which is the ratio of true positives and all actual positives that calculates what proportion of actual positives was predicted correctly, and (4) *F1 score*, which evenly weighs precision and recall.

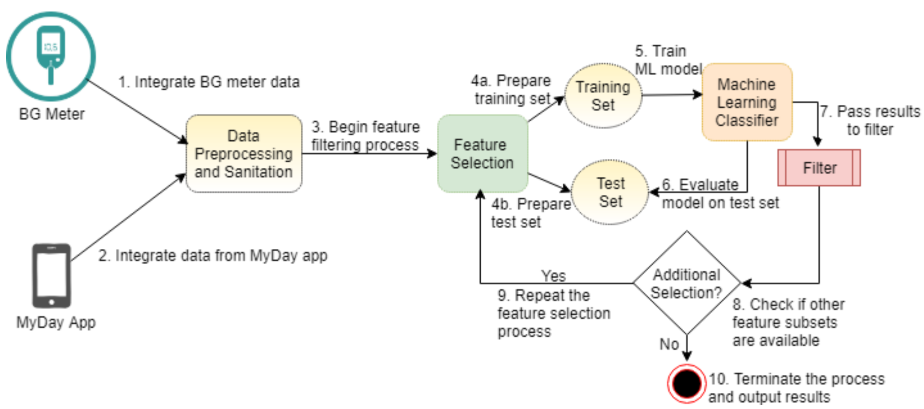

Figure 1: Iterative Process of Our Learned Filtering Architecture (LFA).

These classification results were then sent to the filter component, which compared them with other feature subsets (step 7). The filter component had a configurable tolerance value that was used to select feature subset(s) with 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 outcomes (step 10).

A large portion (75%) of the input data formed a structured training set used to construct a classifier. The remaining data was a hold-out test set used to evaluate the classifier. The classification results were then filtered to extract the best predictor group(s) of the target class variable. For example, if the performance metrics exceed the 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 (n=45). The collected data thus 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 samples attributes by a random amount one-at-a-time within the difference to the neighboring instances.

T-link was applied to remove noisy data 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 borderline instances [49]. To ensure integrity of the test set, SMOTE and T-link were applied only to the training set.

4. Results

This section analyzes the results obtained from the LFA constructed in accordance with the methods described in Section 3.

4.1. Descriptive Statistics of the Sample

The sample of n=45 participants were on average 15.33 years of age (SD 1.67), were 53.33% female, 84.44% 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

A total of 6,524 blood glucose (BG) measurements were obtained from Bluetooth meters used by all participants (n=45). For this analysis the demographic and time variables were related to the outcome of SMBG frequency per day. SMBG frequency ranged between 0-12 measurements per day. The measurements were aggregated 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.

The following distributions of SMBG daily frequency were observed: There were 595 days with "Below 4" frequency and 649 day with "4 or Above". A Random Forest classifier[1] was trained with a 10-fold cross validation and obtained the classification results using the test data. The results are shown in Table 1 for SMBG frequency *Below 4* or *4 and Above*. The filter then compared the benchmark value with the outcome classification results obtained from each variable group. A tolerance value of 15% was configured 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.

[1] Random Forest was the best performing model compared to several other classifiers, such as Support Vector Machine and Naive Bayes.

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

4.2. Missed Mealtime SMBG and Insulin Administration

From the app group (n=31), a total of 1,855 entries were associated with breakfast, lunch, or dinner and used 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. In contrast, 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 (i.e., demographic, time, social context, and psychosocial) using the 75%/25% split for training and testing. A Random Forest classifier with a 10-fold cross validation was the best performing model.

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

Tables 2 and 3 present the classification results of missed SMBG and missed IA. The Random Forest filter selected demographics as the variable group that most accurately predicted missed SMBG. Stress/fatigue/mood and social contexts 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

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

next best accuracy for predicting IA.

5. Discussion

This section discusses the main findings in this study and analyzes limitations regarding this work reported in this paper.

5.1. Main Findings

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

The results indicated that demographic variables were most associated with average daily SMBG frequency, which were the only non-EMA variables included in the study. These 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].

These results support the feasibility and value of integrating EMA and ML to improve behavioral assessment and automate behavioral

pattern recognition in healthcare [52]. The methods described in Section 3 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 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.

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].

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.

5.2. Limitations

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

Moreover, 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. Likewise, 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.

With the above drawbacks notwithstanding, we did not consider these threats to validity crucial to our goals since we were relatively less focused on absolute levels of predictability for this pilot study compared to relative value of predictor groups. General patterns are harder to obscure by adding artificial samples using the algorithms we had chosen.

6. Conclusions

This paper reports 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. The following is a summary of the results reported in this paper:

- Combining EMA data with ML methods show promise to quantify the impact of psychosocial factors on self-management.
- The combined methods will provide the basis for a population-based monitoring system that can help guide automated pattern detection for clinical management.

Future work will enhance MyDay's ability to utilize unobtrusive indicators. For example, experimental unobtrusive indicators of mealtimes are in development and if successful would greatly enhance our methodological approach [56].

Finally, the LFA machine learning methods employed here will be applied to a large diverse sample of patients to confirm and expand results reported in this paper. Future systems will benefit from combining self-report of subjective human experiences together with passive indicators of factors that impact health behavior decision-making in daily life.

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