Understanding Barriers to Self-Management Behavior in Adolescents with Type 1 Diabetes

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***Abstract*—Type 1 diabetes (T1D) is a prevalent pediatric chronic disorder with significant economic and social impact worldwide. Patients with T1DM must perform many daily self-management tasks, including frequent monitoring of blood glucose, administration of insulin, and estimating carbohydrate intake. These tasks help manage glycemic control to avoid or delay serious short- and long-term consequences, such as retinopathy, neuropathy, and mortality. Adolescents and young adults have the worst glycemic control of any age groups. For young people with T1D, living successfully is particularly challenging due to developmental, psychosocial, and contextual barriers.**

A common approach for improving self-management in T1D involves promoting and supporting patient problem solving skills. Patients need to identify potential barriers that interfere with appropriate T1D self-management where and when they occur. Ecological momentary assessment (EMA) methods use technology-mediated approaches to monitor and assess the contexts, subjective experiences, and processes that surround health decisions in daily life. However, rich data that has been generated by patients via EMA has not been frequently utilized in T1D.

This paper makes two contributions to research on self-management in T1D. First, it leverages advanced machine learning methods to investigate whether novel data focused on contextual, psychosocial and time-varying factors relate to patient self-management. Second, it uses EMA factors to construct machine learning classifiers that predict two T1D self-management behaviors: insulin administration and self-monitoring of blood glucose (SMBG). Our results suggest significant impacts of psychosocial factors on those behaviors and the utility of applying machine learning methods on EMA data.

***Index Terms*—Precision Behavioral Medicine, Machine learning, Type 1 Diabetes, Ecological Momentary Assessment**

I. 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 produces little or no insulin and requires patients to perform critical self-management tasks multiple times per day [3]. Self-management in T1D involves frequent monitoring of blood glucose, estimating carbohydrate intake, and administering insulin amongst other regular tasks related to maintenance of devices, supplies, and attention to factors that influence blood glucose variability and patterns.

Inadequate self-management and poor glycemic control is related to serious short- and long-term consequences, including 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 developmental, psychosocial, and contextual barriers to self-management [7], [8], [9].

A common approach used to improve self-management of diabetes involves promoting and supporting problem solving skills [10]. To identify problems related to self-management, patients, caregivers, and clinicians must rely on the review of blood glucose and insulin data from devices along with a patient-generated recall of potentially relevant behavioral, emotional, and/or situational events. This method of utilizing retrospective memory or recall, however, has been identified as generally unreliable and potentially biased in nature [11].

To address the limitations of recall 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 particular, with more relevant, proximal, and frequent observations per patient, EMA methods generate rich data from which to more accurately relate previously identified correlates of health behavior and identify novel correlates for interventional targets [14].

The data generated from EMA systems is particularly suited to analytic techniques that identify patterns. In particular, machine learning methods have been employed to detect type 2 diabetes and identify targets for improvement in diabetes management and outcomes [15], [16], [17]. These advanced methods have been used less frequently, however, to examine patient-generated data, behavioral patterns, and self-management in diabetes. We believe that machine learning methods will ultimately become more effective at identifying meaningful sub-groups of self-management styles and self-management phenotypes upon which to base personalized behavioral treatments [18].

The overall goal of our research is to leverage predictive analytics to help investigate how novel data focused on contextual, psychosocial, and time-varying factors relate to patient self-management. In particular, we devised a learned filtering architecture (LFA) using a Random Forest [19] classifier in this study to extract groups of similar features that are predictive of two self-management behaviors in adolescents with T1D: insulin administration (IA) and self-monitoring of blood glucose (SMBG).

The remainder of this paper is organized as follows: Section II 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 III describes the design and methods we employed in this study; Section IV analyzes the results obtained from the LFA we constructed; Section V discusses our main findings and analyzes limitations regarding our work; and Section VI presents concluding remarks and outlines future work.

II. Background and Related Work

This section summarizes the background of our work and related research, focusing on the use of ecological momentary assessment (EMA) methods and machine learning applications in other diabetes studies. We then present our rationale behind the construction of the learned filtering architecture (LFA).

Prior research [9] has focused on identifying psychosocial correlates and predictors of self-management in chronic illness in general and specifically in diabetes. Our study focuses on factors that were previously associated with self-management, but were also amenable to EMA methods. Factors most appropriately assessed through these methods are those that are

- thought to vary more frequently and/or occur relatively more frequently and
- hard to identify in daily experience to associate them to medical events, health decision-making, and/or symptoms.

Our EMA pilot study [20] assessed a broad sampling of factors that influence diabetes self-management. These factors included stress [21], fatigue [22], mood [23], [24], location [25], and social context [8]. We also collected other factors, including contextual barriers, such as rushing, lack of diabetes supplies (such as blood glucose test strips), and stigma [9], [26].

Our goal in this study is to leverage the EMA data to determine if psychosocial factors impact self-management behavior. If so, we aim to identify the type(s) of features which have relatively greater impact. Understanding the potential connections between psychosocial phenotypes and self-management behavior can help focus behavioral interventions tailored to individual patients.

Machine learning (ML) methods have been applied in various studies focusing on the improvement of diabetes management and control. Studies in [27], [28], [29] constructed and fine-tuned different ML models to predict future blood glucose levels based on historical physiological data, such as readings from continuous glucose monitoring (CGM) systems. Bondia et al. [30] used Support Vector Machines to detect incorrect blood glucose measurements in CGM systems. Sudharsan et al. [31] trained and compared various prediction models to identify hypoglycemia for patients with type 2 diabetes using self-monitored blood glucose (SMBG) readings.

Artificial neural networks were applied in [32] to create a controller for potentially managing insulin dosage. Biester et al. [33] applied ML methods to predict low blood glucose levels for triggering an automatic stop of insulin delivery in a sensor-augmented insulin pump. Machine learning has also been applied to provide lifestyle support, such as the smartphone-based food recognition system described in [34] and the prediction of energy expenditure and type of physical activity using accelerometers [35].

Our application of predictive analytics via LFA differs from other studies outlined above. These other studies focused primarily on predictability, *i.e.*, how accurately a model can predict a specific outcome such as glucose values and hypothermia as we discussed above. In contrast, our study focuses on understanding what phenotypes, conditions, or group(s) of factors are the most impact on the outcome vectors of interest (*e.g.*, diabetes self-management behaviors).

Features in those other studies can still be automatically selected and transformed to reach the best results, while preventing over-fitting or under-fitting of their predictive models. The selected most representative subsets, however, could have features belonging to diverse classes of variables. In such cases, it is hard to determine exactly which type(s) of features would have more impact compared to other categories and vice versa. Conversely, our study focuses on reducing the amount of self-reported inputs by filtering one or more categories of features with the LFA, yet still extracting the necessary clinical insight(s) from the smaller data collection.

III. Research Design and Methods

This section describes the design and methods we employed in our study. We analyzed data from subjects enrolled in a feasibility trial of the mobile EMA and feedback MyDay app using a 30-day assessment period [36]. Subjects were randomized on a 2:1 ratio to the Myday app group + Bluetooth meter (n=31) and a control group (n=15) who provided blood glucose (BG) data only using Bluetooth BG meters.

Figure 1 presents the workflow of our learned filtering architecture (LFA) for processing, analyzing, and extracting insights from the data collection.

As shown in the workflow diagram, we first integrate BG meter data and the EMA data collected from the MyDay app as a complete dataset fed into the LFA (steps 1 and 2). Next, the LFA performs necessary pre-processing and data sanitation, such as normalizing numeric values and removing empty entries (step 3). After this step, we begin the data filtering process where subsets of features are extracted from the cleaned data (either based on configurable human input or automatic selection, and in this particular study, the features are grouped together based on similar types) to create multiple data subsets that are then split for training and testing (steps 4a and 4b).

The training set is used to train a machine learning classifier *i.e.*, Random Forest in our study (step 5), and the test set is used to evaluate the trained model (step 6). The classification results obtained from the current feature subset are then sent to the *Filter* component to be later compared with other feature

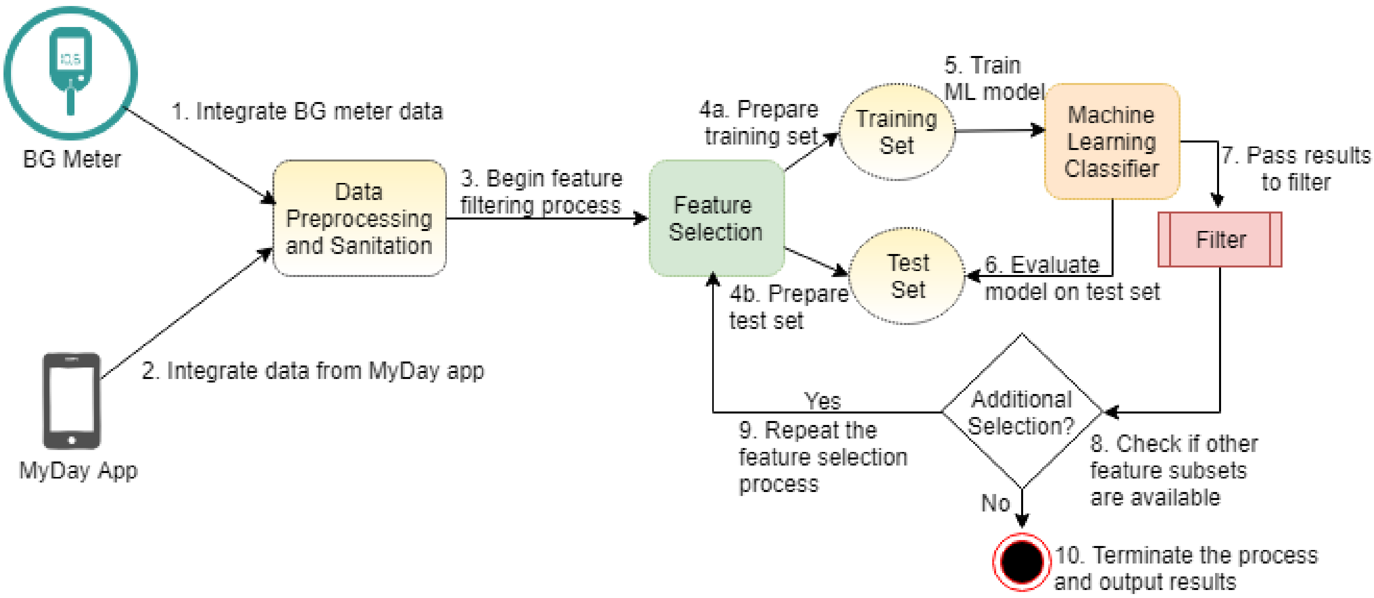

Fig. 1: Iterative Process of Our Learned Filtering Architecture (LFA).

subsets (step 7). The filter component has a configurable tolerance value, which is used to select feature subset(s) that have relatively good classification results compared to the most performant model(s) or other benchmark(s).

Next, the LFA checks whether other feature subsets are available for processing (step 8). If so, the *Feature Selection* process is repeated to create the next subset (step 9). Otherwise, the filtering process terminates and ouputs the filtered results, *i.e.*, feature subsets with relatively strong predictive power of the target outcomes (step 10).

After feature selection, a large portion (*e.g.*, 75%) of the input data forms a structured training set. This training set is used to construct a machine learning classifier. The remaining data becomes a hold-out test set, which is used to evaluate and enhance the classifier.

The classification results then go through a filter component that extracts the most impactful predictor group(s) of the target class variable. For example, if the performance metrics exceed their threshold values, the predictor group is added to the final output queue. When all feature subsets have been evaluated, LFA returns the final insights learned from the input data.

A. Subjects

A total of 49 patients were recruited from an academic pediatric diabetes center. Youth who were patients in the clinic were invited to participate if they were between the age of 13 and 19, had been diagnosed of type 1 diabetes for at least 6 months, owned a smart phone, understood and spoke English, and were willing to use a Bluetooth meter during the study. Three subjects dropped out of the study noting competing demands, leaving 46 for our analyses (n=31 in the app + meter group; n=15 in the meter-only group).

B. Momentary Assessments and Glucose Meter Data

The goal of our study was to examine associations between self-management (SMBG, self-monitored blood glucose and IA, insulin administration) and other relevant collected data, including participant demographics and momentary assessment variables. All blood glucose data for both groups was unobtrusively obtained using iHealth [37] Bluetooth meters. The app group was instructed to use the MyDay mobile app at each mealtime and bedtime to answer questions focused on factors likely to impact self-management of diabetes, including stress, fatigue, mood, social context, location, and contextual barriers to self-care [36]. Mealtime insulin administration was also self-reported into the app.

Blood glucose monitoring was objectively assessed via data transfer from the Bluetooth meters. The MyDay app provided notifications personalized to meal-times identified by participants each day 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 expected at that specific time point as they are with mealtimes. A subset of only mealtime EMA were used in analyses for the app group. At the initial recruitment session, parents of minors and adult participants provided consent, assent, demographic information.

C. Statistical Analyses

We were interested in studying the factors associated with the following

- All daily SMBG frequency in terms of the following two observations for all study participants: (1) if a subject monitored more than 4 times a day (4 being the clinically recommended minimum number of daily BG measurements [38]) and (2) if a subject monitored fewer than 4 times a day,

- Whether SMBG was missed or not at mealtimes, and
- Whether insulin was administered or not at mealtimes.

D. Feature Categories

Based on our hypothesis that different feature types may have varying impact on the self-management outcomes, we configured the LFA to produce data subsets of the following categories (wherever there were data present): demographics, time variables (time of day, weekday/weekend), context (social context and location associated with each mealtime app entry), stress/fatigue/mood values, and situational barriers such as without supplies (dichotomous behavioral questions). By grouping features into categories, we potentially eliminate variables that are less relevant to the outcomes. In turn, we significantly reduce the amount of information requested from MyDay app users in future studies.

Although the number of observations per participant was substantial, the overall number of participants was relatively small. Naturally, because performing self- management tasks is critical for patients with T1D, adolescents are expected to adhere to the daily regimen. As a result, the collected data encountered some imbalance in the distribution of the outcomes, with failure to perform these tasks (particularly missed mealtime insulin) being the minority instances.

It is well-known in the machine learning community that classification models constructed using imbalanced datasets may result in the minority class being neglected [39]. To avoid this problem, we applied an imbalanced learning algorithm that combined the Synthetic Minority Oversampling Technique (SMOTE) [40] and Tomek link [41]. Both SMOTE and Tomek link have been used effectively for training imbalanced data, especially for small datasets [42], [43], [44]. Our combined algorithm oversampled the minority class and cleaned noisy data, but only in the training set.

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

We employed Tomek link to remove noisy data from the majority class that may have been introduced from oversampling. Noisy data is 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 [41]. If the distance between the former pair is smaller, then either one of the samples in that pair is a noise or both are border-line instances [45].

IV. Results

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

A. Descriptive Statistics of the Sample

Table I shows the demographic and clinical characteristics of the study sample.

TABLE I: Characteristics of the Sample (n=46)

Variable		Mean (SD) or %
Age		13.33 (1.67)
Female		53.33%
Race/ethnicity		
	White	84.44%
	African American	10.20%
	Asian	2.22%
	Hispanic	2.22%
	Other	0.00%
Father education		
	Less than high school	2.22%
	High school/GED	28.89%
	2-year college	15.56%
	4-year college	33.33%
	Master's degree	11.11%
	Doctoral degree	0.00%
	N/A	8.89%
Mother education		
	Less than high school	0.00%
	High school/GED	22.22%
	2-year college	26.67%
	4-year college	37.78%
	Master's degree	4.44%
	Doctoral degree	0.00%
	N/A	26.67%
Income		
	Less than $25,000	4.44%
	$25,001-35,000$	6.67%
	$35,001-75,000$	15.56%
	$75,001-100,000$	31.11%
	$100,001-100,000$	26.67%
	More than $70,000	6.67%
	N/A	8.89%
Duration of diabetes (years)		5.47 (3.59)
HbA1c		9.03 (1.91)
Use insulin pump (yes)		57.46%

1) Descriptive Statistics: From all 46 participants, we obtained a total of 6,524 blood glucose measurements from their Bluetooth glucose meters. After aggregating each individual's SMBG counts by day and combining their demographic data, we produced a new dataset with 1,779 daily SMBG entries with the following schema:

1) Feature Category: *Demographics*, including gender, age, father's education, mother's education, family income, and race
2) Feature Category: *Time Variables*, including weekday, weekend, and time of day.

After analyzing the target outcome variables, we observed the distribution as follows: *Below 4* class contains 794 True (count < 4) outcomes and 839 False (count ≥ 4) outcomes, which is a fairly evenly distributed set. For *Above 4*, however, the True (count > 4) outcome had 475 entries, while False (count ≤ 4) had 1158 entries, a fairly imbalanced class.

To minimize the potential imbalance in the training set and maximize learning performance, we first split the dataset into 75% for training and 25% for testing and then applied an automatic imbalanced learning algorithm to the *training set* for a more even distribution for *Above 4*. As discussed in Section III, our imbalanced learning algorithm combines the SMOTE and Tomek Link methods.

2) Classification of Daily SMBG Occurrences: We trained the dataset using a Random Forest classifier with a 10-fold cross validation and obtained the classification results against the test data. The results are shown in Table II for SMBG below 4 and Table III for SMBG above 4.

TABLE II: SMBG Below 4 Classification Performance Metrics

Feature Group	Accuracy	Precision	Recall	F1 Score
Demographics	72.6%	0.73	0.73	0.73
Time variables	49.1%	0.51	0.49	0.47
All	71.2%	0.71	0.71	0.71

TABLE III: SMBG Above 4 Classification Results

Feature Group	Accuracy	Precision	Recall	F1 Score
Demographics	76.5%	0.78	0.77	0.77
Time Variables	55.6%	0.54	0.56	0.55
All	76.5%	0.77	0.77	0.77

As a benchmark for the learned filter component, we used all features for predicting the target variables and recorded the results. The filter then compared the benchmark value with the classification results obtained from each data subset. We configured a tolerance value of 15% for the filter to select subsets of significant predictive power.

B. Missing Mealtime SMBG and Insulin Administration

1) Descriptive Statistics of the Sample: From the app group with 31 subjects (n=31), we collected a total of 2,535 entries. From this data we extracted 1,855 valid entries that are associated with breakfast, lunch, and dinner records to analyze factor(s) that could impact SMBG and IA at mealtimes.

The target class *Insulin Administration* had a distribution of 1:6 for *True* (insulin missed) vs *False* (insulin administered) outcomes; whereas target class *Missing SMBG* had a class distribution of 1:5 for *True* (SMBG missed) vs *False* (SMBG taken). The dataset used to analyze both target classes was divided into the following subsets of features based on our hypothesis regarding features' relativeness:

1) Feature Category: *Demographics*, including gender, age, father's education, mother's education, family income, and race
2) Feature Category: *Time Variables*, including weekday, weekend, and time point (breakfast, lunch, dinner)
3) Feature Category: *Social Context*, who was the teen with at time of self-management as indicated through EMA (including parent, sibling, alone, casual friend, close friend, other family, other person, strangers, and boyfriend/girlfriend), and location, including home, school, work, restaurant, friends house, or on the road
4) Feature Category: *Stress, Energy, Mood*, continuous values within range 0-100
5) Feature Category: *Barriers*, psychosocial indicators (including rushing, tired of diabetes, sick, on the road, hungry, wanting privacy, busy, without supplies, low, high, having fun)

After transforming the input data into various smaller subsets, the LFA created classification models for each predictor group using the same 75%/25% split for creating the training and test sets. Due to the imbalance of the dataset in this experiment, we employed the SMOTE and Tomek Link techniques to create artificial samples for the minority class and perform undersampling to remove noise that may have been introduced, both in the training data to ensure the integrity of the actual test data.

The final class distribution of all datasets had a majority-minority ratio between 1:1 and 1.2:1. After comparing the initial results of three classifiers (random forest, logistic regression, and support vector machine) on the training data, we chose the random forest classifier with a 10-fold cross validation that outperformed other models.

2) Classification Results: Tables IV and V present the classification performance metrics of missing SMBG and missing mealtime IA against their respective tests, using our trained Random Forest classifier.

TABLE IV: Missing Mealtime Blood Glucose Measurement 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
Barriers	75.4%	0.70	0.75	0.68
All	86.7%	0.87	0.87	0.87

TABLE V: Missing Mealtime Insulin Administration 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
Barriers	75.6%	0.77	0.76	0.76
All	80.1%	0.84	0.80	0.82

We configured the filter using the same approach to obtain the benchmark values and tolerance. As a result, the filter selected demographic data as the most predictive group of missing SMBG, while psychosocial barriers and the combination of stress, fatigue, mood values are stronger predictors in the missing IA analyses. We also identified stress, fatigue, mood group and social contexts as the next best predictor subsets for missing SMBG because those values only marginally fell below the tolerance values for the performance metrics that we have configured for the filter.

V. Discussion

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

A. Main Findings

To gain a better understanding of the factors impacting self-management behavior of adolescents with T1DM, our study applied machine learning methods to construct a learning filter architecture (LFA) for novel momentary psychosocial data and other relevant demographic and physiological data.

Based on feature similarities, we configured the LFA into meaningful subsets of variables: demographics; social context; stress, mood, fatigue levels; time variables; and psychosocial barriers.

As a benchmark, we compared the predictability of different subsets of data against the general predictability of the behavior using all the features combined. The LFA applied a 15% threshold to evaluate the performance metrics of all subsets, and the preliminary results indicated that (1) stress, fatigue, and mood levels were stronger predictors of both missed SMBG and IA and (2) demographics factors (such as parents education, family income, and race) was best at predicting average daily SMBG outcomes.

Our methods show promise to quantify the impact of psychosocial factors on self-management on a population level. We also employed a similar research approach in previous case studies [46], [47] in the context of identifying patterns of hand hygiene compliance monitoring, from which we obtained very useful initial insights into which type of features had the most impact on compliance behavior. Based on these promising findings, similar experiments are needed with larger samples to advance the assessment and analytic approaches utilized here.

B. Limitations

For small datasets that have disparities in the frequencies of observed classes or outcomes, applying an oversampling technique is a strategy to mitigate the negative impact this imbalance has on model fitting. Nevertheless, synthetic sampling (undersampling or oversampling) methods have the following drawbacks:

- **Overestimation of performance.** The trained model with synthetic samples may not reflect the class imbalance future studies may encounter, potentially leading to overly optimistic estimates performance.
- **Model uncertainty.** 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.

VI. Concluding Remarks and Future Directions

This paper reports the results of a study that applied machine learning methods to better understand what triggers poor self-management behavior in adolescents with T1D through. We learned the following lessons from our study:

- **LFA can reduce the scale of EMA data collection**. By employing the learned filtering architecture (LFA), we systematically selected the more relevant information by filtering out data fields that had relatively less impact on the outcomes. As we collect larger-scale data, the filtering capability will be useful to reduce information yet guarantee relatively accurate clinical insights.
- **Combining EMA data with machine learning methods may result in enhanced clinical decision-making and just-in-time patient support.** The collection of primarily passive psychosocial and behavioral data streams combined with machine learning methods provides a population-based monitoring systems that can help guide clinical management and just-in-time guidance for self-management problem solving [48].
- **EMA data may be used to create personalized behavioral medicine targeting T1D**. Data from homogeneous sub-groups or even individuals can be used to tailor behavioral treatments and prevent blood glucose excursions and long-term consequences of poor glycemic control for personalized behavioral medicine.

In future work we plan to enhance the MyDay system's ability to utilize unobtrusive indicators as much as possible. For example, experimental unobtrusive indicators of mealtimes are in development and if successful would greatly enhance our methodological approach [49]. 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.

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