Data-Driven Insights on Behavioral Factors that Affect Diabetes Management

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***Abstract*— The prevalence of personal health data from wearable devices enables new opportunities to understand the impact of behavioral factors on health. Unlike consumer devices that are often auxiliary, such as Fitbit and Garmin, wearable medical devices like continuous glucose monitoring (CGM) devices and insulin pumps are becoming critical in diabetes care to minimize the occurrence of adverse glycemic events. Joint analysis of CGM and insulin pump data can provide unparalleled insights on how to modify treatment regimen to improve diabetes management outcomes. In this paper, we employ a data-driven approach to study the relationship between key behavioral factors and proximal diabetic management indicators. Our dataset includes an average of 161 days of time-matched CGM and insulin pump data from 34 subjects with Type 1 Diabetes (T1D). By employing hypothesis testing and association mining, we observe that smaller meals and insulin doses are associated with better glycemic outcomes compared to larger meals and insulin doses. Meanwhile, the occurrence of interrupted sleep is associated with poorer glycemic outcomes. This paper introduces a method for inferring disrupted sleep from wearable diabetes-device data and provides a baseline for future research on sleep quality and diabetes. This work also provides insights for development of decision-support tools for improving short- and long-term outcomes in diabetes care.**

I. INTRODUCTION

Diabetes is a prevalent chronic condition that affects up to 30.3 million Americans and is ranked as the 7-th leading cause of death in the U.S. [1], [2]. It is characterized by impaired glucose metabolism yielding frequent high and low blood glucose (BG) levels that increase the risk of macro- and micro-vascular complications [3]. Proper management of diabetes requires meticulous consideration of various factors that can affect BG levels, which include food, medication, activity, sleep, and other biological, environmental and behavioral factors [4], [5]. Hence, it is well established that behaviors and decisions in daily living directly affect both proximal and distal outcomes in diabetes care.

The American Diabetes Association recommends assessment of sleep patterns as part of a comprehensive medical evaluation [2] due to emerging evidence on the relationship between sleep patterns and diabetes. Majority of studies in the literature have focused on associations between sleep and Type 2 Diabetes (T2D) management, while only a few have investigated the role of sleep in T1D management [6]–[8]. However, recent reviews found that people with T1D experience a higher rate of sleep disturbance and poorer sleep quality than people without diabetes [8], [9]. In this paper, we introduce a novel approach for inferring sleep disturbance and assess the effect of interrupted sleep on glycemic control.

Additionally, several research studies have investigated the effect of different eating patterns on T2D management. However, only a few studies have investigated the effect of eating patterns in T1D management [10]–[12], particularly the effect of meal size on glycemic control [13]. For instance, one study contrasted the effect of low and high carbohydrate (CHO) intake on glycemic variables in 10 subjects with T1D [11]. The authors found that low carbohydrate diets (i.e. $<$ 47g) resulted in more time with glucose values in the healthy range (i.e. 70 - 180 mg/dL) and less glycemic variability. This evidence supports the notion that low carbohydrate diets, defined by the total carbohydrate intake per day, is advantageous for T1D management. However, there is no knowledge on the effect of individual meal sizes on glycemic control. This paper extends prior work by investigating the effect of individual meal size on diabetes management indicators and the association between the meal size and different management outcomes.

To achieve better glycemic control for T1D management, research supports that insulin administration via pump therapy is more effective than multiple dose insulin injections for persons with T1D [14]. In addition, recent research shed light on adjusting insulin doses according to dietary fat and protein intake to achieve better glycemic management [15]. However, the process of determining the insulin dosage (basal and bolus) is still a matter of trial and error. Lower CHO diets should necessitate lower mealtime insulin needs and potentially contribute to more stable blood glucose [11], [12]. However, there is little knowledge on the effect of different insulin dosage amounts on proximal glycemic control. This research extends prior work by investigating the effect and associations of different bolus insulin doses with glycemic control.

In this study, we take a data-driven approach to elucidate the factors associated with different management outcomes in diabetes care as shown in Fig. 1. Using a multivariate dataset from 34 subjects with T1D who use continuous glucose monitoring (CGMs) and insulin pumps for daily self-management, we studied the effect of behavioral factors (i.e. sleep interruption, meal size and insulin dosage) on proximal diabetes outcomes such as time in target range, number of glycemic events, glycemic variability.

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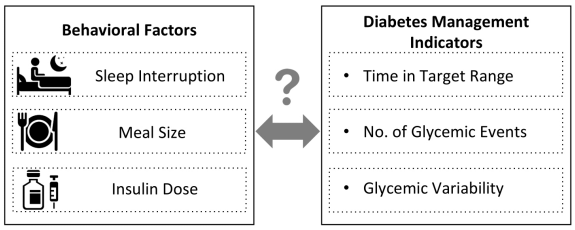

Fig. 1. Research overview outlining the association between behavioral factors and key diabetes management indicators.

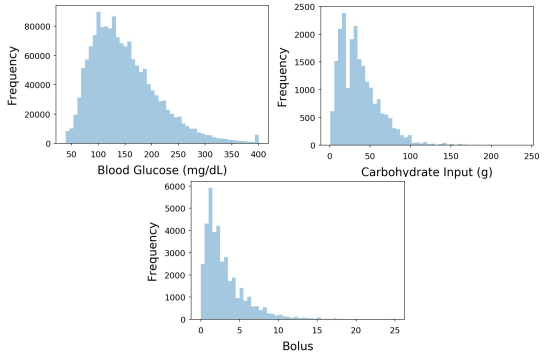

Fig. 2. Top left, top right and bottom: histograms illustrating distributions of BG, CHO intake and bolus dosage respectively.

II. DATA DESCRIPTION

All the data used in this study was contributed to the *Digital SMD* project by members of an online diabetes community [16]. Table I shows a summary of our dataset which contains time-matched CGM and insulin pump data from 34 subjects with T1D (mean age = 39.79 $\pm$ 8.73 yrs., mean time since diagnosis = 18.44 $\pm$ 10.58 yrs.). The dataset includes 100 - 270 days of data from each subject, totaling 1,513,398 BG readings, 37,742 bolus insulin doses, and 21,519 entries of carbohydrate inputs. Important data streams used in this work are BG readings from CGMs, self-reported carbohydrate estimates (known as carb input), and bolus insulin dose amounts from insulin pumps. Our dataset does not include gender of subjects, protein and fat intake, and other activities of daily living such as exercise, therefore no analysis was done in this regard.

TABLE I
DATA DESCRIPTION - AN OVERVIEW OF SUBJECTS, CGM DATA AND INSULIN PUMP DATA USED IN THIS STUDY.

	Attribute	Mean ($\pm$ SD)	Range
Subject	Total Subjects	34	-
	Age	39.8 ($\pm$8.73) $yrs.$	$24-52$ $yrs.$
	Years of Diagnosis	18.4 ($\pm$10.58) $yrs.$	$2-48$ $yrs.$
	No. of Qualified Days	161.2 ($\pm$40.69) $days$	$100-270$ $days$
CGM	Total BG Samples	$1,513,398$	-
	Samples / Subject	$44,511$	$24,523-80,259$
Insulin Pump	Total Bolus Doses	$37,742$	-
	Bolus Doses / Subject	$1,110.1$	$306-2,129$
	Total Carb-Inputs	$21,519$	-
	Carb-Inputs / Subject	632.9	$144-1,039$

III. METHOD

To investigate the effect of key behavioral factors on diabetes management, we employed two methods for analysis, namely, hypothesis testing [17], and association rule mining [18]. The purpose of hypothesis testing was to learn from the data whether statistical differences exist in diabetes management with respect to different categories of behavioral factors. For example, is there a statistically significant difference in proximal diabetes management indicators between eating *small meals* vs. *large meals* or *continuous sleep* vs. *interrupted sleep*? If a difference was found (using two-sample t-test), we then tested the direction of the difference (using one-sample t-test), e.g. are large meals significantly associated with higher or lower glycemic variability in comparison to small meals? In addition, we employed frequent itemset mining to learn associations between behavioral factors and diabetes management outcomes. The following subsections provide more details on the methods used for hypothesis testing and association mining, as well as the parameters used for quantifying diabetes management and behavioral factors.

A. Hypothesis Testing

1) Two-sample t-test: A two-sample t-test evaluates whether there is enough evidence from a population dataset to support the null hypothesis, $H_0 : u_1 = u_2$ or reject the null hypothesis in favor of an alternative hypothesis, $H_a : u_1 \neq u_2$; where u_1 and u_2 represent the mean of the two samples. In this study, the two-sample t-test was used to assess the null hypothesis that there is no difference between the mean of diabetes management indicators for two independent categories of behavioral factors.

2) One-sample t-test: A one-sample t-test evaluates whether there is enough evidence from a population data to support the null hypothesis, $H_0 : u_1 = u_2$ or reject the null hypothesis in favor of an alternative hypothesis, $H_a : u_1 > u_2$ or $H_a : u_1 < u_2$; where u_1 and u_2 represent the mean of two samples. In this study, the one-sample t-test was used to assess the direction of a difference between mean of diabetes management indicators for two independent categories of behavioral factors.

Fig. 2 shows the general distribution of BG values, carb inputs, and bolus insulin doses in our dataset. While all of the three quantities display some degree of skewness, based on the Central Limit Theorem, these distributions are normal and thus fitting for analysis with two- and one-sample t-tests.

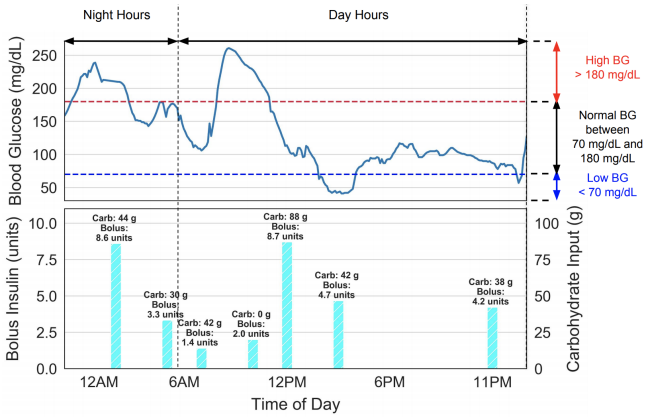

Fig. 3. Sample blood glucose measurements and carbohydrate inputs over the course of a day.

B. Association Mining

Unlike statistical methods for hypothesis testing, data mining aims "to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful" [19]. Therefore, we employed association mining to quantify the relationships between diabetes management indicators and different behaviors. This is assessed using metrics of *support*, which describes the co-occurrence of two events, A and B, in a dataset (e.g. non-interrupted sleep and lower glycemic variability), *confidence*, which describes the probability that event B occurred given event A, and *lift*, which describes the dependence and/or correlation between events A and B. When *lift* is greater than 1, then A and B are positively correlated and the occurrence of one implies the occurrence of the other. Per [18], the formulas for each metric is as follows:

$$\begin{aligned} support(A \Rightarrow B) &= P(A \cup B) \\ confidence(A \Rightarrow B) &= P(B|A) \\ lift(A,B) &= \frac{P(A \cap B)}{P(A)P(B)} \end{aligned} \tag{1}$$

C. Diabetes Management Indicators

These indicators were purposefully chosen from clinical references [20] to encompass important aspects of glycemic control, including percentage of blood glucose values in the target range and measures of glycemic variability. In this paper, we selected three important indicators (time in target range, number of glycemic events, and glycemic variability) to quantify proximal diabetes management within a given time window $[t, t+w]$:

1) Time in Target Range: This metric describes the percentage of blood glucose values within the healthy (or target) range $[70, 180\,mg/dL]$ and is recommended in various consensus reports for quantifying diabetes management [20], [21]. The target goal for persons with T1D is to maintain blood glucose values within the healthy range for $\geq 70\%$ of the time [22]. Therefore, in this work a threshold of 70% was used to demarcate good vs. suboptimal glycemic control.

2) Number of Glycemic Events: This metric refers to the total count of low ($< 70\,mg/dL$) and high ($> 180\,mg/dL$) blood glucose events. According to Danne et al. [20], a low blood glucose event is defined when CGM readings are below the threshold for at least 15-mins while a high blood glucose event is defined when CGM readings are above the threshold for at least 15-mins. A primary objective in diabetes management is to minimize the occurrence of glycemic events. As recommended in prior work [23], a settling time of 30-mins was used so that no more than one glycemic event was recorded within a 30-mins duration. In this work, one glycemic "event" is defined by the crossing of blood glucose values into the high/low region and subsequent crossing of blood glucose values into the normal region.

3) Glycemic Variability: This metric describes blood glucose fluctuations and is an accepted "clinically valuable marker" for assessing diabetes management [20]. Increased glycemic variability is correlated with poor glycemic control and associated with long-term diabetes complications. Per clinical literature, standard deviation is widely-used and is an accepted metric for quantifying glycemic variability [20], [24]. So, the standard deviation was used in this work and calculated using all BG values with the given time window.

D. Quantifying Behavioral Factors

As shown in Fig. 1, three behavioral factors were identified and evaluated to assess potential associations with different diabetes management outcomes. These factors include: sleep interruption, meal size, and insulin dose. Each of these factors were quantified and/or estimated using subject's CGM and insulin pump data (see Fig. 3 for example). Specifics on how each behavioral factor was calculated is below.

1) Sleep Interruption: In this work, we introduce a set of proxies for inferring sleep interruptions using wearable diabetes-device data. To the best of our knowledge, this is a novel contribution, which will enable further research on the effects of nocturnal sleep in diabetes management. Although CGM and insulin pump data does not explicitly include records of sleep, a combination of three proxies are useful for identifying sleep interruption:

$$s_n = \begin{cases} interrupted & : c_n > 0 \parallel b_n > 0 \parallel \uparrow BG \\ continuous & : otherwise \end{cases} \tag{2}$$

where s_n represents the n-th night sleep between the hours of [12AM, 6AM], c_n represents the total night-time carb-input, b_n represents night-time bolus insulin dose, $\uparrow BG$ represents a sharp increase in blood glucose values, and $\parallel$ is the mathematical symbol for a logical "or" operator. The intuition behind equation 2 is that a carb-input (or meal entry) is indicative of a person being awake. Similarly, a high blood glucose event calls for a correction dose of bolus insulin (with no carb-input), therefore, indicative of a person being awake. Lastly, food intake with a missed insulin dose is also indicative of a person being awake and this will often lead to a sharp increase in blood glucose values. DeSalvo et al. recommend a rate of change of $> 4mg/dL$ to detect missed meal boluses with relatively low false alarm rate [25].

In the event that any of these three activities occur during the night-hours of [12AM, 6AM], it implies that the user has had their sleep interrupted. It is important to note that this is a proxy and there are a few cases in which the assumption will fail (e.g. night awakening with no diabetes-related regimen and for persons with diabetes caregivers - such as young children with parents who wake up to administer nighttime bolus insulin, when needed). However, as shown in Table I, the minimum age of subjects in this study is 24 yrs., therefore our dataset does not include young children.

In this study, we assessed the effect of sleep interruption on next-day diabetes management between [6AM, 12AM]. This goal was informed by related references which suggests that "not getting enough sleep leads to higher blood sugar [glucose]" in the daytime hours [4]. Building on this, diabetes management indicators were calculated to quantify the next-day glycemic control following nights marked with *interrupted* vs. *continuous* sleep. Based on equation 2, our dataset includes a total of 2382 nights with interrupted sleep, and 2787 nights with continuous sleep.

2) Meal Size: To calculate the appropriate amount of bolus insulin needed to compensate for an expected increase in BG stemming from consumption of food/beverages, insulin pump users need to "announce meals" by estimating the food content [26]–[28]. Given this, insulin pump data includes self-reported estimates of meal sizes. In this work, we aimed to evaluate the effect of various meal sizes on diabetes management.

To this end, the first step was to determine a time window around each carb-input on which to calculate diabetes management indicators. This required two considerations: 1) the duration of insulin action which indicates the time in which a dose of insulin will be active in the body [27], 2) the time difference between two adjacent meal entries (or carb-inputs). Given that food/beverage intake is often associated with a bolus insulin dose, the objective is to quantify the effect of these choices on glucose control by calculating diabetes management indicators for the related time window associated with each carb-input. According to Walsh et al., the best time estimate for duration of insulin action in the body is 5 - 6 hrs for most insulin doses [27]. Therefore, a time window of 5.5 hrs was chosen for calculating diabetes management indicators around every carb-input. This included 1-hr before the carb-input timestamp to account for the potential of late entries and 4.5 hours after the carb-input timestamp.

Informed by prior literature [27], two time thresholds were set to handle adjacent entries within the selected 5.5 hr window: 1) *combine time* - this was set to 0.5 hrs and allowed for combining adjacent carb-input entries less than 0.5 hrs apart given that majority ($\geq 90\%$) of the insulin dose is not yet active, 2) *maximum time* - this was set to 4.5 hrs and allowed for disregarding the former of adjacent carb-input entries with a timestamp difference greater than the time in which they could be combined but less than 4.5 hours. Scenarios with adjacent carb-input entries outside of the above-stated constraints were disregarded completely. Following this, all carb-input entries were split into three categories to assess management outcomes related to each:

$$c_i = \begin{cases} small & : \mu_c - 2\sigma_c \leq c_i < \mu_c - 1\sigma_c \\ medium & : \mu_c - 1\sigma_c \leq c_i \leq \mu_c + 1\sigma_c \\ large & : c_i > \mu_c + 1\sigma_c \end{cases} \quad (3)$$

where c_i represents the i-th carb-input, μ_c represents the mean of carb-inputs across all subjects and days, and σ_c represents the standard deviation of carb-inputs across all subjects and days. The construction of above criteria comes from the Chebyshev's inequality, which ensures at least $1 - \frac{1}{k^2}$ values are within k standard deviations of the mean.

3) Insulin Dose [Bolus]: Similar to the considerations taken into account for meal size described above, a time window of 5.5 hrs was chosen for calculating diabetes management indicators immediately following each bolus insulin dose. Additionally, all bolus insulin doses were split into three categories to quantify diabetes management outcomes related to each:

$$b_i = \begin{cases} small & : b_i < \mu_b - 0.75\sigma_b \\ large & : b_i > \mu_b + 0.75\sigma_b \\ medium & : otherwise \end{cases} \quad (4)$$

where b_i presents the i-th bolus insulin dose in the dataset from insulin pump, μ_b represents the mean of all bolus insulin doses across subjects and days, and σ_b represents the standard deviation of bolus insulin doses across all subjects and days.

IV. RESULTS

1) Hypothesis Testing Results: Table II shows a summary of the results from hypothesis testing. Given that a one-sample t-test provides more information (i.e. direction) than the two-sample t-test and there were no conflicts in the results, we show the one-sample t-test results. Statistical testing was done using three levels of alpha i.e., $\alpha = 0.001$, 0.01 and 0.05, marked as "***", "**" and "*", respectively, for p less than α; else $p > 0.05$ and was marked as "x" for "not significant".

Our results show that behavioral choices related to meal size and insulin dose (i.e. small, medium, and large) have significantly different effects on diabetes management, especially as it relates to glycemic variability, and time in target range. This result supports to reject the null hypothesis that the effect of these choices on diabetes management is the same. For example, in the comparison of large meals vs. small meals, large meals were associated with more suboptimal outcomes, like the higher glycemic variability ($p < 0.001$), and more glycemic events ($p < 0.001$), while small meals were associated with more positive outcomes, such as higher time in target range ($p < 0.001$). The same effect was found in the comparison between large insulin doses vs. small insulin doses. However, interrupted sleep showed to be only associated with the number of glycemic events as opposed to glycemic variability and time in target

TABLE II
ONE-SAMPLE T-TEST RESULTS: BEHAVIORAL FACTORS VS. DIABETES MANAGEMENT INDICATORS

Behavioral Factor	Test Group	Time in Target Range	No. of Glycemic Events	Glycemic Variability
Meal Size	Large Meal vs. Small Meal	$***$, $p < 0.001$ (Small > Large)	$***$, $p < 0.001$ (Large > Small	$***$, $p < 0.001$ (Large > Small)
	Large Meal vs. Medium Meal	$***$, $p < 0.001$ (Medium > Large)	$\times$, $p = 0.334$ (Failed to Reject Null)	$***$, $p < 0.001$ (Large > Medium)
	Medium Meal vs. Small Meal	$***$, $p < 0.001$ (Small > Medium)	$***$, $p < 0.001$ (Medium > Small)	$***$, $p < 0.001$ (Medium > Small)
Insulin Dose	Large Dose vs. Small Dose	$***$, $p < 0.001$ (Small > Large)	$***$, $p < 0.001$ (Large > Small)	$***$, $p < 0.001$ (Large > Small)
	Large Dose vs. Medium Dose	$***$, $p < 0.001$ (Medium > Large)	$***$, $p < 0.001$ (Large > Medium)	$***$, $p < 0.001$ (Large > Medium)
	Medium Dose vs. Small Dose	$***$, $p < 0.001$ (Small > Medium)	$*$, $p = 0.013$ (Medium > Small)	$***$, $p < 0.001$ (Medium > Small)
Sleep Interruption	Interrupted Sleep vs. Continuous Sleep	$\times$, $p = 0.27$ (Failed to Reject Null)	$***$, $p < 0.001$ (Interrupted > Continuous)	$\times$, $p = 0.17$ (Failed to Reject Null)
Key	$***$, $**$, $*$ = Significant at $\alpha = 0.001,\ 0.01,\ 0.05$, respectively			$\times$ = Not Significant

TABLE III
ASSOCIATION MINING RESULTS:
BEHAVIORAL FACTORS $\Rightarrow$ RECOMMENDED T1D TARGET

	Association Rule	Count	Support	Confidence	Δ Confidence	Lift
Meal Size	Small Meals $\Rightarrow$ $\geqslant 70\%$ Time in Target Range	390	4.17%	59.00%	-	1.08
	Large Meals $\Rightarrow$ $\geqslant 70\%$ Time in Target Range	1,024	10.95%	47.81%	11.19%	0.88
	Small Meals $\Rightarrow$ Glycemic Variability < 50mg/dL	589	6.30%	89.11%	-	1.09
	Large Meals $\Rightarrow$ Glycemic Variability < 50mg/dL	1,640	17.54%	76.56%	12.55%	0.94
Insulin Dose	Small Bolus Dose $\Rightarrow$ $\geqslant 70\%$ Time in Target Range	124	3.60%	76.54%	-	1.29
	Large Bolus Dose $\Rightarrow$ $\geqslant 70\%$ Time in Target Range	659	19.15%	51.12%	25.42%	0.86
	Small Bolus Dose $\Rightarrow$ Glycemic Variability < 50mg/dL	158	4.59%	97.53%	-	1.12
	Large Bolus Dose $\Rightarrow$ Glycemic Variability < 50mg/dL	1,058	30.75%	82.08%	15.45%	0.94
Sleep Interruption	Continuous Sleep $\Rightarrow$ $\geqslant 70\%$ Time in Target Range	1,488	28.79%	53.39%	-	1.00
	Interrupted Sleep $\Rightarrow$ $\geqslant 70\%$ Time in Target Range	1,274	24.65%	53.48%	-0.09%	1.00
	Continuous Sleep $\Rightarrow$ Glycemic Variability < 50mg/dL	1,787	34.57%	64.12%	-	1.01
	Interrupted Sleep $\Rightarrow$ Glycemic Variability < 50mg/dL	1,507	29.16%	63.27%	0.85%	0.99

range. More specifically, interrupted sleep was associated with a greater number of glycemic events ($p < 0.001$) than continuous (or non-interrupted sleep).

2) Association Mining Results: Results in this section provide concrete probabilities on the relationship between two events as learned from our dataset. Metrics for evaluating associations include *support*, *confidence*, and *lift* as shown in equation 1. These were calculated for all three behavioral factors in relation to two recommended T1D targets identified in the literature. Firstly, a recent consensus report on clinical targets for CGM data recommends a goal of $\geq 70\%$ Time in Target Range for persons with T1D [22]. Hence, we evaluated the association between categories of each behavioral factors and $\geq 70\%$ Time in Target Range. Secondly, experts recommend a goal of $<$ 33 - 36% for coefficient of variation (%) defined as [standard deviation of glucose/mean glucose] $\times$ 100 [29]. This equates to a target of $<$ 50 - 55 mg/dL in standard deviation based on the goal of maintaining a mean blood glucose $<$ 154 mg/dL for persons with T1D [2]. In this work, we evaluated the association between categories of behavioral factors yielding a standard deviation of $<$ 50 mg/dL.

Table III shows a summary of all results from association mining. Our result shows a 59% confidence for association between small meals and the recommended target goals of $\geq$ 70% Time in Target. Meanwhile, there is a lower confidence of 47.81% for the association between large meals and the recommended target goals of $\geq$ 70% Time in Target. Therefore, based on our dataset, small meals are 11.19% more probable to yield the recommended goal for Time in Target Range than large meals. It is important to note that small meals $\Rightarrow \geq$ 70% Time in Target Range has a *lift* of $>$ 1 meanwhile large meals $\Rightarrow \geq$ 70% Time in Target Range has a *lift* of $<$ 1. This means that the occurrence of small meals and $\geq$ 70% Time in Target Range appear more than the baseline probability (i.e. positively correlated), meanwhile the occurrence of large meals and $\geq$ 70% Time in Target Range occur less than the baseline probability (i.e. negative effect). Similar results were found between small meals and glycemic variability, where small meals $\Rightarrow$ glycemic variability $<$ 50 mg/dL was 12.55% more probable than large meals $\Rightarrow$ glycemic variability. The association between small bolus insulin doses and target time in range and glycemic variability was even higher with a greater confidence of 25.42% and 15.45%, respectively, compared to the association between large insulin doses and target time in range and glycemic variability. These findings are in agreement with the results from hypothesis testing which supports that there is a significant difference between the effects of meal size on diabetes management indicators - particularly time in target range and glycemic variability.

Conversely, results from this study show approximately no difference for sleep interruption on the recommended goals of $\geq$ 70% Time in Target Range and glycemic variability of $<$ 50 mg/dL. These findings align in the majority with the results from hypothesis testing which supports to reject the null hypothesis that interrupted sleep (vs. not) show no statistical differences for the indicators of Time in Target Range and Glycemic Variability. However, as seen in the earlier results, the effects of sleep interruption only showed significant differences in relationship to number of glycemic events. However, there is no known recommended target for the number of glycemic events in diabetes management indicators other than to minimize the occurrence of glycemic events. Hence, no analysis was done for this factor.

V. CONCLUSION

The advent of wearable devices, especially for management of chronic conditions, provide unparalleled opportunities to understand the relationships between behavioral and health outcomes. Unlike randomized control trials which are expensive and subjective self-report questionnaires which are erroneous, knowledge discovery from personal health data is relatively under-utilized in the literature. However, this approach has the potential to identify valid, actionable and interpretable information that can guide manual and automated treatment strategies. Following this work, future research will investigate the potential benefit of adding behavioral insights in predictive models for detecting of adverse glycemic events in diabetes management. Further research will also validate the associations between interrupted sleep and diabetes management using wearable activity trackers.

VI. ACKNOWLEDGMENT

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