Original Paper

Understanding Associations Between Behavioral Factors and Glycemic Outcomes in Patients With Type 1 Diabetes Using Automated Insulin Delivery Systems: Longitudinal Observational Study

Saman Khamesian[1,2], MSc; Asiful Arefeen[1,2], MSc; Maria Adela Grando[1], MCS, PhD; Bithika M Thompson[3], MD; Curtiss B Cook[3], MD; Hassan Ghasemzadeh[1], PhD

[1]College of Health Solutions, Arizona State University, Phoenix, AZ, United States
[2]School of Computing and Augmented Intelligence, Arizona State University, Tempe, AZ, United States
[3]Division of Endocrinology, Mayo Clinic in Arizona, Scottsdale, AZ, United States

Corresponding Author:

Saman Khamesian, MSc
College of Health Solutions
Arizona State University
319 Health Futures Center, 6161 E Mayo Blvd
Phoenix, AZ 85054
United States
Phone: 1-480-884-2639
Email: skhamesi@asu.edu

Abstract

Background: Despite advances in continuous glucose monitoring (CGM) and automated insulin delivery (AID) systems, many individuals with type 1 diabetes (T1D) fail to achieve recommended glycemic targets. Although behavioral factors (eg, physical activity, sleep, diet, and insulin timing) influence glucose outcomes, the behavioral context under free-living conditions remains insufficiently characterized.

Objective: This study examines associations between real-world behavioral patterns and glycemic outcomes in individuals with T1D using AID systems by analyzing multimodal data from wearable sensors, mobile food logs, and CGM.

Methods: We conducted a prospective observational study involving 19 adults with T1D using AID systems over a 30-day period. Participants wore a smartwatch to capture behavioral metrics, including step count, exercise duration, and sleep duration, and used a custom mobile app to log time-stamped food intake. Wearable and mobile app data were integrated with AID system data to construct a multimodal dataset. Behavioral-glycemic relationships were analyzed using a complementary framework combining unsupervised clustering and correlation analyses across individuals.

Results: Clustering revealed distinct groups with similar overall activity and intake patterns but different percentages of time-in-range (TIR≈69%-86%), indicating that comparable behavioral profiles were associated with different levels of glycemic control. Insulin timing relative to meals consistently differentiated glycemic profiles, whereas physical activity and carbohydrate intake alone showed weaker separation. Correlation analysis identified the average meal-bolus delay as one of the strongest behavioral correlates of glycemic outcomes, with negative associations with TIR ($\rho \approx -0.67$) and postprandial time-in-range (PP-TIR; $\rho \approx -0.57$), and a positive association with hyperglycemic events ($\rho \approx 0.67$). Sleep duration showed a moderate positive association with TIR and an inverse association with glucose variability, while activity- and intake-related measures were strongly interrelated but less directly associated with glycemic metrics.

Conclusions: Glycemic differences appear to be more closely associated with how behaviors are coordinated, particularly insulin timing relative to meals, than with exercise or carbohydrate intake alone. These findings highlight the importance of incorporating behavioral context to explain heterogeneity in real-world diabetes management and to support personalized, behavior-aware strategies.

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Keywords: type 1 diabetes; automated insulin delivery; behavioral analysis; real-world data; wearable sensors

Introduction

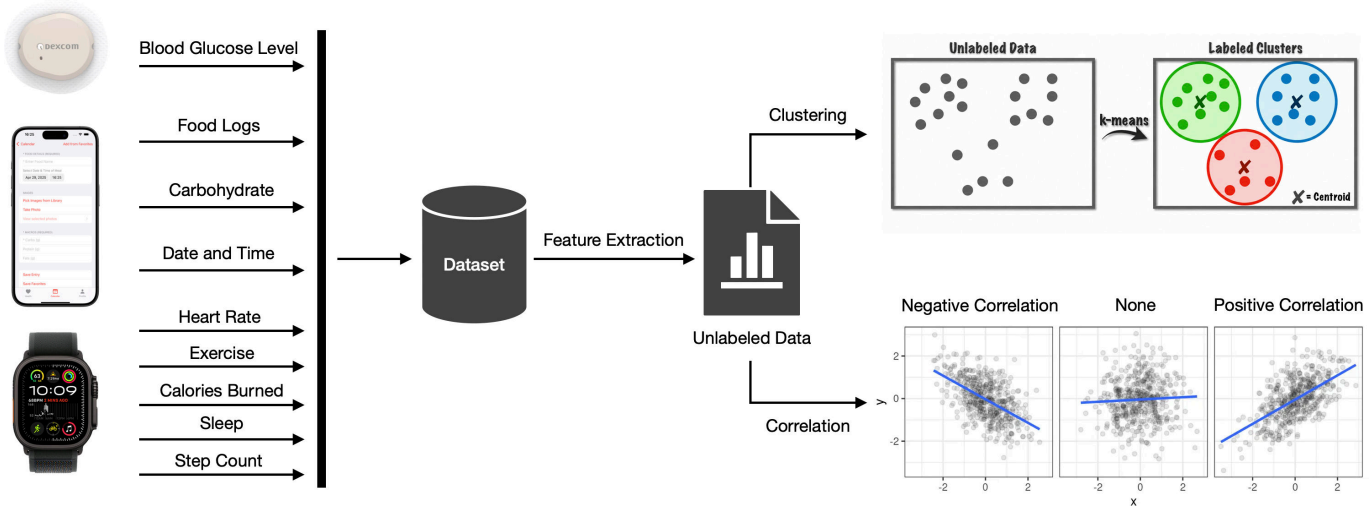
Type 1 diabetes (T1D) is a chronic autoimmune condition characterized by the destruction of pancreatic β-cells, resulting in lifelong dependence on exogenous insulin for glycemic regulation [1,2]. Effective management of T1D requires continuous decision-making around insulin dosing, meal timing, physical activity, and daily routines, all of which directly influence blood glucose dynamics [3,4]. In recent years, major advances in diabetes technologies, including continuous glucose monitoring (CGM) [5,6] and automated insulin delivery (AID) platforms [7,8], have substantially improved glycemic monitoring and insulin administration [9-11]. These systems have been shown to reduce glycemic variability [3,4], increase time-in-range (TIR; 70-180 mg/dL), and lower the risk of severe hypoglycemia compared to traditional insulin therapy [12-15]. Despite substantial technological progress, nearly 80% of the overall population with T1D do not meet key clinical targets recommended by the American Diabetes Association, such as achieving at least 70% TIR and maintaining a hemoglobin A_{1c} level near 7% [3,16-19]. Even among individuals using AID systems, approximately 30% do not achieve these targets [20].

One contributing reason for the continued difficulty in achieving recommended glycemic targets is that current diabetes technologies offer limited visibility into the behavioral context in which glucose regulation occurs [21-23]. While these systems provide continuous and detailed glucose measurements, they do not comprehensively capture many influential behaviors, including physical activity patterns, exercise duration and intensity, sleep characteristics, and daily routines [24-27]. Glycemic outcomes emerge from the interaction of multiple behavioral and lifestyle factors that extend beyond insulin delivery alone, such as step count, exercise timing, sleep patterns, and the temporal relationship between eating and insulin administration [21,28]. Although these factors are widely recognized in clinical practice, their combined and interacting influence on glycemic outcomes remains insufficiently characterized in real-world, free-living settings [22,24].

Prior work has explored associations between selected behavioral factors and glycemic outcomes, but a comprehensive understanding of how multiple behaviors jointly relate to clinically meaningful metrics such as TIR remains limited [3,29-31]. Glycemic control reflects the interaction of several behaviors rather than any single factor in isolation, and substantial variability persists across individuals even when similar technologies are used. A data-driven analysis that jointly considers behavioral features and glucose outcomes is therefore needed to capture heterogeneity in self-management behaviors and to identify common behavioral patterns associated with different glycemic profiles. Such approaches can help clarify why some individuals consistently achieve better glucose outcomes than others under comparable treatment conditions.

To address this gap, we conducted a 30-day prospective real-world study involving 19 individuals with T1D to examine the relationship between behavioral factors and glucose outcomes. Participants wore a smartwatch to capture physiological and behavioral metrics and used a custom mobile app to log time-stamped dietary intake. These data were integrated with glucose measurements to construct a multimodal dataset reflecting daily behaviors under free-living conditions. Using this dataset, we analyzed how behavioral factors influence glucose control across patients. We applied 2 complementary analytical approaches. First, we used unsupervised machine learning [32,33] techniques to cluster patients based on behavioral variables and glycemic outcomes, enabling the identification of groups with similar behavioral patterns and glucose control profiles. Second, we conducted statistical correlation [34,35] analyses to quantify associations between behavioral features and TIR, assessing the strength and direction of these relationships across patients. Together, these analyses provided a systematic and interpretable characterization of how real-world behavioral patterns contribute to variability in glycemic outcomes among individuals with T1D and offered insights that may inform future behavior-aware and personalized diabetes management strategies. Figure 1 provides an overview of the study workflow, illustrating the progression from data collection to the analytical methods.

Figure 1. Overview of the study workflow. Multimodal data collected from continuous glucose monitoring, food logging, and wearable sensors are aggregated into a unified dataset and transformed through feature extraction. The resulting unlabeled feature representations are analyzed using unsupervised clustering (k-means) to identify recurring behavioral-glycemic patterns and using correlation analyses to quantify associations between behavioral features and glycemic outcomes.



Methods

Ethical Considerations

This study was approved by the Institutional Review Board of Arizona State University and Mayo Clinic Arizona (IRB number 24-010332). All participants provided informed consent prior to enrollment. The study collected behavioral and physiological data under free-living conditions without altering participants' clinical care. No personally identifiable information was collected or stored, and all data were handled in accordance with institutional privacy and security policies.

Study Design

This prospective observational study was conducted as a collaboration between the Arizona State University College of Health Solutions and the Mayo Clinic Arizona Department of Endocrinology. A total of 19 adults with T1D using a Tandem t X2 insulin pump [36] and Dexcom CGM system [36,37] were recruited from the outpatient endocrinology clinic. All participants provided informed consent before enrollment. Participant age at consent, sex, and recorded ethnicity are summarized in Table 1. The study was designed to evaluate real-world, multimodal behavioral and physiological data collected during routine diabetes self-management without altering participants' standard clinical care. Participants were provided with an Apple Watch Series 10 and our custom mobile app, ExActHealth, developed for this study. They were instructed to wear the smartwatch continuously throughout the study period, including during sleep, and to remove it only for charging or showering. The smartwatch was used to collect health-related metrics, including physical activity, heart rate, step count, and sleep duration. The mobile app was used for self-reporting daily food intake, including meal time and date, macronutrient content, and optional food images. Participants completed the study over a 30-day period, during which insulin pump data, CGM data, smartwatch data, and food logs were continuously collected.

Table 1. Demographic characteristics of the 19 participants included in the analysis.[a]

ID	Age (y)	Sex	Ethnicity
S01	73	Male	White
S02	36	Female	White
S03	29	Female	Asian Indian
S04	52	Female	White
S05	28	Male	White
S06	50	Male	Asian Indian
S07	72	Male	White
S08	73	Female	White
S09	33	Female	White
S10	47	Female	White
S11	61	Female	White
S13	64	Female	Hispanic or Latino
S14	69	Male	White

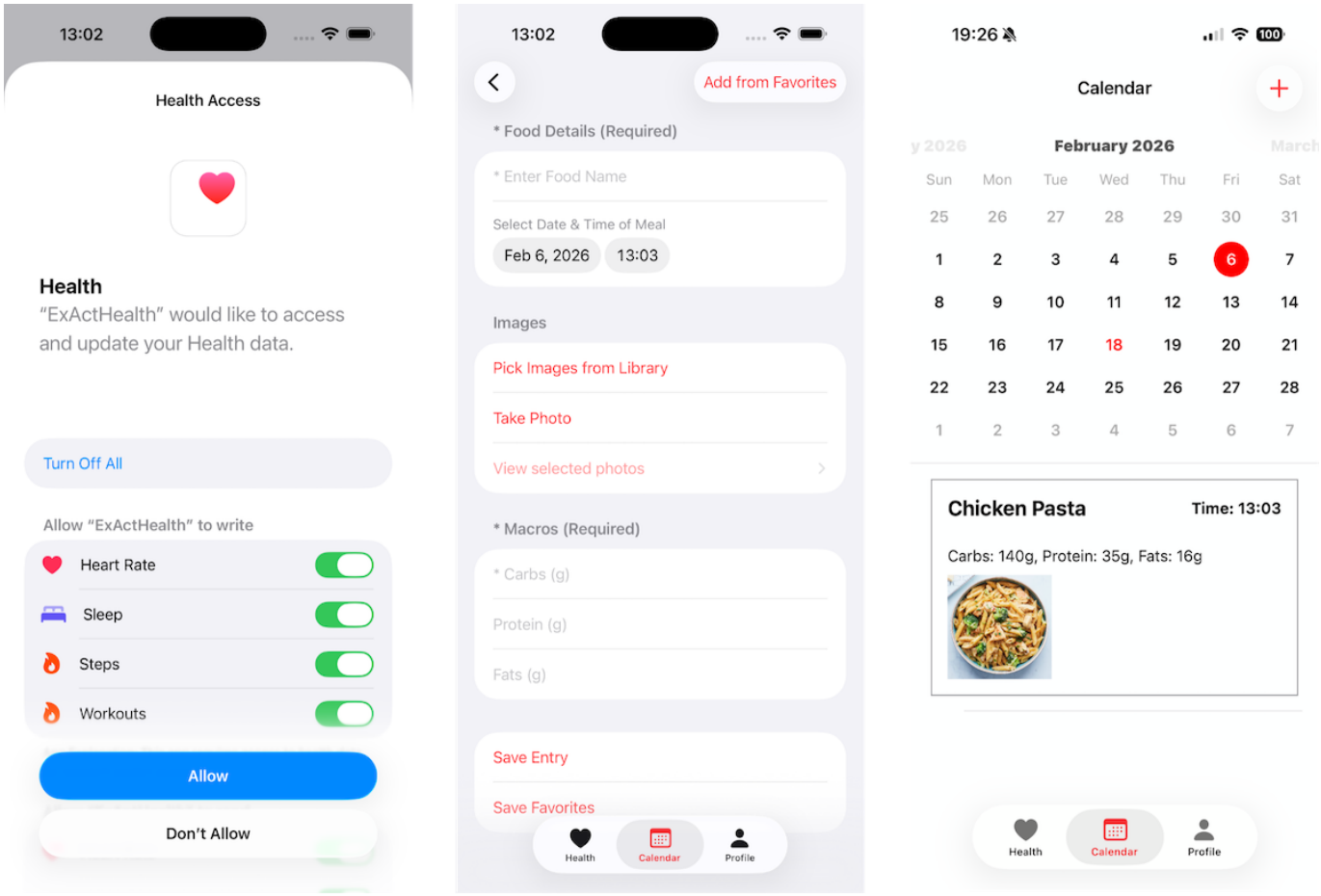
ID	Age (y)	Sex	Ethnicity
S15	42	Female	White
S16	27	Male	White
S17	29	Female	White
S18	46	Female	White
S19	70	Female	White
S20	39	Female	White

[a]Age was calculated in completed years at the time of consent. Ethnicity is reported as recorded in the participant log, which combines race and ethnicity categories. S indicates the participant identifier.

ExActHealth Mobile App

We developed a custom iOS mobile app, ExActHealth, to support the collection of real-world behavioral and lifestyle data during the study period (Figure 2). The app was designed specifically for observational use under free-living conditions, with the goal of enabling detailed, time-aligned data capture while minimizing participant burden.

Figure 2. ExActHealth iOS mobile app interfaces used for data collection. The left panel shows the Apple Health authorization screen, where participants granted ExActHealth permission to access smartwatch-derived health metrics, including heart rate, step count, sleep, and workout activities. The middle panel shows the food-logging interface used to record the meal name, date and time of consumption, mandatory carbohydrate amount, optional protein and fat values, and optional food images captured using the device camera or selected from the photo library. The right panel shows the calendar interface, including a saved meal entry with its nutritional information.



The ExActHealth app enables participants to self-report detailed food intake information, including food name, date and time of consumption, and macronutrient content. Entry of the carbohydrate amount was mandatory for all food logs, while protein and fat entries were optional. Participants could also attach one or more food images captured with the device camera or selected from the photo library. All food entries were time-stamped to ensure accurate temporal alignment with CGM records and AID data. To reduce repetitive data entry, the app allowed participants to save frequently consumed foods and reuse them for future entries.

In addition to dietary data, ExActHealth integrates with Apple Health to collect smartwatch-derived behavioral and physiological metrics through a paired Apple Watch Series 10. With explicit user authorization, the app accessed heart

rate, step count, sleep duration, and workout activity data. Participants were instructed to wear the smartwatch continuously throughout the study period, including during sleep, and to remove it only for charging or showering. They were also asked to actively record workout sessions, including gym-based exercises as well as walking and running activities, to ensure accurate capture of physical activity.

All collected data, including food logs, smartwatch metrics, and associated timestamps, were securely transmitted to a cloud-based server for storage and subsequent analysis. Participants accessed the app using study-specific credentials generated at enrollment, and all data handling procedures complied with institutional privacy and security requirements.

Feature Representation

Across the study, 570 days of analyzable data were collected, with each participant contributing approximately 30 days. Daily features were selected through expert-informed feature engineering to represent glycemic outcomes and behavioral context using measurements available from CGM, AID, food logs, and smartwatch data. To obtain a single representation per participant, daily features were averaged across all available days to form a single 17D vector representing each participant's glycemic and behavioral profile. This approach was consistent with the arithmetic-mean centroids used in k-means clustering and preserved the frequency and magnitude of intermittent behaviors, such as exercise, for which the median could be 0 despite meaningful activity on some days.

Following CGM reporting recommendations [3], glycemic features included TIR (70-180 mg/dL), level 1 time-below-range (TBR1; 54-70 mg/dL), and level 2 time-below-range (TBR2; <54 mg/dL). Above-range exposure was separated into level 1 time-above-range (TAR1; 180-250 mg/dL) and level 2 time-above-range (TAR2; >250 mg/dL). Each measure was calculated as the percentage of daily CGM readings within the corresponding range, with the boundary values of 70 and 180 mg/dL included in TIR. The coefficient of variation (CV) described glucose variability, while the numbers of hypoglycemic and hyperglycemic events (N_HypoEvents and N_HyperEvents) described episode frequency. Events required at least 15 consecutive minutes of CGM readings below 70 mg/dL or above 180 mg/dL, respectively, with each continuous qualifying episode counted once [3,38].

The behavioral and related features were drawn from data collected during the study. Food logs provided total daily carbohydrate intake and average carbohydrate intake per meal, distinguishing overall intake from typical meal size. Protein and fat entries were optional and inconsistently recorded, so they were excluded; food images were retained for future investigation but were not used in this analysis. Smartwatch records provided calories burned during exercise, exercise duration, step count, average heart rate, and sleep duration, describing activity and related physiological context. Paired food logs and AID records provided average meal-bolus delta time, describing insulin timing relative to meals. Physical activity and meal-related insulin timing are established considerations in T1D management [9,25].

For each meal recorded in the ExActHealth app, the participant-reported meal date and time were used to align the food log with CGM data and to identify the nearest insulin bolus administered that same day. Meal-bolus delta time was calculated as bolus time minus meal time, with negative values indicating insulin administration before the meal. Postprandial time-in-range (PP-TIR) was calculated separately for each meal as the percentage of valid CGM readings between 70 and 180 mg/dL during the 2 hours following the reported meal time. These meal-specific PP-TIR values were then averaged across all meals recorded that day to calculate daily PP-TIR. Because meal times and carbohydrate amounts were self-reported, logging errors may affect both the estimated meal-bolus interval and PP-TIR.

Analysis Methods

The k-means clustering [32,39,40] was used to characterize differences in behavioral and glycemic profiles. Given observations x_i, k-means partitions them into k clusters by minimizing the within-cluster sum of squared distances:

$$\min_{\{C_j\}_{j=1}^{k}} \sum_{j=1}^{k} \sum_{x_i \in C_j} \|x_i - \mu_j\|_2^2$$

Here, C_j is the set of observations assigned to cluster j, and its centroid is defined as follows:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i$$

The mean silhouette coefficient [41] provides a criterion for choosing the number of clusters, k. For each participant, it compares the average distance to other participants in the same cluster with the average distance to participants in the nearest other cluster. Averaging these coefficients across participants gives 1 score for each candidate value of k; higher scores indicate more cohesive and better-separated clusters.

To quantify overall multivariate separation among the identified clusters, the participant feature vectors were first standardized to 0 mean and unit variance, and permutational multivariate ANOVA (PERMANOVA) was then applied. Euclidean distance was used to measure differences among participants across the combined 17 behavioral and glycemic features. Statistical significance was calculated using 10,000 permutations. The pseudo-F statistic was calculated by comparing variation between cluster centers with variation among participants within the clusters. R^2 was calculated as the effect size and represents the proportion of total multivariate variation explained by cluster membership.

Pearson and Spearman correlation coefficients [42,43] were calculated across participants, using the same participant-level mean feature vectors described in the Feature Representation section, to examine relationships among all feature pairs. Pearson correlation measures linear association,

while Spearman correlation measures monotonic association based on ranks.

Results

Food Logging and Recorded Physical Activity

Across 570 (19 participants observed for 30 days each) participant-days, participants recorded 2984 food-log entries on 532 (93.3%) participant-days. The median number of entries per participant was 142 (IQR 129.5-171.5), with food logging occurring on a median of 30 (IQR 29-30) days per participant. The median carbohydrate content was 20 (IQR 12-31) g per entry, excluding 1 entry with missing carbohydrate content. Of the recorded entries, 2969 were temporally aligned with the analysis data. Food-log entries could represent individual foods, snacks, drinks, or meals and therefore were not equivalent to distinct meal occasions. Participants recorded 451 workout sessions on 296 (51.9%) participant-days, with a median of 17 (IQR 10-30) workouts per participant, occurring on a median of 15 (IQR 9.5-24) days per participant. The median recorded workout duration was 37.2 (IQR 23.0-56.1) minutes. Figures 3 and 4 summarize participant-level variation in food logging and recorded workouts, respectively, including their frequency, the number of days with records, and the distributions of carbohydrate content and workout duration. Protein and fat were excluded, as described in the Methods section. Exercise intensity was not available as a separate variable in the workout exports and thus was not classified.

Figure 3. Food logging during the 30-day study period. For each participant, the panels present (A) the total number of food-log entries, (B) the number of days with at least 1 record, and (C) the median carbohydrate content per food log (points) and IQR (horizontal lines). Food-log entries may represent foods, snacks, drinks, or meals. Carbohydrate summaries exclude 1 missing value.

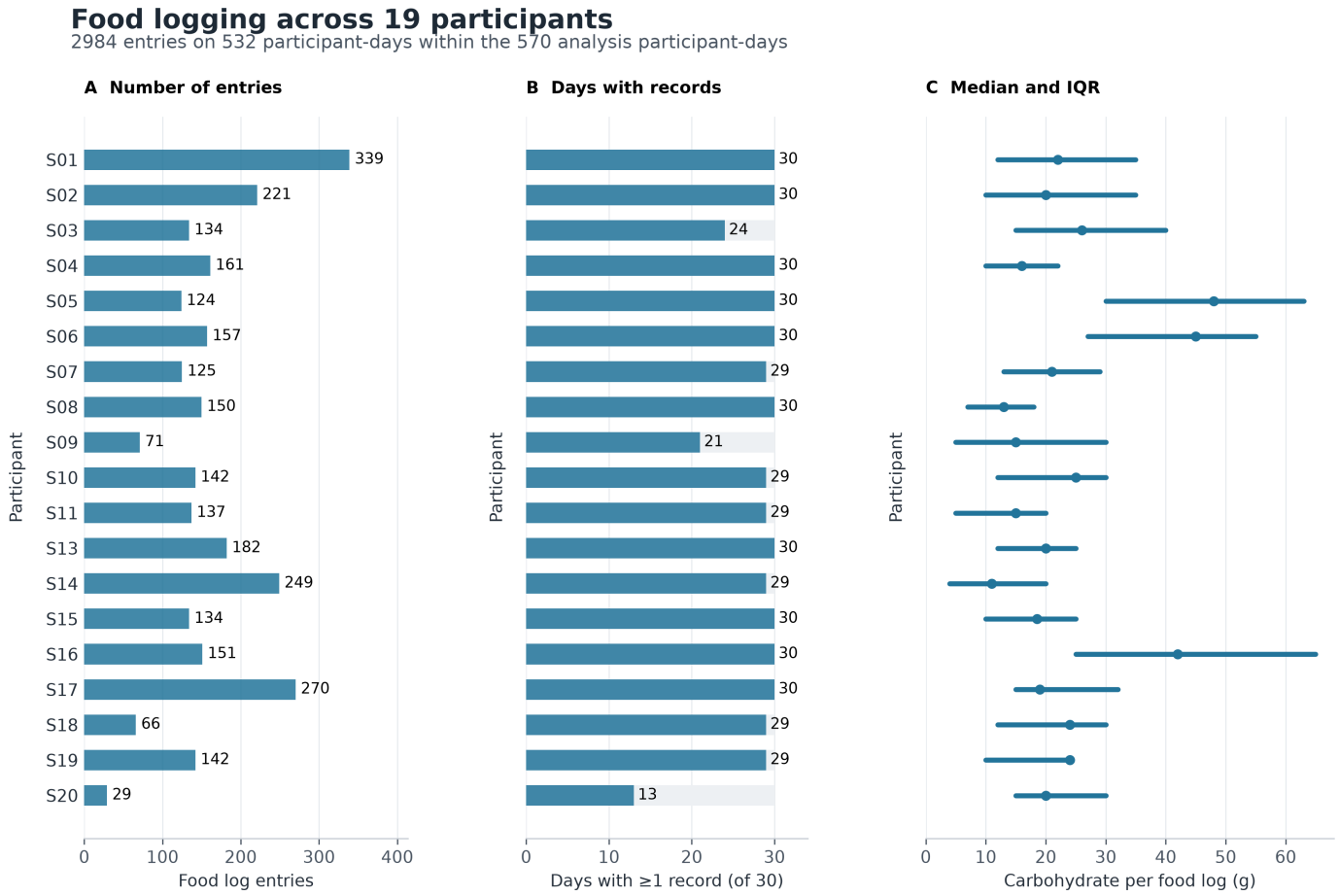
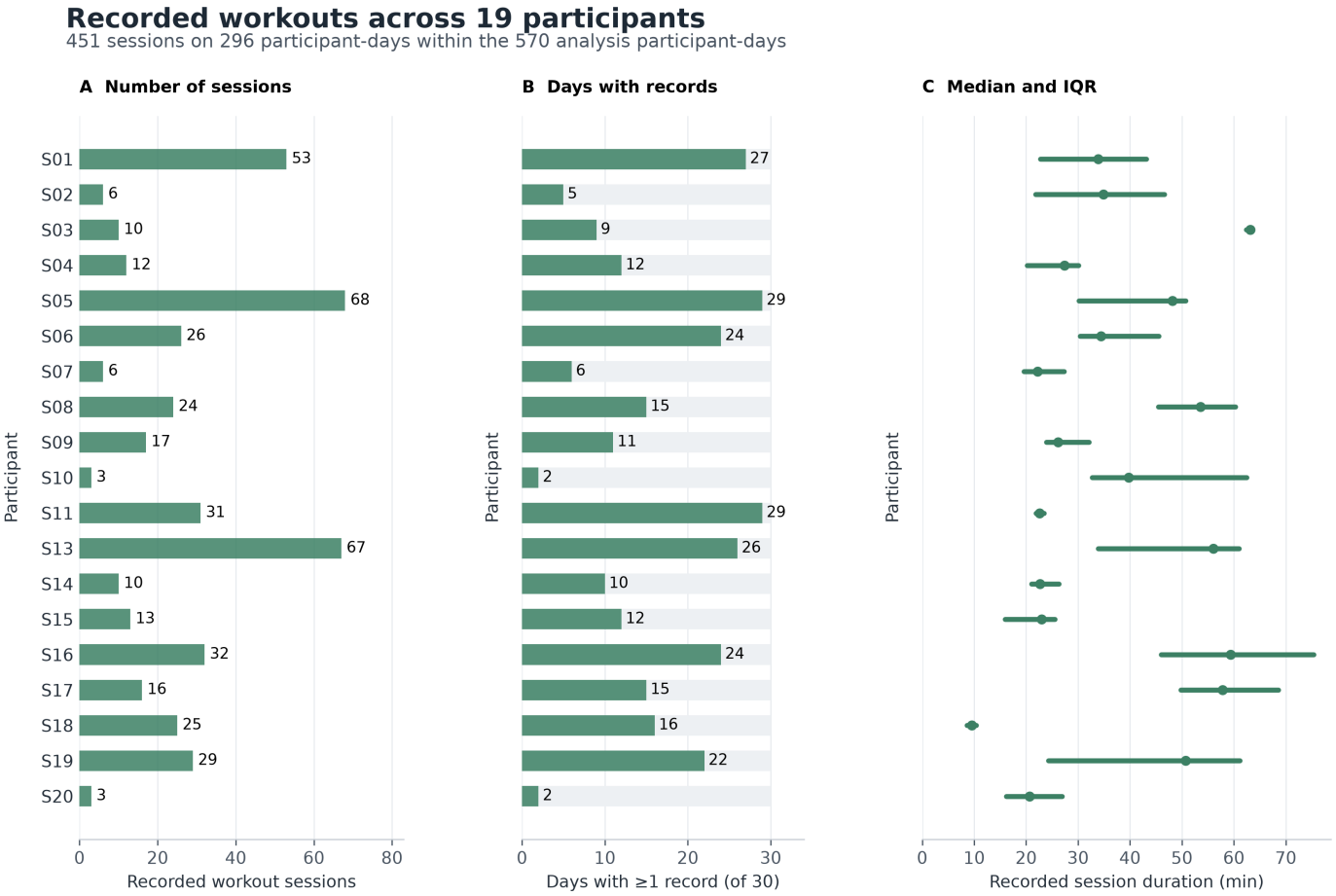


Figure 4. Recorded physical activity during the 30-day study period. For each participant, the panels present (A) the total number of recorded workout sessions, (B) the number of days with at least 1 recorded workout, and (C) the median recorded workout duration (points) and IQR (horizontal lines). Duration is based on the original workout duration field; no intensity variable was available in the exports.



Participant-Level Feature Vectors

Before clustering, daily features were summarized separately for each participant across the 30-day observation period. The mean of each feature formed the 17D vector used for clustering, while the corresponding SD quantified day-to-day within-participant variability and was not included as a clustering feature. For clarity and ease of comparison, the glycemic and behavioral components of the participant feature vectors were presented separately in Tables 2 and 3, respectively. Participant-level mean TIR ranged from 50.3% (SD 16.4%) to 94.3% (SD 5.9%), with within-participant TIR SDs ranging from 93.1 (SD 5.7) to 66.0 (SD 21.1) percentage points. Behavioral features also varied substantially across participants, particularly in activity, carbohydrate intake, sleep, and meal-bolus timing.

Table 2. Participant-level glycemic features before clustering.[a]

ID	TIR[b] (%), mean (SD)	TBR1[c] (%), mean (SD)	TBR2[d] (%), mean (SD)	TAR1[e] (%), mean (SD)	TAR2[f] (%), mean (SD)	PP-TIR[g] (%), mean (SD)	CV[h] (%), mean (SD)	Hypo events, mean (SD)	Hyper events, mean (SD)
S01	78.9 (9.8)	1.8 (2.6)	0.7 (1.5)	16.7 (8.7)	1.9 (3.0)	75.9 (12.7)	30.3 (5.6)	1.2 (1.7)	3.5 (1.5)
S02	73.2 (9.5)	3.2 (2.5)	1.3 (1.8)	16.3 (6.5)	6.0 (6.0)	63.4 (17.8)	36.3 (6.7)	2.4 (1.8)	4.4 (1.7)
S03	72.6 (12.1)	2.3 (2.1)	1.0 (2.4)	19.7 (10.0)	4.4 (6.1)	66.2 (22.8)	30.6 (9.0)	1.6 (1.4)	5.0 (2.9)
S04	79.6 (11.6)	0.7 (1.1)	0.1 (0.3)	17.8 (10.0)	1.9 (2.9)	70.6 (21.7)	27.9 (5.0)	0.5 (0.7)	3.1 (1.4)
S05	91.6 (6.8)	2.3 (2.3)	0.5 (1.0)	5.1 (5.9)	0.5 (1.5)	82.7 (18.5)	26.4 (5.5)	1.6 (1.4)	2.0 (1.5)
S06	90.8 (7.8)	1.3 (1.9)	0.2 (0.6)	7.6 (7.1)	0.0 (0.1)	90.7 (11.6)	23.8 (4.5)	0.8 (0.7)	1.9 (1.2)
S07	88.8 (10.8)	4.2 (4.4)	0.7 (1.5)	5.3 (7.5)	1.0 (5.3)	87.8 (14.1)	25.4 (5.2)	2.5 (2.2)	1.7 (1.8)
S08	80.3 (14.2)	1.2 (1.7)	0.0 (0.1)	14.9 (10.1)	3.6 (6.7)	70.5 (25.0)	28.7 (6.8)	0.9 (1.0)	2.6 (1.3)
S09	93.1 (5.7)	2.9 (2.7)	0.6 (0.8)	3.3 (4.3)	0.1 (0.4)	90.3 (9.9)	23.6 (4.9)	1.9 (1.6)	1.7 (1.5)
S10	90.3 (6.6)	0.6 (1.0)	0.0 (0.2)	8.2 (5.5)	0.9 (2.6)	83.2 (16.1)	25.3 (5.9)	0.6 (0.9)	3.5 (2.0)
S11	94.3 (5.9)	1.2 (1.4)	0.2 (0.7)	4.2 (4.7)	0.1 (0.3)	89.8 (9.1)	21.2 (5.6)	1.8 (1.9)	2.1 (1.7)

ID	TIR[b] (%), mean (SD)	TBR1[c] (%), mean (SD)	TBR2[d] (%), mean (SD)	TAR1[e] (%), mean (SD)	TAR2[f] (%), mean (SD)	PP-TIR[g] (%), mean (SD)	CV[h] (%), mean (SD)	Hypo events, mean (SD)	Hyper events, mean (SD)
S13	66.0 (21.1)	1.5 (1.8)	0.4 (0.8)	20.1 (10.4)	12.0 (16.9)	54.3 (27.7)	32.1 (7.7)	1.1 (1.3)	3.8 (1.7)
S14	73.3 (9.9)	0.6 (1.0)	0.1 (0.2)	19.1 (7.8)	6.9 (6.1)	52.0 (23.0)	34.0 (7.2)	0.7 (1.0)	4.5 (1.9)
S15	78.8 (10.0)	1.0 (1.6)	0.3 (0.7)	16.3 (6.6)	3.6 (6.7)	66.7 (16.3)	28.5 (5.8)	1.0 (1.4)	4.6 (2.0)
S16	77.0 (11.0)	0.7 (0.7)	0.2 (0.4)	17.8 (8.1)	4.3 (6.1)	67.9 (14.1)	29.0 (6.7)	1.1 (1.0)	5.9 (3.1)
S17	79.5 (9.7)	0.8 (1.3)	0.3 (1.2)	15.4 (8.3)	4.0 (5.1)	72.3 (17.1)	28.5 (8.2)	0.8 (0.9)	5.0 (3.3)
S18	85.1 (10.4)	5.1 (4.5)	1.0 (1.5)	8.1 (7.9)	0.7 (3.4)	76.4 (22.8)	28.4 (8.7)	2.6 (2.3)	3.8 (2.6)
S19	83.4 (10.3)	0.5 (0.9)	0.0 (0.1)	13.8 (8.4)	2.3 (5.4)	71.5 (17.6)	26.9 (7.7)	0.5 (1.0)	3.2 (2.0)
S20	50.3 (16.4)	0.1 (0.4)	0.1 (0.7)	30.3 (11.1)	19.2 (14.7)	42.2 (18.7)	28.9 (6.0)	0.2 (0.7)	4.8 (2.0)

[a]Values are presented as mean (SD) across 30 daily observations for each participant. Participant means were included in the clustering feature vectors; SDs characterize within-participant variability. S indicates the participant identifier.
[b]TIR: time-in-range.
[c]TBR1: level 1 time-below-range.
[d]TBR2: level 2 time-below-range.
[e]TAR1: level 1 time-above-range.
[f]TAR2: level 2 time-above-range.
[g]PP-TIR: postprandial time-in-range.
[h]CV: coefficient of variation.

Table 3. Participant-level behavioral features before clustering.[a]

ID	Calories burned (kcal), mean (SD)	Exercise duration (min), mean (SD)	Total carbohydrates (g), mean (SD)	Carbohydrates per meal (g), mean (SD)	Heart rate (bpm), mean (SD)	Step count, mean (SD)	Sleep duration (min), mean (SD)	Meal-bolus (Δt; min), mean (SD)
S01	6746 (12,568)	79.2 (65.5)	266.4 (67.2)	37.1 (7.7)	50.4 (3.7)	10633 (3359)	389 (77)	–0.2 (35.7)
S02	384 (1305)	15.8 (47.4)	180.7 (74.6)	28.7 (13.5)	84.1 (6.8)	6746 (2930)	360 (154)	+7.8 (34.1)
S03	790 (1280)	20.8 (33.9)	131.8 (89.5)	34.3 (9.2)	85.0 (4.4)	3629 (2360)	281 (162)	+12.7 (19.5)
S04	251 (397)	10.3 (13.3)	97.4 (28.5)	24.1 (8.3)	79.3 (3.6)	3576 (3079)	388 (162)	+13.6 (33.3)
S05	5071 (3351)	98.3 (40.7)	216.5 (57.0)	53.7 (13.2)	82.9 (11.8)	12482 (3755)	446 (146)	–11.3 (21.5)
S06	1358 (1130)	32.3 (19.1)	208.4 (31.0)	41.0 (4.9)	67.5 (3.5)	10971 (2331)	367 (90)	–7.4 (18.8)
S07	63 (139)	4.8 (10.2)	97.4 (35.8)	24.2 (6.2)	57.8 (4.7)	8096 (2248)	441 (185)	–1.2 (19.3)
S08	1663 (1993)	40.0 (45.3)	69.5 (31.1)	17.2 (5.1)	78.7 (5.1)	4764 (2307)	457 (107)	–4.8 (35.6)
S09	241 (349)	14.5 (20.3)	46.9 (43.6)	20.6 (7.7)	73.6 (13.3)	3676 (3531)	N/A[b]	–1.4 (18.2)
S10	204 (1051)	5.0 (23.1)	115.1 (55.4)	28.6 (13.7)	95.1 (5.4)	5223 (2968)	427 (173)	+5.7 (15.1)
S11	396 (124)	23.2 (6.9)	64.3 (18.2)	14.8 (3.8)	73.5 (4.0)	6779 (1864)	519 (112)	–6.0 (18.2)
S13	3620 (2162)	103.3 (54.9)	110.4 (43.3)	23.5 (6.8)	61.4 (3.5)	13315 (5733)	N/A	+3.6 (34.0)
S14	556 (2418)	11.3 (23.0)	101.6 (45.1)	18.8 (6.5)	65.1 (9.4)	7462 (2850)	367 (127)	+6.8 (18.1)
S15	202 (434)	10.2 (15.5)	87.1 (29.7)	22.7 (7.6)	82.1 (4.5)	8020 (2202)	452 (99)	+4.1 (15.5)
S16	13,159 (19,613)	77.7 (75.2)	236.3 (64.7)	49.1 (11.1)	85.8 (14.4)	8167 (4505)	354 (211)	+7.2 (38.1)
S17	1274 (1540)	29.0 (31.6)	247.1 (85.9)	30.3 (7.8)	72.9 (7.0)	4880 (2041)	427 (124)	+58.7 (92.3)
S18	25 (142)	8.3 (12.2)	58.7 (34.2)	29.1 (16.5)	90.1 (4.2)	3354 (2339)	359 (278)	–8.7 (13.7)
S19	1680 (1902)	45.8 (37.1)	90.0 (24.7)	19.7 (2.5)	65.4 (5.6)	7645 (3284)	419 (176)	–7.4 (16.0)
S20	72 (291)	2.2 (8.3)	21.5 (30.9)	21.8 (8.7)	88.3 (6.6)	1740 (2616)	117 (220)	+11.0 (17.9)

[a]Values are presented as mean (SD) across 30 daily observations for each participant. Participant means were included in the clustering feature vectors; SDs characterize within-participant variability. S indicates the participant identifier.
[b]N/A: not available.

Clustering

Participant-level 17D feature vectors, including PP-TIR, were standardized to 0 mean and unit variance before k-means clustering. Candidate solutions with k=2 through k=6 were evaluated. The highest mean silhouette scores were obtained for k=2 (0.155015) and k=3 (0.175630), so these 2 solutions were retained for further analysis (Table 4). Table 4 also reports the Davies-Bouldin indices and cluster sizes for all candidate solutions. For each retained solution, cluster centroids were computed as the mean feature values of participants assigned to each cluster. The centroid values for all features are summarized in Table 5.

Table 4. Silhouette scores, Davies-Bouldin indices, and cluster sizes for participant-level k-means solutions with k ranging from 2 to 6.[a]

K	Silhouette score	Davies-Bouldin index	Cluster sizes
2	0.155015	1.607532	15, 4
3	0.175630	1.476973	10, 3, 6
4	0.136384	1.237358	9, 3, 6, 1
5	0.152554	1.061206	10, 3, 4, 1, 1
6	0.138349	0.972195	9, 1, 4, 1, 1, 3

[a]Cluster sizes represent the numbers of participants assigned to each cluster.

Table 5. Cluster-level behavioral and glycemic feature values for k-means solutions with k=2 and k=3.[a]

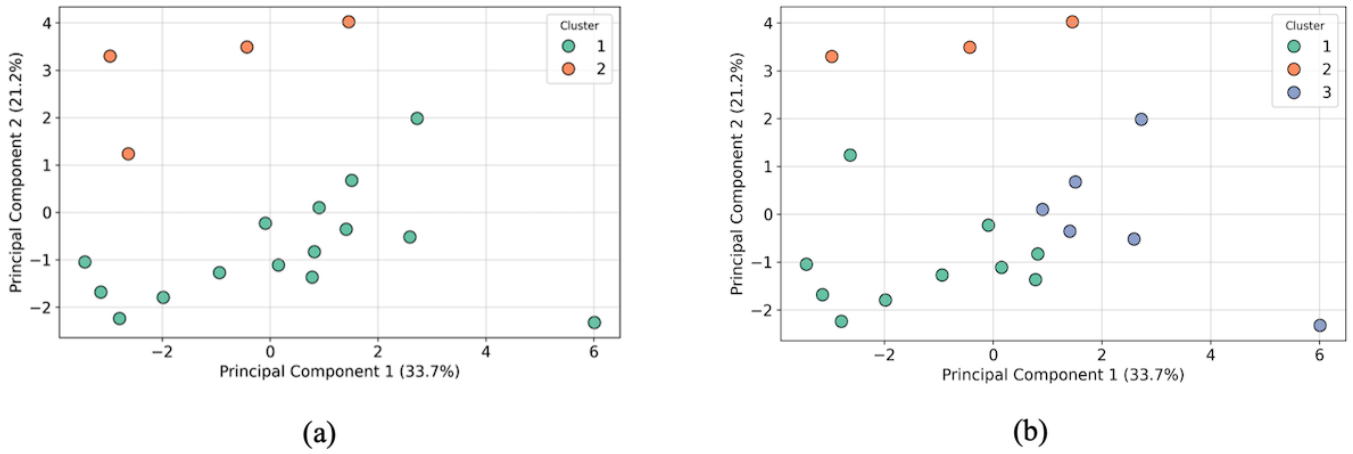
Features	K=2		K=3		
	Cluster 1 (n=15), mean (SD)	Cluster 2 (n=4), mean (SD)	Cluster 1 (n=10), mean (SD)	Cluster 2 (n=3), mean (SD)	Cluster 3 (n=6), mean (SD)
TIR[b] (%)	79.25 (11.38)	84.57 (7.69)	86.46 (5.77)	82.49 (7.92)	69.17 (10.17)
TBR1[c] (%)	1.72 (1.48)	1.55 (0.70)	1.87 (1.62)	1.61 (0.85)	1.41 (1.15)
TBR2[d] (%)	0.40 (0.40)	0.42 (0.21)	0.32 (0.32)	0.47 (0.22)	0.52 (0.48)
TAR1[e] (%)	14.19 (7.28)	11.78 (6.36)	9.95 (5.28)	13.18 (7.01)	20.16 (5.31)
TAR2[f] (%)	4.43 (5.16)	1.69 (1.92)	1.40 (1.38)	2.25 (1.92)	8.74 (5.86)
PP-TIR[g] (%)	70.49 (14.02)	79.31 (9.72)	79.77 (9.58)	75.51 (7.40)	58.39 (10.93)
CV[h] (%)	28.42 (3.86)	27.36 (2.87)	25.97 (2.56)	28.55 (1.98)	31.74 (3.00)
Number of hypoglycemic events	1.28 (0.81)	1.19 (0.34)	1.32 (0.83)	1.31 (0.29)	1.12 (0.79)
Number of hyperglycemic events	3.58 (1.17)	3.34 (1.87)	2.81 (0.98)	3.81 (1.99)	4.59 (0.45)
Calories burned (kcal)	761 (966)	6583 (4928)	608 (674)	8325 (4269)	1116 (1291)
Exercise duration (min)	22.98 (25.62)	71.88 (27.99)	19.45 (15.05)	85.06 (11.52)	30.42 (36.84)
Total carbohydrates (g)	101.31 (55.19)	231.93 (25.81)	93.49 (45.42)	239.77 (25.13)	132.18 (76.45)
Carbohydrates per meal (g)	23.90 (5.40)	45.20 (7.56)	24.19 (7.43)	46.61 (8.59)	26.25 (5.82)
Heart rate (bpm)	76.83 (11.04)	71.64 (16.29)	76.30 (11.29)	73.03 (19.66)	76.15 (11.32)
Step count	5927 (2845)	10,563 (1788)	6210 (2504)	10,427 (2164)	6295 (4017)
Sleep duration (min)	334.71 (164.40)	389.62 (40.52)	383.50 (142.75)	396.89 (46.32)	258.92 (166.03)
Meal-bolus (Δt; min)	+6.29 (16.21)	–2.93 (8.14)	–1.35 (7.16)	–1.45 (9.29)	+16.76 (20.78)

[a]Values are presented as mean (SD) across participant-level aggregated feature vectors assigned to each cluster. Cluster sizes are shown in the column headings.
[b]TIR: time-in-range.
[c]TBR1: level 1 time-below-range.
[d]TBR2: level 2 time-below-range
[e]TAR1: level 1 time-above-range.
[f]TAR2: level 2 time-above-range.
[g]PP-TIR: postprandial time-in-range.
[h]CV: coefficient of variation.

PERMANOVA showed statistically significant multivariate differences among participant clusters for both k=2 (pseudo-$F_{1,17}$=3.511; P=.002; R^2=0.171) and k=3 (pseudo-$F_{2,16}$=4.597; P<.001; R^2=0.365). Cluster membership explained 17.1% and 36.5% of the total multivariate variation, respectively, indicating greater overall multivariate separation for the 3-cluster solution.

To facilitate visualization of the high-dimensional clustering results, principal component analysis (PCA) [44] was applied to the standardized participant feature vectors. PCA is a linear dimensionality reduction technique that projects the original features onto a lower-dimensional space by identifying orthogonal directions, referred to as principal components, that capture the greatest variance in the data. The first 2 principal components were used to obtain a 2D representation. The first and second principal components explained 33.7% and 21.2% of the total variance, respectively, accounting for 55.0% cumulatively. The resulting projections are shown in Figure 5 for both k=2 and k=3, where each point represents a participant and is colored according to its assigned group. PCA was used solely for visualization purposes; all clustering assignments were performed in the full feature space.

Figure 5. The 2D principal component analysis (PCA) visualization of participant-level behavioral and glycemic clusters identified using k-means. PC1 and PC2 explained 33.7% and 21.2% of the total variance, respectively (55.0% cumulatively). The left panel (a) shows the k=2 solution, and the right panel (b) shows the k=3 solution; each point represents 1 participant.

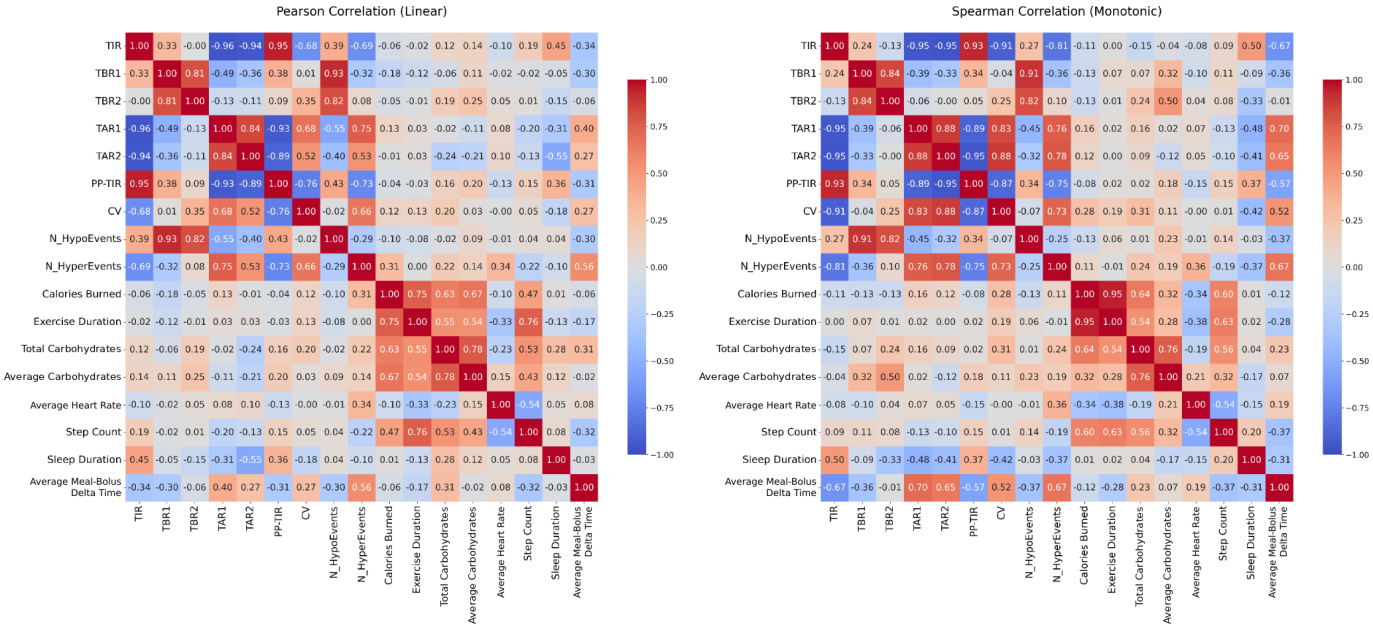


Correlation

Correlation analyses were performed using participant-level mean feature vectors aggregated across days throughout the study period to examine associations between behavioral characteristics and glycemic outcomes in the cohort. Participants were the unit of analysis. Pearson (r) and Spearman (ϱ) correlation coefficients were computed for all variable pairs to capture linear and monotonic relationships, respectively. Correlation strength was interpreted using conventional thresholds based on the absolute value of the coefficient (|r| or |ϱ|), where values below 0.30 were considered weak, between 0.30 and 0.50 moderate, and 0.50 or greater strong.

The resulting matrices summarize the direction and magnitude of associations among glycemic metrics (TIR, TBR1, TBR2, TAR1, TAR2, PP-TIR, and CV), hypoglycemic and hyperglycemic events, and behavioral features including carbohydrate intake, physical activity, heart rate, step count, sleep duration, and meal-bolus delta time. Pearson and Spearman results are reported jointly to provide complementary perspectives and to account for relationships that may be monotonic but not strictly linear. The corresponding correlation matrices are shown in Figure 6.

Figure 6. Pearson (left) and Spearman (right) correlation matrices computed from data aggregated across the study period for each individual. The matrices illustrate associations between average behavioral characteristics and glycemic outcomes. Warmer colors (red) indicate positive correlations, cooler colors (blue) indicate negative correlations, and the color intensity represents the magnitude of the correlation coefficient. CV: coefficient of variation; TAR: time-above-range; TBR: time-below-range; TIR: time-in-range.



Discussion

Clustering Analysis

Clustering based on participant feature vectors revealed systematic differences in average behavioral patterns and glycemic outcomes across participants. With k=2, the analysis separated participants into cluster 1 and cluster 2, which differed primarily in activity level, carbohydrate intake, and insulin timing, while differences in glycemic outcomes were present but relatively modest (Table 5). Participants in cluster 2 were substantially more active, with longer exercise duration (mean 71.88, SD 27.99 vs mean 22.98, SD 25.62 minutes per day) and a higher step count (mean 10,563, SD 1788 vs mean 5927, SD 2845 steps per day) and consumed more carbohydrates on average (mean 231.93, SD 25.81 vs mean 101.31, SD 55.19 g per day). This group also administered insulin closer to meals, with an average meal-bolus delta time of –2.93 (SD 8.14) minutes and achieved slightly better glycemic outcomes, including higher TIR (mean 84.57%, SD 7.69% vs mean 79.25%, SD 11.38%) and lower TAR1 (mean 11.78%, SD 6.36% vs mean 14.19%, SD 7.28%) and TAR2 (mean 1.69%, SD 1.92% vs mean 4.43%, SD 5.16%). In contrast, cluster 1 was characterized by lower activity levels, lower carbohydrate intake, and delayed insulin administration relative to meals (average +6.29, SD 16.21 minutes), and exhibited lower TIR and higher TAR1 and TAR2 despite similar glucose variability and comparable numbers of hypo- and hyperglycemic events. Overall, the k=2 solution indicated that broad differences in activity and intake were associated with only limited separation in average glycemic control.

Increasing the number of clusters to k=3 uncovered structure that was not apparent in the k=2 analysis. In this setting, cluster 2 continued to be characterized by higher activity levels and carbohydrate intake, although its size and centroid values changed (Table 5). Cluster 1 and cluster 3 exhibited markedly different glycemic outcomes. Cluster 1 achieved the highest average TIR (mean 86.46%, SD 5.77%) and lowest TAR1 (mean 9.95%, SD 5.28%) and TAR2 (mean 1.40%, SD 1.38%), while cluster 3 showed substantially lower TIR (mean 69.17%, SD 10.17%) and elevated TAR1 (mean 20.16%, SD 5.31%) and TAR2 (mean 8.74%, SD 5.86%). This difference was also evident during postprandial periods, with higher PP-TIR in cluster 1 than in cluster 3 (mean 79.77%, SD 9.58% vs mean 58.39%, SD 10.93%).

The PERMANOVA results provided statistical support for differences among the combined behavioral and glycemic profiles of the clusters. Both retained solutions showed statistically significant multivariate separation. The larger R^2 effect size for k=3 indicated that the 3-cluster solution explained a greater proportion of the variation among participant profiles than the 2-cluster solution.

Importantly, cluster 1 and cluster 3 in the k=3 analysis had broadly similar activity levels, step counts, and carbohydrate intake despite markedly different glycemic outcomes (Table 5). A notable difference was insulin timing relative to meals: cluster 3 (TIR mean 69.17%, SD 10.17%) exhibited delayed bolus insulin administration, with an average meal-bolus delta time of +16.76 (SD 20.78) minutes, whereas cluster 1 (TIR mean 86.46%, SD 5.77%) administered insulin, on average, slightly before meals (mean –1.35, SD 7.16 minutes). These aggregated profiles suggest that meal-bolus timing helped distinguish clusters with different glycemic outcomes despite similarities in overall activity and intake.

At the same time, comparison across all k=3 clusters showed that favorable glycemic outcomes were achieved under different behavioral patterns. In addition to cluster 1, which achieved the highest TIR with relatively modest activity and intake, cluster 2 also demonstrated good glycemic outcomes (TIR mean 82.49%, SD 7.92%) despite substantially higher physical activity and carbohydrate intake. Together, these results indicate that no single behavioral pattern uniquely characterized good glycemic outcomes; rather, different combinations of activity, intake, and insulin timing were associated with similarly favorable average glycemic control across participants.

Correlation Analysis

Correlation analysis was performed using participants' feature vectors to examine associations between average behavioral characteristics and average glycemic outcomes across individuals (Figure 6). Strong correlations were observed among core glycemic metrics, with TIR exhibiting pronounced inverse relationships with TAR1, TAR2, glucose variability, and the frequency of hyperglycemic events, reflecting the tight coupling among participant-level glycemic measures.

Beyond these expected relationships, the average meal-bolus delta time emerged as one of the behavioral features most strongly associated with glycemic outcomes, particularly in the Spearman analysis. Larger average meal-bolus delta times, indicating later bolus insulin administration relative to meals, were associated with lower TIR ($r\approx-0.34$; $\varrho\approx-0.67$), lower PP-TIR ($r\approx-0.31$; $\varrho\approx-0.57$), higher TAR1 ($r\approx0.40$; $\varrho\approx0.70$) and TAR2 ($r\approx0.27$; $\varrho\approx0.65$), increased glucose variability ($r\approx0.27$; $\varrho\approx0.52$), and a greater number of hyperglycemic events ($r\approx0.56$; $\varrho\approx0.67$). The association with PP-TIR extends the relationship between meal-bolus timing and glycemic outcomes to postprandial periods. Associations were in the same direction in both analyses, with stronger Spearman correlations for TIR, PP-TIR, TAR1, TAR2, and CV. These associations aligned with the clustering results, where differences in meal-bolus timing distinguished groups of participants with differing glycemic outcomes.

Sleep duration showed moderate positive correlations with TIR ($r\approx0.45$; $\varrho\approx0.50$) and PP-TIR ($r\approx0.36$; $\varrho\approx0.37$), as well as moderate negative correlations with TAR1 ($r\approx-0.31$; $\varrho\approx-0.48$). The negative correlation with TAR2 was strong in the Pearson analysis and moderate in the Spearman analysis ($r\approx-0.55$; $\varrho\approx-0.41$). These findings indicate that longer sleep duration was associated with higher TIR and PP-TIR and lower above-range exposure. The inverse association with CV was weak in the Pearson analysis and moderate in the Spearman analysis ($r\approx-0.18$; $\varrho\approx-0.42$), indicating that the association with lower glucose variability was more apparent in the Spearman analysis. Physical activity

measures, including exercise duration, calories burned, and step count, exhibited weak correlations with TIR, PP-TIR, TAR1, TAR2, and CV. Similarly, total carbohydrate intake and average carbohydrate intake per meal showed limited associations with TIR, PP-TIR, and above-range exposure. An additional exploratory finding was the positive correlation between average carbohydrate intake per meal and TBR2, which was weak in the Pearson analysis and strong in the Spearman analysis ($r \approx 0.25$; $\varrho \approx 0.50$).

Overall, the correlation analysis indicates that meal-bolus timing and, to a lesser extent, sleep duration, were associated with participant-level glycemic outcomes, although association strength varied by outcome and correlation methods. These exploratory findings are consistent with the clustering patterns and highlight behavioral features that may help characterize differences in glycemic profiles beyond activity or intake magnitude alone.

Conclusions

Among adults with T1D using AID systems, clustering identified different glycemic profiles despite broadly similar activity and carbohydrate intake. Meal-bolus timing, reflecting when individuals administer insulin relative to eating, emerged as a particularly relevant self-management behavior. Larger average meal-bolus delta times, indicating later bolus administration relative to meals, were associated with lower overall TIR ($r \approx -0.34$; $\varrho \approx -0.67$), lower postprandial TIR ($r \approx -0.31$; $\varrho \approx -0.57$), greater above-range exposure, and more hyperglycemic events ($r \approx 0.56$; $\varrho \approx 0.67$). Sleep duration showed moderate positive associations with TIR and PP-TIR, whereas activity and carbohydrate intake generally showed weaker associations with these outcomes. These findings highlight the importance of the timing of everyday self-management actions for understanding differences in glycemic outcomes among individuals using AID systems.

These findings may inform the design of anticipatory behavioral frameworks that complement AID by incorporating individual routines and meal-bolus timing into personalized support. Building on existing research on probabilistic modeling of eating behavior [45] and anticipation of exercise in closed-loop systems [46], future frameworks could combine meal patterns, bolus history, activity, sleep, and glucose trajectories to anticipate periods when behavioral support may be useful. In particular, the association between later bolusing and poorer glycemic outcomes motivates the evaluation of personalized prompts around anticipated meals to support timely meal-related insulin administration. Research frameworks such as GUIDE (Glucose Intelligence Decision Engine) [47], which represents behavioral actions through their type, magnitude, and timing, offer a route for investigating adaptive recommendations. Shapley-informed reinforcement learning [48] provides an approach to incorporating feature explanations into decision support, while peer-grounded counterfactual path planning [49] offers a complementary approach to structuring gradual behavioral changes using observed peer profiles. Our analysis identifies candidate behavioral features and targets for these approaches. Larger longitudinal studies and prospective evaluations are needed to establish whether such support improves meal-bolus coordination and glycemic outcomes while accounting for individual physiology, adherence, and hypoglycemia risk.

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Generative AI Use

The authors declare the use of generative AI (GenAI) in the research and writing process. According to the Generative AI Delegation Taxonomy (GAIDeT; 2026), proofreading and editing and reformatting were delegated to GenAI tools under full human supervision. The GenAI tool used was ChatGPT (Sol-6; OpenAI). Responsibility for the final manuscript lies entirely with the authors. GenAI tools are not listed as authors and do not bear responsibility for the final outcomes.

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Data Availability

The datasets generated and analyzed during this study are not publicly available but can be obtained from the corresponding author upon reasonable request.

Authors' Contributions

SK conceived and designed the study. SK, AA, MAG, BMT, and CBC acquired data for the study. SK analyzed the data for the study. SK and HG interpreted the data for the study. SK contributed to the drafting of the article. SK, AA, MAG, BMT, CBC, and HG critically revised the work for important intellectual content. SK had full access to the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. HG provided supervision and leadership throughout the study. All authors made the decision to submit this article for publication.

Conflicts of Interest

None declared.

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Abbreviations

AID: automated insulin delivery
CGM: continuous glucose monitoring
CV: coefficient of variation
GUIDE: Glucose Intelligence Decision Engine
PCA: principal component analysis
PERMANOVA: permutational multivariate ANOVA
PP-TIR: postprandial time-in-range
T1D: type 1 diabetes
TAR1: level 1 time-above-range
TAR2: level 2 time-above-range
TBR1: level 1 time-below-range
TBR2: level 2 time-below-range
TIR: time-in-range

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