Association of Blood Glucose Data with Physiological and Nutritional Data from Dietary Surveys Investigated Using Publicly Available Wearable-type Databases

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Abstract

Background: Wearable devices can simultaneously collect data on multiple items in real-time and are used for disease detection, prediction, diagnosis, and treatment decision-making. Many factors such as diet and exercise influence blood glucose levels; however, the relationship between blood glucose and these factors has not been evaluated in real practice.

Objective: This study aimed to investigate the association of blood glucose data with each physiological index and nutritional values using wearable devices and dietary survey data from PhysioNet, a public database.

Methods: Three analytical methods were used: 1) analysis of the correlation between each physiological indicator and blood glucose; 2) multiple regression analysis and 3)one-way analysis of variance on the pre- and post-peak slopes in postprandial glucose over time, and the association between each physiological indicator and nutritional value.

Results: Three analytical methods were used: 1) analysis of the correlation between each physiological indicator and blood glucose and 2) multiple regression analysis and 3) one-way analysis of variance on the pre- and post-peak slopes in postprandial glucose over time and the association between each physiological indicator and nutritional value.

Conclusions: Similar results were obtained from the three analyses, consistent with previous reports, and the relationship between blood glucose, diet, and physiological indices in the real world was examined. Data sharing facilitates accessibility of wearable data and enables statistical analyses from various angles.

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Abstract

Background: Wearable devices can simultaneously collect data on multiple items in real-time and are used for disease detection, prediction, diagnosis, and treatment decision-making. Many factors such as diet and exercise influence blood glucose levels; however, the relationship between blood glucose and these factors has not been evaluated in real practice.
Objective: This study aimed to investigate the association of blood glucose data with each physiological index and nutritional values using wearable devices and dietary survey data from PhysioNet, a public database.
Methods: Three analytical methods were used: 1) analysis of the correlation between each physiological indicator and blood glucose and 2) multiple regression analysis and 3) one-way analysis of variance on the pre- and post-peak slopes in postprandial glucose over time and the association between each physiological indicator and nutritional value.
Results: Correlations were observed among physical activity, heart rate, skin temperature, and electrodermal activity. The physiological indices included body temperature, physical activity, skin temperature, skin electrical activity, and heart rate, whereas the nutritional indices included carbohydrates and sugar.
Conclusion: Similar results were obtained from the three analyses, consistent with previous reports, and the relationship between blood glucose, diet, and physiological indices in the real world was examined. Data sharing facilitates accessibility of wearable data and enables statistical analyses from various angles. This type of research is expected to become more commonly performed in the future.
Keywords: PhysioNet; Empatica; Dexcom; acceleration; heart rate; temperature; electrodermal activity

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Introduction

Wearable devices are becoming increasingly capable of measuring a range of bio-data. Real-world data, which collects and analyzes activity and physiological measurements from participants in clinical studies, can provide more sensitive measures of disease activity than traditional scales, thereby enabling faster and more objective readings in clinical trials [1]. Wearable devices can continuously collect multiple items of biological data in real-time. Depending on the size and complexity of the raw data obtained from the device, data pre-processing, feature extraction, and selection are performed through data processing, such as data mining, and are applied toward abnormality detection, prediction, diagnosis, and decision-making [2]. Conversely, data repositories have advanced in recent years, making large, open databases available for wearable devices. Data mining techniques have advanced significantly in the last few years, and with the availability of these open data, opportunities emerged to devise algorithms suitable for wearable sensors [2].
Supplementary Table S1 depicts studies that applied existing open datasets. A number of studies were conducted to establish algorithms and prediction models based on machine learning from sensor data [3-20].
Open datasets are available on the following websites: (i) IEEE Data Port, a research data platform designed to store research data and provide global access to research data across various fields [3]; (ii) the Open Wearables Initiative (OWEAR), which aims to promote the effective use of high-quality sensor-generated health measurements in clinical research by openly sharing algorithms and datasets [4]; and (iii) PhysioNet, a searchable database containing a collection of cardiopulmonary, neurological, and other biomedical signals from healthy individuals and patients with several serious health conditions, including congestive heart failure, epilepsy, gait disturbance, sleep apnea, and aging [5].

Notably, many factors influence blood glucose levels, including diet [6], physical activity, exercise [7], stress [8], circadian rhythm [9], and heart rate (HR) [10]. However, although some factors associated with blood glucose variability, such as HR [10], body temperature [11], and autonomic functions [12], including sweating motor response [13] have been reported [14], other factors associated with blood glucose have not been evaluated in the real world. Therefore, we conducted an exploratory study of the association between blood glucose and each physiological index using existing data from PhysioNet.

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Methods

Database selection and datasets creation

A database search was conducted using the word “Wearable” from PhysioNet, which yielded 11 hits. Among these, we focused on wristband-type wearable devices and searched the relevant databases since the major market share is dominated by wristband- and watch-types devices [15]. The search resulted in 7 of 11 studies with wristband-type wearable devices (Empatica: five; Apple watch: two; Fitbit: two; Garmin: one; Samsung Galaxy watch: one; Xiaomi: one; and Biovotion Everion: one study) (Table 1).

Table 1. Results of the search for a database of wearable-type device research in PhysioNet

No	Database name	Author	Devices	Participants	Endpoint
1	CogWear: Can we detect cognitive effort with consumer-grade wearables?	Michal K Grzeszczyk	Empatica E4 Samsung Galaxy Watch4 Muse S EEG headband	Pilot trials: 11 cases Gaming trials: 13 cases	Detection of cognitively demanding task performance
2	SCG-RHC: Wearable seismocardiogram signal and right heart catheter database	Michael Chan	Electrocardiogram (ECG) Tri-axial seismocardiogram (SCG)	73 patients referred for hemodynamic evaluation of heart failure (HF) status	Assessment of patient's clinical condition for HF
3	BIG IDEAs lab glycemic variability and wearable device data	Peter Cho	Dexcom G6 CGM Empatica E4	16 patients with pre-diabetic HbA1c levels between 5.3 and 6.4%	Generation of mHealth-based digital biomarkers of prediabetes and hyperglycemia risk
4	Wearable-based signals during physical exercises from patients with frailty after open-heart surgery	Daivaras Sokas	Polar H10	80 older patients with frailty who participated in a cardiac rehabilitation program after open heart surgery	Assessment of frail health status in a series of exercise tests

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5	In-Gauge and En-Gage: Understanding the occupants' behavior, engagement, emotion, and comfort indoors with heterogeneous sensors and wearables	Nan Gao	Empatica E4	23 student cases, 4 teacher cases	Examination of thermal comfort, engagement in learning, and emotions at school with daily surveys
6	Motion and heart rate from a wrist-worn wearable and labeled sleep from polysomnography	Olivia Walch	Apple Watch	31 cases	Recording of raw acceleration and heart rate using Apple watch while monitoring sleep via polysomnography
7	A wearable exam stress dataset for predicting cognitive performance in real-world settings	Md Rafiul Amin	Empatica E4	10 cases	Measurement of the effect of stress on test performance
8	Electrocardiogram, skin conductance, and respiration from spider-fearing individuals watching spider video clips	Frank R Ihmig	Wearable BITalino biosignal measurement device	57 cases of participants with arachnophobia	Detection of online anxiety levels from biometric signals
9	GLOBEM dataset: multi-year datasets for longitudinal human behavior modeling generalization	Xuhai Xu	Fitbit	497 cases	Collection of data on longitudinal behavioral modeling physical activity and sleep behavior
10	Gesture Recognition and Biometrics ElectroMyogram (GRABMyo)	Ning Jiang	EMGUSB2 OT Bioelecttronica	43 healthy participants	EMG-based gesture recognition research
11	BigIdeasLab_STEP: Heart rate measurements captured by smartwatches for differing skin tones	Brinnae Bent	Apple Watch 4 Fitbit Charge 2 Garmin Vivosmart 3 Xiaomi Miband 3 Empatica E4	53 cases	Investigation of the accuracy of wearables Investigation of covariates such as skin

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			Biovotion Everion		color, signal lag, and device type

Wristband wearable devices are in underlined.

In this search, we selected one study that investigated Empatica E4, the most widely used wristband-type wearable device. The dataset, "BIG IDEAs Lab Glycemic Variability and Wearable Device Data (version 1.1.1)" by Cho et al. (version 1.1.1)" [16,17] was selected to examine the correlation between each physiological index and blood glucose as well as conduct multiple regression analysis and one-way analysis of variance (ANOVA) of the slope in postprandial glucose over time with each physiological index and nutrient value. The main eligibility criteria in the study included men and women (postmenopausal women for women), aged 35–65 years, with point-of-care glycated hemoglobin (HbA1c) measurements between 5.2% and 6.4%.

Sixteen patients (seven men and nine women) with high normal and prediabetic range (5.3–6.4%, mean: 5.73%, standard deviation [SD]: 0.28%) were included and monitored for 8–10 days using the Dexcom G6 CGM and Empatica E4 wrist-worn wearable-type device [16].
The demographic characteristics of the participants are listed in Table 2.

Table 2. Demographic characteristics of the participants in the database

ID	SEX	HbA1c (%)
a01	Female	5.5
a02	Male	5.6
a03	Female	5.9
a04	Female	6.4
a05	Female	5.7
a06	Female	5.8
a07	Female	5.3
a08	Female	5.6
a09	Male	6.1
a10	Female	6.0
a11	Male	6.0
a12	Male	5.6
a13	Male	5.7
a14	Male	5.5
a15	Female	5.5
a16	Male	5.5

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HbA1c: glycated hemoglobin

Notably, all data were time-shifted (by date) to prevent re-identification; the Dexcom G6 measured interstitial glucose concentration (mg/dL) every 5 min using a continuous glucose monitor (CGM), and the Empatica E4 measured photoelectric volumetric pulse wave (PPG), electrical activity: electrodermal activity (EDA), temperature (TEMP), and tri-axial accelerometer derived acceleration (ACC), for seven functions. PPG was sampled at 64 Hz, and HR and blood volume pulse (BVP) signals were obtained every second, from which the inter-beat interval (IBI) data were calculated. EDA and TEMP were sampled at 4 Hz, whereas accelerometry was sampled at 32 Hz. For ACC, triaxial data were calculated using the Euclidean norm as a measure of average motion in the three axes using the following formula [18]:

$$\mathrm{ACC} = \sqrt{(ACC\,\mathrm{x}) + (ACC\,\mathrm{y}) + (ACC\,\mathrm{z})}$$

Each physiological index (ACC, HR, TEMP, EDA, BVP, and IBI) collected using Empatica was also extracted at 5-min intervals to match blood glucose, which had the longest measurement interval (5-min).

In addition, when the Cho et al. [16] dataset was updated from version 1.0.0 to version 1.1.0 on March 6, 2023, the results of nutrient value calculations from the dietary survey records were added to the analysis dataset. The parameters of the calculated nutritional values were calories, total carbohydrate (carbon), dietary fiber, sugar, protein, and total fat (fat). The values of these nutritional assessment indices at each time point were summed.

Correlation analyses between the mean and SD of blood glucose and each physiological index

The correlation of each physiological index (ACC, HR, TEMP, EDA, BVP, and IBI) was calculated and examined to determine whether their mean values or SDs affected the mean value of blood glucose. Mean values and SDs were calculated for blood glucose and each physiological index at three 5-min time points in the same individual (15 min in total), and their correlation coefficients were calculated. To examine the impact of each physiological

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indicator on blood glucose before and after the time of collection of blood glucose data, lag data (data on physiological indicators before glucose data collection at eight time points [120, 105, 90, 75, 60, 45, 30, and 15 min] and after blood glucose data collection at eight time points [15, 30, 45, 60, 75, 90, 105, and 120 min]), and correlation coefficient between blood glucose and each physiological indicator, were calculated for each physiological index.

Lag data for physiological indicators before glucose data collection was created by time-shifting each physiological indicator every 15 min until 120 min (Figure 1). Lag data for physiological index data after blood glucose data collection were time-shifted by 15 min for each glucose reading to 120 min (Figure 2).

The purpose of creating lag data is to calculate the correlation between glucose levels and ACC (ACC values 15, 30, 45, 60, 75, 90, 105, and 120 min) before and after measurement.

The correlation coefficient was calculated using Spearman's correlation.

Multiple regression analysis of the slopes of the rise to the peak and fall after the peak in postprandial blood glucose over time and the mean and SD of each physiological index and nutrient value

To examine the relationship between postprandial blood glucose rise and fall and physiological and dietary nutritional assessment indices, multiple regression analysis was performed on the relationship between the slope before and after the peak in postprandial glucose over time and physiological and dietary nutritional indices. Multiple regression analysis was performed using objective and explanatory variables.

Objective variables

The objective variables include the slope of postprandial blood glucose rise to the peak, and the slope of postprandial blood glucose from the peak to the lowest point.
The following formula was used to calculate the slope:

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$$b=\frac{\sum(x-\acute{x})(y-\acute{y})}{\sum(x-\acute{x})^2}$$

x: time (min), y: blood glucose (mg/dL)

Explanatory variables

The explanatory variables comprised the calculated nutritional value of the diet (carbon, protein, calories, sugar, dietary fiber, protein, and fat); and the mean and SD of physiological indices (ACC, HR, TEMP, EDA, BVP, and IBI) at the following time points (Figure 3):

(1) Time from the most recent postprandial glucose to peak glucose level
(2) Time from peak glucose to the lowest glucose level (excluded from the analysis of the slope of peak ascent owing to limited data)
(3) Time from the most recent postprandial glucose peak to 30 min before the most recent postprandial glucose
(4) Time from 30 min before the most recent postprandial glucose to 60 min before
(5) Time from 60 min before the most recent postprandial glucose to 90 min before

Multiple regression analysis was performed using the variable reduction method, and the significance level used as the criterion for variable reduction was p=0.20.

One-way ANOVA for the slopes of the postprandial rise and fall in blood glucose and groups above and below the mean of each physiological indicator and the median dietary nutrient value

As a supplementary analysis to the multiple regression analysis, a one-way ANOVA was performed to compare the relationship between the upward and downward slopes of blood glucose and the groups above and below the median for each indicator. The groups below the median were used as comparison controls.
The following variables were used in the one-way ANOVA.

Objective variables

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Same variables as those in the multiple regression analysis.

Explanatory variables

For the following indices, variables were created through patterns of group combinations using the physiological index mean and dietary nutrient value, with groups above and below the median for each index as 1 and 0, respectively. Group combinations that contained missing measures or extremely low group combinations were not included in the analysis population.

- The mean values of physiological indices (ACC, HR, TEMP, and EDA) at three 5-min intervals (15 min in total) in the same participant at the following times.
- Nutritional value of the diet (carbon, protein, calories, sugar, and dietary fiber).

Notably, the results of the multiple regression analysis showed that the physiological indicators associated with the slope of the rise and fall of blood glucose were TEMP, ACC, HR, and EDA, and the nutritional value indicators were carbon, protein, calories, sugar, and dietary fiber. Therefore, we focused on the following indicators:

Times:
(1) Time from the most recent postprandial glucose to peak glucose level
(2) Time point from peak glucose to lowest glucose level (excluded from this analysis.)
(3) Time from the most recent postprandial glucose to 30 min before
(4) Time from 30 min before the most recent postprandial glucose to 60 min before
(5) Time from 60 min before the most recent postprandial glucose to 90 min before

Patterned combination of groups by physiological indicator mean and dietary nutrient value:
(1) Combination patterns of physiological index mean groups
Combination pattern of TEMP, ACC, HR, and EDA; for example:

- Combination pattern for groups with TEMP, ACC, HR, and EDA below the median (used as a comparison)

TEMP: ACC: HR: EDA = 0000

- Combination pattern for groups with TEMP, ACC, HR, and EDA higher than the median

TEMP: ACC: HR: EDA = 1111

- Combination pattern for groups where TEMP and EDA were above the median and all other values were below the median

TEMP: ACC: HR: EDA = 1001

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(2) Combination patterns for dietary nutrient value groups; for example:

- Combination patterns for all indicators of dietary nutritional value (used as comparisons and controls) below the median

Calories: Carbon: Dietary fiber: Sugar: Protein = 00000

- Combination patterns for all indicators of dietary nutritional value above the median

Calories: Carbon: Dietary fiber: Sugar: Protein = 11111

- Combinations patterns for carbon and sugar above the median and all other indicators of dietary nutritional value below the median.

Calories: Carbon: Dietary fiber: Sugar: Protein = 01010

All analyses were performed using JMP Pro 16.10, SAS 9.4 (SAS Institute, Cary, NC, USA), and Microsoft Excel for Mac version 16 (Microsoft, WA, USA).

Results

Analysis of the correlation between blood glucose and each physiological index

Correlation coefficients between blood glucose mean and the mean of lag data for each physiological indicator

Lag data for each physiological indicator before blood glucose data collection (-120, 105, 90, 75, 60, 45, 30, and 15 min)

A graph and table illustrating the evolution of the correlation coefficients of the lag data between the mean values of blood glucose and physiological indices are shown in Supplementary Figure S1 and Table 3, respectively. In HR, the correlation remained negative, peaking at the -15 min value of the lag data (R = −0.147). For TEMP, the correlation remained positive, with a peak at the 0-min value (R = 0.135). For EDA, the correlation remained negative, peaking at the -15 min value of lag data (R= -0.164).

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Table 3. Trends in correlations between blood glucose mean and the mean of lag data for each physiological indicator (lag data for physiological indicators before blood glucose data collection)

Mean Glucose lag	**Mean ACC**			**Mean HR**			**Mean TEMP**			**Mean EDA**			**Mean BVP**			**Mean IBI**		
	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*
−120	9491	0.001	.93	9491	−0.068	<**.001**	9491	0.080	<**.001**	9069	−0.115	<**.001**	9491	0.021	**.043**	5558	0.049	<**.001**
−105	9507	0.004	.71	9507	−0.076	<**.001**	9507	0.081	<**.001**	9084	−0.119	<**.001**	9507	0.026	**.010**	5568	0.051	<**.001**
−90	9523	0.007	.50	9523	−0.084	<**.001**	9523	0.080	<**.001**	9099	−0.127	<**.001**	9523	0.029	**.005**	5580	0.050	<**.001**
−75	9539	0.008	.43	9539	−0.088	<**.001**	9539	0.080	<**.001**	9114	−0.133	<**.001**	9539	0.020	**.045**	5590	0.049	<**.001**
−60	9555	0.015	.14	9555	−0.097	<**.001**	9555	0.086	<**.001**	9129	−0.138	<**.001**	9555	0.017	.10	5601	0.051	<**.001**
−45	9571	0.022	**.030**	9571	−0.109	<**.001**	9571	0.096	<**.001**	9144	−0.141	<**.001**	9571	0.015	.14	5610	0.052	<**.001**
−30	9587	0.019	.07	9587	−0.129	<**.001**	9587	0.111	<**.001**	9159	−0.151	<**.001**	9587	0.016	.11	5618	0.051	<**.001**
−15	9603	0.015	.13	9603	**−0.147**	<**.001**	9603	0.126	<**.001**	9174	**−0.164**	<**.001**	9603	0.014	.18	5624	0.048	<**.001**
0	9619	0.015	.15	9619	−0.143	<**.001**	9619	**0.135**	<**.001**	9189	−0.161	<**.001**	9619	0.008	.43	5629	0.049	<**.001**

N: number of data, R: correlation coefficient, P: p-value; ACC: acceleration; HR: heart rate; TEMP: skin temperature; BVP: blood volume pulse; EDA: electrodermal activity; IBI: inter-beat interval

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Lag data for each physiological indicator after blood glucose data collection (15, 30, 45, 60, 75, 90, 105, and 120 min)

A graph and table illustrating the evolution of the correlation coefficients of the lag data for the mean values of glucose and physiological indices are shown in Supplementary Figure S2 and Table 4, respectively.

For HR, the correlation remained negative and peaked at the 45-min value of lag data (R = −0.147). For TEMP, the correlation remained positive, peaking at the 60-min value of lag data (R = 0.161). For EDA, the correlation remained negative, with a peak at 0 min (R = −0.161). For IBI, the correlation remained positive, peaking at the 120-min lag data value (R = 0.120).

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Table 4. Trends in correlations between blood glucose mean and the mean of lag data for each physiological indicator mean (lag data for physiological indicators since blood glucose data collection)

Mean Glucose lag	Mean ACC			Mean HR			Mean TEMP			Mean EDA			Mean BVP			Mean IBI		
	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*
0	9619	0.015	.15	9619	−0.143	**<.001**	9619	0.135	**<.001**	9189	**−0.161**	**<.0001**	9619	0.008	0.429	5629	0.049	**<.001**
15	9603	0.009	.39	9603	−0.133	**<.001**	9603	0.138	**<.001**	9173	−0.151	**<.0001**	9603	0.009	0.376	5622	0.053	**<.001**
30	9587	0.008	.46	9587	−0.140	**<.001**	9587	0.144	**<.001**	9157	−0.142	**<.0001**	9587	0.001	0.895	5617	0.061	**<.001**
45	9571	0.013	.22	9571	**−0.148**	**<.001**	9571	0.155	**<.001**	9141	−0.132	**<.0001**	9571	0.005	0.640	5609	0.066	**<.001**
60	9555	0.026	**.010**	9555	−0.139	**<.001**	9555	**0.161**	**<.001**	9125	−0.123	**<.0001**	9555	0.002	0.839	5601	0.073	**<.001**
75	9539	0.035	**.001**	9539	−0.124	**<.001**	9539	0.157	**<.001**	9109	−0.108	**<.0001**	9539	0.002	0.821	5593	0.083	**<.001**
90	9523	0.029	**.005**	9523	−0.120	**<.001**	9523	0.154	**<.001**	9093	−0.092	**<.0001**	9523	0.005	0.643	5588	0.098	**<.001**
105	9507	0.033	**.001**	9507	−0.122	**<.001**	9507	0.153	**<.001**	9077	−0.076	**<.0001**	9507	0.002	0.877	5579	0.106	**<.001**
120	9491	0.033	**.001**	9491	−0.121	**<.001**	9491	0.152	**<.001**	9061	−0.062	**<.0001**	9491	0.001	0.915	5573	**0.120**	**<.001**

N: number of data, R: correlation coefficient, P: p-value; ACC: acceleration; HR: heart rate; TEMP: skin temperature; BVP: blood volume pulse; EDA: electrodermal activity; IBI: inter-beat interval

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Correlation coefficients between blood glucose mean and SD of lag data for each physiological indicator

Lag data for each physiological indicator before blood glucose data collection (-120, 105, 90, 75, 60, -45, 30, and 15 min)

A graph and table illustrating the evolution of the correlation coefficients of the lag data of the mean blood glucose values and SDs of physiological indices are shown in Supplementary Figure S3 and Table 5, respectively.

Regarding the evolution of the correlation coefficient of lag data, which is the data at and after the time of blood glucose measurement, the correlation remained negative and peaked at the 15 min value of lag data (R = −0.190) for ACC. For HR, the correlation remained negative, peaking at the 15 min value of lag data (R = −0.121). For TEMP, the correlation remained negative, with a peak at the 0-min value (R = −0.121). For EDA, the correlation remained negative, peaking at the 15 min value of lag data (R = −0.237).

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Table 5. Trends in correlations between blood glucose mean and standard deviation of lag data for each physiological indicator (lag data for physiological indicators before blood glucose data collection)

Mean Glucose lag	SD ACC			SD HR			SD TEMP			SD EDA			SD BVP			SD IBI		
	N	R	*P*	N	R	*P*	N	R	P	N	R	*P*	N	R	P	N	R	*P*
−120	8824	−0.101	**<.001**	8824	−0.055	**<.001**	8824	−0.075	**<.001**	8401	−0.170	**<.001**	8824	−0.043	**<.001**	3370	−0.021	.23
−105	8839	−0.105	**<.001**	8839	−0.060	**<.001**	8839	−0.075	**<.001**	8415	−0.172	**<.001**	8839	−0.040	**<.001**	3374	−0.024	.16
−90	8854	−0.110	**<.001**	8854	−0.065	**<.001**	8854	−0.068	**<.001**	8429	−0.182	**<.001**	8854	−0.035	**<.001**	3379	−0.025	.14
−75	8869	−0.112	**<.001**	8869	−0.066	**<.001**	8869	−0.066	**<.001**	8443	−0.189	**<.001**	8869	−0.029	**<.001**	3383	−0.023	.19
−60	8884	−0.120	**<.001**	8884	−0.073	**<.001**	8884	−0.074	**<.001**	8457	−0.193	**<.001**	8884	−0.028	**<.001**	3390	−0.026	.13
−45	8899	−0.136	**<.001**	8899	−0.085	**<.001**	8899	−0.087	**<.001**	8471	−0.204	**<.001**	8899	−0.038	**<.001**	3396	−0.021	.23
−30	8914	−0.167	**<.001**	8914	−0.105	**<.001**	8914	−0.107	**<.001**	8485	−0.223	**<.001**	8914	−0.049	**<.001**	3403	−0.016	.35
−15	8929	**−0.190**	**<.001**	892	**−0.121**	**<.001**	8929	−0.120	**<.001**	8499	**−0.237**	**<.001**	8929	−0.054	**<.001**	3407	−0.024	.16

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				9														
0	8938	−0.185	**<.001**	893 8	−0.117	**<.001**	8938	**−0.121**	**<.001**	8507	−0.236	**<.001**	8938	−0.049	**<.001**	3409	−0.020	.24

N: number of data, R: correlation coefficient, P: p-value, SD: standard deviation; ACC: acceleration; HR: heart rate; TEMP: skin temperature; BVP: blood volume pulse; EDA: electrodermal activity; IBI: inter-beat interval

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Lag data for each physiological indicator after blood glucose data collection (15, 30, 45, 60, 75, 90, 105, and 120 min)

A graph and table illustrating the evolution of the correlation coefficients of lag data for the mean blood glucose values and SDs of physiological indices are shown in Supplementary Figure S4 and Table 6, respectively.

Regarding the evolution of the correlation coefficients of lag data, which are the data at and after the time when blood glucose was measured, the correlation remained negative and peaked at the 0-min value (R = −0.185) for ACC. For HR, the correlation remained negative, peaking at the 45-min lag data value (R = −0.127). For TEMP, the correlation remained negative, with a peak at 0 min value (R = −0.121). For EDA, the correlation remained negative, with a peak at the 0-min value (R = −0.236).

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Table 6. Trends in correlations between glucose mean and standard deviation of lag data for each physiological indicator (lag data for physiological indicators after glucose data collection)

Mean Glucose lag	**SD ACC**			**SD HR**			**SD TEMP**			**SD EDA**			**SD BVP**			**SD IBI**		
	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*
0	8938	**−0.185**	**<.001**	8938	−0.117	**<.001**	8938	**−0.121**	**<.001**	8507	**−0.236**	**<.001**	8938	−0.049	**<.001**	3409	−0.020	.24
15	8923	−0.170	**<.001**	8923	−0.111	**<.001**	8923	−0.117	**<.001**	8492	−0.229	**<.001**	8923	−0.049	**<.001**	3405	−0.025	.15
30	8908	−0.171	**<.001**	8908	−0.120	**<.001**	8908	−0.113	**<.001**	8477	−0.222	**<.001**	8908	−0.056	**<.001**	3403	−0.038	.03
45	8893	−0.182	**<.001**	8893	**−0.127**	**<.001**	8893	−0.119	**<.001**	8462	−0.213	**<.001**	8893	−0.061	**<.001**	3401	−0.035	.04
60	8878	−0.171	**<.001**	8878	−0.117	**<.001**	8878	−0.116	**<.001**	8447	−0.196	**<.001**	8878	−0.059	**<.001**	3401	−0.036	.04
75	8863	−0.158	**<.001**	8863	−0.108	**<.001**	8863	−0.107	**<.001**	8432	−0.177	**<.001**	8863	−0.053	**<.001**	3397	−0.030	.08
90	8848	−0.151	**<.001**	8848	−0.106	**<.001**	8848	−0.094	**<.001**	8417	−0.160	**<.001**	8848	−0.047	**<.001**	3393	−0.029	.09
105	8833	−0.141	**<.001**	8833	−0.104	**<.001**	8833	−0.084	**<.001**	8402	−0.144	**<.001**	8833	−0.043	**<.001**	3390	−0.036	.04
120	8818	−0.132	**<.001**	8818	−0.096	**<.001**	8818	−0.078	**<.001**	8387	−0.131	**<.001**	8818	−0.039	**<.001**	3386	−0.032	.06

N: number of data, R: correlation coefficient, P: p-value, SD: standard deviation; ACC: acceleration; HR: heart rate; TEMP: skin temperature BVP: blood volume pulse; EDA: electrodermal activity; IBI: inter-beat interval

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Correlation coefficients between SD of blood glucose and SD of lag data for each physiological indicator

Lag data for each physiological indicator before blood glucose data collection (120, 105, 90, 75, 60, 45, 30, and 15 min)

A graph and table illustrating the evolution of the correlation coefficients of lag data for the SD of blood glucose and physiological indices are shown in Supplementary Figure S5 and Table 7, respectively.

Regarding the evolution of the correlation coefficients for the lag data, which is the data at and after the time of glucose measurement, the correlation remained positive, with a peak at the 0-min value (R = 0.157) for ACC. For HR, the correlation remained positive, with a peak at the 0-min value (R = 0.142). For TEMP, the correlation remained positive, with a peak at the 0-min value (R = 0.127).

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Table 7. Trends in correlations between standard deviations of blood glucose values and standard deviations of lag data for each physiological indicator.

SD Glucose lag	SD ACC			SD HR			SD TEMP			SD EDA			SD BVP			SD IBI		
	N	R	P	N	R	P	N	R	P	N	R	P	N	R	P	N	R	P
−120	8818	0.112	**<.001**	8818	0.081	**<.001**	8818	0.038	**<.001**	8395	0.032	**<.001**	8818	−0.031	**.003**	3369	0.003	.88
−105	8833	0.140	**<.001**	8833	0.096	**<.001**	8833	0.049	**<.001**	8409	0.044	**<.001**	8833	−0.021	**.049**	3373	0.005	.76
−90	8848	0.137	**<.001**	8848	0.109	**<.001**	8848	0.067	**<.001**	8423	0.048	**<.001**	8848	−0.025	**.018**	3377	−0.019	.28
−75	8863	0.143	**<.001**	8863	0.101	**<.001**	8863	0.080	**<.001**	8437	0.039	**<.001**	8863	−0.008	.428	3382	−0.039	**.025**
−60	8878	0.152	**<.001**	8878	0.112	**<.001**	8878	0.089	**<.001**	8451	0.030	**.005**	8878	−0.012	.244	3387	−0.033	**.053**
−45	8893	0.149	**<.001**	8893	0.122	**<.001**	8893	0.103	**<.001**	8465	0.029	**.007**	8893	−0.012	.245	3393	−0.039	**.022**
−30	8908	0.150	**<.001**	8908	0.102	**<.001**	8908	0.087	**<.001**	8479	0.021	.06	8908	−0.023	.033	3400	−0.067	<**.001**
−15	8923	0.155	**<.001**	8923	0.132	**<.001**	8923	0.098	**<.001**	8493	0.013	.25	8923	−0.019	.068	3406	−0.039	**.023**
0	8938	**0.157**	**<.001**	8938	**0.142**	**<.001**	8938	**0.127**	**<.001**	8507	0.018	.10	8938	−0.017	.105	3409	−0.051	**.003**

N: number of data, R: correlation coefficient, P: p-value, SD: standard deviation; ACC: acceleration; HR: heart rate; TEMP: skin temperature; BVP: blood volume pulse; EDA: electrodermal activity; IBI: inter-beat interval

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Lag data for each physiological indicator after blood glucose data collection (15, 30, 45, 60, 75, 90, 105, and 120 min)

A graph and table illustrating the evolution of the correlation coefficients of the lag data for the SD of glucose and physiological indices are shown in Supplementary Figure S6 and Table 8, respectively.

For the transition of correlation coefficients for lag data, which is the data at and after the time of glucose measurement, the correlation remained positive and peaked at the 0-min value (R = 0.157) for ACC. For HR, the correlation remained positive, with a peak at the 0-min lag data (R = 0.142). For TEMP, the correlation remained negative, with a peak at the 0-min value (R = 0.127).

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Table 8. Trends in correlations between standard deviations of blood glucose values and standard deviations of lag data for each physiological indicator (lag data for physiological indicators before blood glucose data collection).

SD Glucose lag	SD ACC			SD HR			SD TEMP			SD EDA			SD BVP			SD IBI		
	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*	N	R	*P*
0	8938	**0.157**	**<.001**	8938	**0.142**	**<.001**	8938	**0.127**	**<.001**	8507	0.018	0.100	8938	−0.017	.105	3409	−0.051	**.003**
15	8923	0.132	**<.001**	8923	0.100	**<.001**	8923	0.094	**<.001**	8492	0.000	0.964	8923	−0.023	**.027**	3405	−0.074	**<.001**
30	8908	0.125	**<.001**	8908	0.107	**<.001**	8908	0.079	**<.001**	8477	0.011	0.316	8908	−0.034	**.001**	3403	−0.057	**<.001**
45	8893	0.126	**<.001**	8893	0.106	**<.001**	8893	0.085	**<.001**	8462	0.017	0.117	8893	−0.025	**.018**	3401	−0.066	**<.001**
60	8878	0.119	**<.001**	8878	0.101	**<.001**	8878	0.098	**<.001**	8447	0.001	0.899	8878	−0.019	.08	3401	−0.080	**<.001**
75	8863	0.088	**<.001**	8863	0.073	**<.000**	8863	0.068	**<.001**	8432	−0.010	0.348	8863	−0.031	**.003**	3397	−0.079	**<.001**
90	8848	0.086	**<.001**	8848	0.063	**<.001**	8848	0.058	**<.001**	8417	−0.013	0.221	8848	−0.023	**.032**	3393	−0.100	**<.001**
105	8833	0.066	**<.001**	8833	0.051	**<.001**	8833	0.051	**<.001**	8402	−0.001	0.941	8833	−0.021	.05	3390	−0.067	**<.001**
120	8818	0.057	**<.001**	8818	0.033	**<.002**	8818	0.034	**<.001**	8387	0.000	0.984	8818	−0.028	**.009**	3386	−0.069	**<.001**

N: number of data, R: correlation coefficient, P: p-value, SD: standard deviation; ACC: acceleration; HR: heart rate; TEMP: skin temperature; BVP: blood volume pulse; EDA: electrodermal activity; IBI: inter-beat interval

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Results of regression analysis between the slopes of the rise to the peak and the fall from the peak in glucose over time after a meal and each physiological index and nutrient value

Results of multiple regression analysis between the slope of the peak of blood glucose rise and the mean values of physiological and nutritional assessment indices

The results of multiple regression analysis between the slopes of the peak of elevated blood glucose and the mean values of physiological indices and nutritional assessment indices are shown in Tables 9 and 10.

The physiological index [TEMP (t-value: 2.52; *P*-value = .012)], and nutritional assessment indices [calorie (t-value: −3.98; *P*-value <.001), Carbon (t-value: 6.53; *P*-value <.001), dietary fiber (t-value: −2.51; *P*-value = .013) and protein (t-value: 3. 82, *P*-value = <.001)] suggest that the mean values of these nutritional measures were significantly associated with the slope of the peak blood glucose elevation

Table 9. Results of multiple regression analysis of the slope of the peak of elevated blood glucose and the mean values of physiological and nutritional assessment indices.

Term	Estimate	Std Error	t Ratio	*P*-value
Intercept	−0.475	0.495	−0.96	.34
Mean (TEMP)	0.038	0.015	2.52	**.012***
Mean (Calorie)	−0.001	0.000	−3.98	**<.001***
Mean (Carbon)	0.010	0.001	6.53	**<.001***

Mean (Dietary fiber)	−0.020	0.008	−2.51	<**.013***
Mean (Protein)	0.011	0.003	3.82	<**.001***

Table 10. Analysis of variance for the slopes of the peak of elevated blood glucose and the mean values of physiological indices and nutritional assessment indices

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	27.67	5.53	16.05
Error	457	157.53	0.34	F−value
C.Total	462	185.19		<**.001***

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Results of multiple regression analysis between the slope of the descending peak of blood glucose and the mean values of physiological and nutritional assessment indices

The results of multiple regression analysis between the slope of the blood glucose descending peak and the mean values of physiological and nutritional assessment indices are shown in Tables 11 and 12.

The physiological indices [ACC (t-value: 2.67; *P*-value =.008), HR_af (t-value:3.86; *P*-value <.001), and HR_90 (t-value: 2.27; *P*-value =.024), and nutritional assessment index [sugar (t-value: −3.72; *P*-value; <.001)] suggest that the mean values of these physiological and nutritional assessment measures were significantly associated with the slope of the descending peak of blood glucose.

Table 11. Results of multiple regression analysis between the slope of the descending peak of blood glucose and the mean values of physiological and nutritional assessment indices

Term	Estimate	Std Error	t Ratio	*P*-value
Intercept	−1.779	0.715	−2.49	**.013***
Mean (ACC)	0.029	0.011	2.67	**.008***
Mean (HR_af)	−0.010	0.002	−3.86	**<.001***
Mean (HR_60)	−0.005	0.003	−1.82	.07
Mean (HR_90)	0.006	0.003	2.27	**.024***
Mean (Calorie)	0.000	0.000	1.57	.12
Mean (Sugar)	−0.006	0.002	−3.72	**<.001***
Mean (Protein)	−0.003	0.002	−1.35	.18

Table 12. Analysis of variance for the slope of the blood glucose descending peak and the mean values of physiological and nutritional assessment indices

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	10.34	1.48	5.88
Error	365	91.62	0.25	F-value
C.Total	372	101.96		**<.001***

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Results of multiple regression analysis between the slope of the peak of blood glucose rise and SD of physiological and nutritional assessment indices

The results of multiple regression analysis between the slope of the peak of elevated blood glucose and the SD of physiological indices are shown in Tables 13 and 14.

The physiological indices [ACC (t-value: −2.06; *P*-value = .040), HR_30 (t-value: −2.12; *P*-value = .035), and EDA_90 (t-value: 1.97; *P*-value = .049) suggest that the SD of these physiological indicators was significantly associated with the slope of the peak glucose rise.

Table 13. Results of multiple regression analysis of the slope of the peak of elevated blood glucose and standard deviation of physiological indices.

Term	Estimate	Std Error	t Ratio	*P*-value
Intercept	1.114	0.072	15.50	**<.001***
Standard deviation (ACC)	−0.015	0.007	−2.06	**.040***
Standard deviation (HR_30)	−0.010	0.005	−2.12	**.035**
Standard deviation (TEMP_60)	−0.048	0.031	−1.58	.12
Standard deviation (EDA_90)	0.043	0.022	1.97	**.049***

Table 14. Analysis of variance the slope of the peak of elevated blood glucose and standard deviation of physiological indices

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	5.71	1.43	3.80
Error	413	154.94	0.38	F-value
C.Total	417	160.65		**.005***

Results of multiple regression analysis between the slope of the descending peak of blood glucose and SD of physiological and nutritional assessment indices

The results of multiple regression analysis between the slope of the blood glucose descending

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peak and SD of physiological and nutritional assessment indices are shown in Tables 15 and 16.

None of the physiological indices showed a significant association between the SD of the physiological index and the slope of the blood glucose elevation peak.

Table 15. Results of multiple regression analysis between the slope of the descending peak of blood glucose and standard deviation of physiological and nutritional assessment indices.

Term	Estimate	Std Error	t Ratio	*P*-value
Intercept	−0.673	0.050	−13.57	**<.001***
Standard deviation (EDA_af)	0.028	0.020	1.36	.17
Standard deviation (HR_60)	−0.005	0.004	−1.42	.16

Table 16. Analysis of variance for the slope of the descending peak of blood glucose and standard deviation of physiological and nutritional assessment indices

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	1.01	0.503	1.89
Error	377	100.62	0.267	F-value (Prob>F)
C.Total	379	101.63		0.1532

Results of the one-way ANOVA for the slopes of rise and fall in postprandial blood glucose levels and groups above and below each physiological indicator and the median dietary nutrient value

Results of one-way ANOVA of the slope of the elevated postprandial blood glucose and the combined pattern for groups above and below the median of the mean of each physiological index (TEMP, ACC, HR, and EDA)

The results of the one-way ANOVA of the combined pattern of elevated slope of blood glucose and the mean values of physiological indicators (TEMP, ACC, HR, and EDA) are

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shown in Supplementary Figure S7 and Tables 17 and 18.

The combination patterns of the group with a greater upward slope of blood glucose than the group with TEMP, ACC, HR and EDA values all below the median (TEMP: ACC: HR: EDA = 0000 mean value of upward slope 0.803) were TEMP: ACC: HR: EDA = 0101 (mean value of upward slope 1.110), 1000 (mean value of upward slope 1.140), 1011 (mean value of upward slope 1.048) and 1101 (mean value of upward slope 1.303), respectively, with a larger upward slope in the population with higher TEMP and EDA.
Combination patterns with slightly larger values were TEMP: ACC: HR: EDA = 0001 (mean value of upward slope 0.920), 0010 (mean value of upward slope 0.940), 0011 (mean value of upward slope 0.946), 0111 (mean value of upward slope 0.970), 1001 (mean value of upward slope 0.916), 1010 (mean value of upward slope 0.975), 1100 (mean value of upward slope 0.969) and 111 (mean value of upward slope 0.922) were also similar to the larger combination pattern groups.

Table 17. Relationship between the slope of blood glucose rise and combination patterns (TEMP, ACC, HR, and EDA)

Source	DF	Sum of Squares	Mean Square	F Ratio	*P*-value
TEMP □ ACC □ HR □ EDA	15	8.54	0.57	1.48	.11
Error	448	172.75	0.39		
C. Total	463	181.29			
TEMP □ ACC □ HR □ EDA	N	Mean	Std Error	Lower 95%	Upper 95%
0000	37	0.803	0.102	0.603	1.004
0001	25	0.920	0.124	0.676	1.164
0010	31	0.940	0.112	0.721	1.159
0011	19	0.946	0.142	0.666	1.226
0100	34	0.775	0.107	0.566	0.985
0101	14	1.110	0.166	0.784	1.436
0110	34	0.734	0.107	0.525	0.944
0111	41	0.971	0.097	0.780	1.161

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1000	35	1.140	0.105	0.934	1.347
1001	40	0.916	0.098	0.723	1.109
1010	15	0.975	0.160	0.660	1.290
1011	27	1.048	0.120	0.813	1.283
1100	24	0.969	0.127	0.720	1.218
1101	24	1.303	0.127	1.054	1.552
1110	23	0.876	0.129	0.621	1.130
1111	41	0.922	0.097	0.731	1.113

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Table 18. Summary of results

TEMP□ACC□HR□ EDA	N	Mean	Large or small
0000	37	0.803	Reference
0001	25	0.920	Slightly large
0010	31	0.940	Slightly large
0011	19	0.946	Slightly large
0111	41	0.971	Slightly large
1001	40	0.916	Slightly large
1010	15	0.975	Slightly large
1100	24	0.969	Slightly large
1111	41	0.922	Slightly large
0101	14	1.110	Large
1000	35	1.140	Large
1011	27	1.048	Large
1101	24	1.303	Large

Results of the one-way ANOVA of the combined pattern for groups with a downward slope of postprandial blood glucose and higher and lower than median values of each physiological index mean

The results of the one-way ANOVA of the combined pattern of the descending slope of blood glucose and mean physiological indices (TEMP, ACC, HR, and EDA) are shown in Supplementary Figure S8 and Tables 19 and 20.

The combination pattern with a greater downward slope of blood glucose compared with the group with TEMP, ACC, HR, and EDA all below the median (TEMP: ACC: HR: EDA = 0000, mean value of downward slope −0.663) was TEMP: ACC: HR: EDA = 1011 (mean value of downward slope = −1.045), with a greater downward slope in the population with higher TEMP, HR, and EDA.

Slightly larger combined patterns were TEMP: ACC: HR: EDA = 0111 (mean value of downward slope = −0.751), 1000 (mean value of downward slope = −0.752), 1010 (mean value of downward slope = −0.785), 1100 (mean value of downward slope −0.787) and 1110 (mean value of downward slope −0.713), with the pattern combining HR and ACC with TEMP and EDA having a higher downward slope.

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Table 19. Relationship between the downward slope of blood glucose and the combination pattern (TEMP, ACC, HR, EDA)

Source	DF	Sum of Squares	Mean Square	F Ratio	*P*-value
TEMP□ACC□HR□EDA	15	4.24	0.28	1.02	.43
Error	394	109.24	0.28		
C. Total	409	113.47			
TEMP□ACC□HR□ EDA	N	Mean	Std Error	Lower 95%	Upper 95%
0000	33	−0.663	0.092	−0.843	−0.483
0001	23	−0.635	0.110	−0.851	−0.419
0010	30	−0.672	0.096	−0.861	−0.483
0011	18	−0.627	0.124	−0.871	−0.383
0100	29	−0.707	0.098	−0.899	−0.515
0101	12	−0.695	0.152	−0.994	−0.396
0110	29	−0.588	0.098	−0.780	−0.396
0111	37	−0.751	0.087	−0.921	−0.580
1000	33	−0.752	0.092	−0.932	−0.572
1001	32	−0.689	0.093	−0.872	−0.506
1010	8	−0.785	0.186	−1.151	−0.419
1011	25	−1.045	0.105	−1.252	−0.838
1100	24	−0.787	0.107	−0.998	−0.575
1101	18	−0.588	0.124	−0.832	−0.344
1110	20	−0.713	0.118	−0.944	−0.481
1111	39	−0.678	0.084	−0.844	−0.512

Table 20. Summary of results

TEMP□ACC□HR□EDA	N	Mean	Large or small
0000	33	−0.663	Reference
0111	37	−0.751	Slightly large
1000	33	−0.752	Slightly large
1010	8	−0.785	Slightly large

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1100	24	−0.787	Slightly large
1110	20	−0.713	Slightly large
1011	25	−1.045	Large

Results of the one-way ANOVA of the slope of the postprandial rise in blood glucose and the combined pattern for groups above and below the median for each dietary nutrient value

The results of the one-way ANOVA of the combined pattern of the upward slope of blood glucose and dietary nutrient values (carbon, protein, calories, sugar, and fiber) are shown in Supplementary Figure S9 and Tables 21 and 22.

A slightly smaller upward slope of blood glucose was observed compared with the group where carbon, protein, calories, sugar, and fiber were all below the median (carbon: protein: calories: sugar: fiber = 00000; the mean value of upward slope 0.599), the combination pattern was carbon: protein: calorie: sugar: fiber = 01001 (mean value of the upward slope 0.506), which was a combination of protein and fiber.
The larger combination patterns were carbon: protein: calorie: sugar: fiber = 01010 (mean value of upward slope 1.296), 11110 (mean value of upward slope 1.389), and 10010 (mean value of upward slope 1.675), with high calories and sugar and the upward slope of the low fiber group was large.

Slightly larger combination patterns were observed for carbon: protein: calories; sugar: fiber = 00001 (mean value of upward slope 0.751), 00010 (mean value of upward slope 0.784), 01101 (mean value of upward slope 0.792), 00001 (mean value of upward slope 0. 793), 11101 (mean value of upward slope 1.019), 10111 (mean value of upward slope 1.084), 01011 (mean value of upward slope 1.084), 10110 (mean value of upward slope 1.132), 11100 (mean value of upward slope 1.168), 11111 (mean value of upward slope 1.172) and 10011 (mean value of the upward slope 1.181). Compared to the combination of carbon and sugar above the median, the combination of carbon and sugar above the median and fiber above the median had a smaller upward slope. [carbon: protein: calorie: sugar: fiber = 01010 (mean value of upward slope 1.296) and 01011 (mean value of upward slope 1.084)), 11110 (mean value of upward slope; 1.389) and 11111 (mean value of upward slope 1.172), 10010 (mean value of upward slope 1.675) and 10011 (mean value of upward slope 1.181)].

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Table 21. Relationship between the slope of the rise in blood glucose and dietary nutrient combination patterns (carbon, protein, calories, sugar, and fiber)

Source	DF	Sum of Squares	Mean Square	F Ratio	*P*-value
Carbon: Protein: Calorie: Sugar: Fiber	16	49.61	3.10	10.01	<.001*
Error	414	128.27	0.31		
C. Total	430	177.88			
Carbon: Protein: Calorie: Sugar: Fiber	N	Mean	Std Error	Lower 95%	Upper 95%
00000	91	0.599	0.058	0.484	0.714
00001	19	0.793	0.128	0.542	1.044
00010	26	0.784	0.109	0.569	0.998
01000	9	0.751	0.186	0.386	1.116
01001	17	0.506	0.135	0.241	0.771
01010	11	1.296	0.168	0.966	1.626
01011	6	1.084	0.227	0.638	1.531
01100	16	0.528	0.139	0.255	0.802
01101	21	0.792	0.121	0.554	1.031
10010	40	1.675	0.088	1.502	1.848
10011	6	1.181	0.227	0.734	1.627
10110	20	1.132	0.124	0.887	1.376
10111	10	1.084	0.176	0.738	1.430
11100	6	1.168	0.227	0.721	1.614
11101	38	1.019	0.090	0.841	1.196
11110	11	1.389	0.168	1.059	1.719
11111	84	1.172	0.061	1.052	1.291

Table 22. Summary of results

Carbon: Protein: Calorie: Sugar: Fiber	N	Mean	Large or small
00000	91	0.599	Reference
01001	17	0.506	Slightly small

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01000	9	0.751	Slightly large
00010	26	0.784	Slightly large
01101	21	0.792	Slightly large
00001	19	0.793	Slightly large
11101	38	1.019	Slightly large
10111	10	1.084	Slightly large
01011	6	1.084	Slightly large
10110	20	1.132	Slightly large
11100	6	1.168	Slightly large
11111	84	1.172	Slightly large
10011	6	1.181	Slightly large
01010	11	1.296	Large
11110	11	1.389	large
10010	40	1.675	large

Results of the one-way ANOVA of the downward slope of postprandial blood glucose and the combined pattern for groups above and below the median for each dietary nutrient

The results of a one-way ANOVA of the combined pattern of the downward slope of blood glucose and dietary nutrient values (carbon, protein, calories, sugar, and fiber) are shown in Supplementary Figure S10 and Tables 23 and 24.

The combination pattern of carbon: protein: calories: sugar: fiber = 01100 (mean value of the downward slope -0.408), which was a combination of protein and calories, showed a slightly smaller downward slope in blood glucose than the group where carbon, protein, calorie, sugar, and fiber were all below the median (carbon: protein: calories: sugar: fiber = 00000 mean value of the downward slope -0.525).

The larger combination patterns were carbon: protein: calories: sugar: fiber = 01010 (mean value of the downward slope -1.012), 10111 (mean value of the downward slope -0.978) and 10010 (mean value of the downward slope -1.028); and the slightly larger combination patterns were carbon: protein: calories: sugar: fiber = 01011 (mean value of downward slope −0.626), 11101 (mean value of downward slope −0.762), 11100 (mean value of downward slope −0.769) and 11110 (mean value of downward slope −0.783), 00010 (mean value of downward slope −0.793), 10110 (mean value of downward slope −0.826) and 10011 (mean

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value of downward slope −0.884), compared with those wherein the carbon and sugar were above the median. Compared to the combination of carbon and sugar higher than the median, the combination of carbon and sugar higher than the median and fiber or protein higher than the median had a smaller downward slope [carbon: protein: calorie: sugar: fiber =01010 (mean of downward slope -1.012) and 01011 (mean of upward slope -0.626), 10111 (mean of upward slope; -0.978) and 11111 (mean of upward slope -0.769), 10010 (mean value of upward slope; -1.028) and 10011 (mean value of upward slope; -0.884)].

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Table 23. Relationship between the downward slope of blood glucose and the combination pattern (carbon, protein, calories, sugar, and fiber)

Source	DF	Sum of Squares	Mean Square	F Ratio	*P*-value
Carbon: Protein: Calorie: Sugar: Fiber	16	11.03179	0.689487	2.6295	<.001*
Error	364	95.44425	0.262209		
C. Total	380	106.47604			
Carbon: Protein: Calorie: Sugar: Fiber	N	Mean	Std Error	Lower 95%	Upper 95%
00000	79	−0.525	0.058	−0.639	−0.412
00001	16	−0.577	0.128	−0.829	−0.325
00010	21	−0.793	0.112	−1.013	−0.574
01000	8	−0.526	0.181	−0.882	−0.170
01001	18	−0.616	0.121	−0.854	−0.379
01010	10	−1.012	0.162	−1.331	−0.694
01011	6	−0.626	0.209	−1.038	−0.215
01100	13	−0.408	0.142	−0.687	−0.128
01101	17	−0.575	0.124	−0.819	−0.331
10010	36	−1.028	0.085	−1.196	−0.860
10011	5	−0.884	0.229	−1.334	−0.434
10110	18	−0.826	0.121	−1.063	−0.588
10111	8	−0.978	0.181	−1.334	−0.622
11100	4	−0.769	0.256	−1.272	−0.265
11101	30	−0.762	0.093	−0.946	−0.578
11110	11	−0.783	0.154	−1.086	−0.479
11111	81	−0.769	0.057	−0.881	−0.657

Table 24. Summary of results

Carbon: Protein: Calorie: Sugar: Fiber	N	Mean	Large or small
00000	79	−0.525	Reference
01100	13	−0.408	Slightly small
01011	6	−0.626	Slightly large

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11101	30	−0.762	Slightly large
11100	4	−0.769	Slightly large
11111	81	−0.769	Slightly large
11110	11	−0.783	Slightly large
00010	21	−0.793	Slightly large
10110	18	−0.826	Slightly large
10011	5	−0.884	Slightly large
10111	8	−0.978	Large
01010	10	−1.012	Large
10010	36	−1.028	Large

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Discussion

Correlation analyses between the mean and SD of glucose and the mean of each physiological index

We reviewed the evolution of the correlation coefficients including lag data for glucose to examine whether the impact of each physiological indicator on glucose was influenced by physiological indicators before and after the time the glucose data were collected (Table 25).

Table 25. Summary of correlations between blood glucose and physiological indices

	Before blood glucose data collection	After blood glucose data collection
Correlation coefficients between mean values of blood glucose and mean values of physiological indices	• HR: negative correlation, peaking at -15 min of lag data (R= −0.147) • TEMP: positive correlation, peaking at 0 min (R= 0.135) • EDA: negative correlation, peaking at 15 min of lag data (R= −0.164)	• HR: negative correlation, peaking at 45 min of lag data (R= −0.147) • TEMP: positive correlation, peaking at 60 min of lag data (R= 0.161) • EDA: negative correlation, peaking at 0 min (R= −0.161) • IBI: positive correlation, peaking at 120 min of lag data (R= 0.120)
Correlation coefficients between mean values of blood glucose and standard deviations of physiological indices	• ACC: negative correlation, peaking at 15 min (R= -0.190) • HR: negative correlation, peaking at 15 min of lag data (R= -0.121) • TEMP: negative correlation, peaking at 0 min (R= −0.121) • EDA: negative correlation with EDA, peaking at 15 min of lag data (R= −0.237)	• ACC: negative correlation, peaking at 0 min (R= −0.185) • HR: negative correlation, peaking at 45 min of lag data (R= −0.127) • TEMP: negative correlation, peaking at 0 min of lag data (R= −0.121) • EDA: negative correlation, peaking at 0 min (R=

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		−0.236)
Correlation coefficients between standard deviation of blood glucose and standard deviation of physiological indices	ACC: positive correlation, peaking at 0 min (R=0.157) HR, Positive correlation, peaking at 0 min (R = 0.142) TEMP: positive correlation, peak at 0 min (R=0.127)	ACC: positive correlation, peaking at 0 min (R=0.157) HR: positive correlation, peaking at 0 min (R=0.142) TEMP: positive correlation, peak at 0 min (R=0.127)

ACC: acceleration; BVP: blood volume pulse; EDA: electrodermal activity; HR: heart rate; IBI: inter-beat interval; TEMP: skin temperature

The results showed that some indices such as ACC, TEMP, EDA, and IBI showed data correlations before and after the collection of blood glucose data. Activity, exercise, and stress are factors that influence blood glucose levels. Factors such as HR, body temperature, and autonomic nervous system function, including the sweating motor response, were associated with blood glucose variability [14]. The mean blood glucose and ACC SDs were negatively correlated; however, the uptake of blood glucose by mild to moderate physical activity is reported to cause decreased blood glucose levels and increased glucose production in the liver, leading to increased blood glucose [19]. This may be attributed to fluctuations in physical activity. The mean values of blood glucose and HR were negatively correlated; however, previous reports have indicated a negative relationship between blood glucose and HR variability, as sympathetic dominance increases with increasing blood glucose [20,21], which contradicts the previous results. This could be attributed to factors such as increase in HR due to fasting-related hypoglycemia [21] and mild-to-moderate physical activity [19].

Regarding the correlation between mean blood glucose and mean TEMP, intravenous administration of blood glucose increased heat production by 20%, accompanied by an increase in TEMP after 55 min, which was presumed to be caused by this effect [22]. Regarding the correlation between blood glucose and EDA, EDA can increase during stress and is mediated by stress-induced activation of adrenergic hormones and cortisol. This increases blood glucose production, and thus is positively related. Blood glucose levels increase in some individuals and decrease in others in response to stressful situations. Naturally occurring daily stressors may be associated with increased glycemic instability from hypoglycemia and decreased food intake, which may be due to these factors [23].

The mean blood glucose and SD of the physiological indices were negatively correlated.

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This is because the mean and SD of physiological indicators were calculated from the mean and SD of the three-time points at individual 5-min intervals, and the variation in physiological indicators was greater before and after the peak rise in glucose, whereas the variation in relevant physiological indicators was smaller at the peak of the rise in blood glucose. Meanwhile, the SD of blood glucose and physiological indicators were positively correlated, which was attributed to the increased variability in the SD of physiological indicators and blood glucose at times of blood glucose fluctuation (pre-peak and peak transition).

Slopes of the rise to the peak and fall after the peak in blood glucose over time after a meal and the results of the regression analysis of the mean and SD of each physiological index and nutrient value

To investigate the relationship between the slopes of the blood glucose rise and fall peaks and the mean values of physiological indices and nutritional assessment indices as well as the relationship between the slope of the blood glucose rise and fall peaks and the mean values of physiological indices, a multiple regression analysis was conducted. The summary of the results is shown in Table 26.

Table 26. Summary of the relationship between the slopes of the blood glucose rise and fall peaks and the mean values of physiological and nutritional assessment indices as well as the relationship between the slope of the blood glucose rise and fall peaks and the mean values of physiological indices

	Slope of peak blood glucose increase	Slope of blood peak glucose decrease
Results of multiple regression analysis between the slope of the glucose peak and the mean values of physiological indices and nutritional assessment indices	Physiological indices: TEMP (t Ratio: 2.52; *P*-value = .012) Nutritional assessment indices: calorie(t Ratio:−3.98; *P*-value <.001), carbon (t Ratio:6.53: *P*-value; <.001), dietary fiber (t Ratio:−2.51,*P*-value =.013), protein (t Ratio:3.82; *P*-value;	Physiological indices: ACC (t Ratio: 2.67; *P*-value= .008), HR_af (t Ratio: 3.86; *P*-value <.001), HR_90 (t Ratio:2.27; *P*-value; .024) Nutritional assessment index: sugar (t Ratio: −3.72; *P*-value <.001)

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	<.001)	
Results of multiple regression analysis between the slope of the glucose peak and the standard deviation of physiological indices	Physiological indices: ACC (t Ratio:−2.06: *P*-value =.040), HR_30 (t Ratio:−2.12; *P*-value =.034) EDA_90 (t Ratio:1.97; *P*-value = .049)	-

The physiological and nutritional assessment indices associated with the slope of the peak blood glucose increase were TEMP, calories, carbon, dietary fiber, protein, ACC, HR_30, and EDA_90. For TEMP, a positive association was observed; however, this was presumably due to the reported association between increased glucose and TEMP [22]. For carbon, a positive association was found, which was thought to be because carbohydrates contribute to the increase in blood glucose, although they are not absorbed as rapidly as glucose [24].

Although the upward slope of blood glucose and the calorie mean were negatively associated, the one-way ANOVA revealed a positive association, as did carbon. Therefore, this result may be due to the multicollinearity effect of simultaneously introducing carbon and calorie (R = 0.78, $P < .001$), which are strongly correlated with each other, as explanatory variables.

Dietary fiber intake is known to lower postprandial and average daily blood glucose levels [25]. Protein intake does not increase plasma glucose levels, but rather decreases; thus, protein intake with glucose suppresses the postprandial increase in glucose [26], which is the opposite of the expected result. This was inferred to be due to increased carbohydrate intake since total carbon and protein intake were positively correlated (R = 0.49, $P<.001$). A negative association was found for ACC and HR, which was presumed to be physical activity-related increased HR, accompanied by decreased blood glucose levels [19]. A positive relationship was found for EDA_90. EDA increases during stress, and is mediated by stress-induced activation of adrenergic hormones and cortisol, which increases gluconeogenesis [23].

The physiological and nutritional assessment indices associated with the slope of the descending glucose peak were ACC, sugar, HR_af, and HR_90; positive associations were found between the downward slope of blood glucose and ACC and HR mean values. The decrease in blood glucose is potentially due to increase from mild to moderate physical

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activity (HR also increased with physical activity), resulting in a smaller upward slope of blood glucose, and therefore creating a smaller downward slope [19]. Although a negative relationship was observed between the downward slope of blood glucose and sugar, similar with carbohydrates, sugar intake has been reported to increase blood glucose [27], and that the upward slope of blood glucose is greater when carbohydrate intake is higher, and therefore the downward slope is also greater.

One-way ANOVA for groups with higher and lower than median blood glucose rise and fall slopes and mean values of each physiological indicator and dietary nutrient value

As a supplementary analysis to the multiple regression analysis, a one-way ANOVA was performed to compare the relationship between the upward and downward slopes of blood glucose and the groups above and below the median for each indicator, using variables created by patterned group combinations by physiological indicator mean and dietary nutrient value. In addition, below-median groups were used as comparison controls. A summary of the results is presented in Table 27.

Table 27. Summary of results of ANOVA for groups with higher and lower than median blood glucose elevation and descent slopes and mean values of each physiological index and dietary nutrient values.

Results of one-way analysis of variance between blood glucose slope and mean values of physiological indicators and combined

□ Elevated slope of glucose — TEMP□ACC□HR□EDA

TEMP□ACC□HR□EDA	N	Mean	Large or small
0000	37	0.803	reference
0001	25	0.920	Slightly large
0010	31	0.940	Slightly large
0011	19	0.946	Slightly large
0111	41	0.971	Slightly large
1001	40	0.916	Slightly large
1010	15	0.975	Slightly large
1100	24	0.969	Slightly large
1111	41	0.922	Slightly large
0101	14	1.110	large
1000	35	1.140	large
1011	27	1.048	large
1101	24	1.303	large

□ Elevated slope of glucose — Carbon: Protein: Calorie: Sugar: Fiber

Carbon: Protein: Calories: Sugar: Fiber	N	Mean	Large or small
00000	91	0.599	reference
01001	17	0.506	Slightly small
01000	9	0.751	Slightly large
00010	26	0.784	Slightly large
01101	21	0.792	Slightly large
00001	19	0.793	Slightly large
11101	38	1.019	Slightly large
10111	10	1.084	Slightly large
01011	6	1.084	Slightly large
10110	20	1.132	Slightly large

The downward slope of glucose — TEMP□ACC□HR□EDA

TEMP□ACC□HR□EDA	N	Mean	Large or small
0000	33	−0.663	reference
0111	37	−0.751	Slightly large
1000	33	−0.752	Slightly large
1010	8	−0.785	Slightly large
1100	24	−0.787	Slightly large
1110	20	−0.713	Slightly large
1011	25	−1.045	large

The downward slope of glucose — Carbon: Protein: Calorie: Sugar: Fiber

Carbon: Protein: Calorie: Sugar: Fiber	N	Mean	Large or small
00000	79	−0.525	reference
01100	13	−0.408	Slightly small

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	Elevated slope of glucose				The downward slope of glucose			
patterns of nutritional assessment indicators					01011	6	−0.626	Slightly large
					11101	30	−0.762	Slightly large
					11100	4	−0.769	Slightly large
	11100	6	1.168	Slightly large	11111	81	−0.769	Slightly large
	11111	84	1.172	Slightly large	11110	11	−0.783	Slightly large
	10011	6	1.181	Slightly large	00010	21	−0.793	Slightly large
	01010	11	1.296	large	10110	18	−0.826	Slightly large
	11110	11	1.389	large	10011	5	−0.884	Slightly large
	10010	40	1.675	large	10111	8	−0.978	large
					01010	10	−1.012	large
					10010	36	−1.028	large

The results of the multiple regression analysis showed that the physiological indicators associated with the slope of rising and falling blood glucose were TEMP, ACC, HR, and EDA, whereas the nutritional indicators were carbon, protein, calories, sugar, and dietary fiber; therefore, these indicators were of interest.

The combination pattern of physiological indicators TEMP: ACC: HR: EDA, which included TEMP and EDA, showed that the upward and downward slopes of blood glucose were greater in the group above than in the group below the median. The effect on the upward slope of blood glucose was particularly large, similar to the results of multiple regression analysis. The combination pattern TEMP:ACC:HR: EDA = 1011, which had a large upward slope of blood glucose, was due to stress, with high EDA and HR. The combination patterns TEMP:ACC:HR: EDA = 1101 and 1111 also reported high glucose levels during and after moderate-intensity exercise [28] and high EDA due to exercise-induced sweating [29]. TEMP and EDA are strongly associated with autonomic nervous system function, which, in turn, is sensitive to glucose fluctuations, especially hyperglycemia. Therefore, we inferred that a high association exists between these indicators and the increase and fall in blood glucose slopes [30].

Conversely, for ACC and HR, the upward and downward slopes of blood glucose were slightly smaller in the group above than in the group below the median, accompanied by decreased blood glucose levels due to mild-to-moderate increases in physical activity [19] and physical activity-related increased HR similar to the results of the multiple regression analysis.

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In the combination pattern of the nutrient indices carbon: protein: calories: sugar: fiber, the combination pattern including carbon, calories, and sugar showed a greater upward and downward slope of blood glucose in the group above than in the group below the median.

Dietary fiber reduces postprandial and mean daily blood glucose levels [25]; however, a group pattern of combinations with a greater rise and fall slope in blood glucose levels exists, with fiber above the median. The rise and fall slopes were smaller than those for groups of combinations below the median, similar to the results of the multiple regression analysis.

Previous analyses

Two previous studies have used data from “BIG IDEA Lab’s Blood Glucose Variability and Wearable Device Data.” The first of the two reports demonstrate the feasibility of predicting blood glucose changes by continuously detecting individualized blood glucose deviations and determining the contribution of each variable to the interstitial glucose prediction. The LOPOCV random forest regression model was used to examine the importance of the characteristics, resulting in the extraction of “diet,” “circadian rhythm,” “stress,” “activity,” “body temperature,” “heart rate,” “skin electrical activity,” “biological sex,” and “HbA1c” [14].

The second study evaluated methods for detecting prediabetes and estimating HbA1c and glucose variability using digital biomarkers from wearables. The relationships between features extracted from wearables and blood glucose variability and HbA1c were investigated, and the results showed that glucose variability indices and HbA1c could be estimated with high accuracy. The HbA1c estimation model developed from a noninvasive wrist-worn wearable was as accurate as the invasive CGM-based American Diabetes Association estimated A1c. Notably, all the sensors used in this study (ACC, HR, SDA, and TEMP) were important for estimating glucose variability indices and HbA1c, although EDA and TEMP were the most important indicators when estimating HbA1c [30].

The results of the present study are consistent with these results, although the methods of analysis are different.

Other publicly available open datasets on diabetes are shown in Supplementary Table S1. Four studies were conducted using PhysioNet's D1NAMO Multimodal Dataset for Noninvasive Type 1 Diabetes Management Studies (2018) dataset. This dataset was collected

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to contribute to the development of data-centric algorithms and diabetes monitoring techniques by providing an openly available multimodal dataset. It was obtained from real patients in a nonclinical setting, containing electrocardiogram signals, respiratory signals, accelerometer output, blood glucose level information, and a set of annotated food photographs [31]. Studies conducted with this dataset include the following: a study that used machine learning to predict blood glucose in patients with type 1 diabetes [32]; one aimed at improving the accuracy of CGM systems [33]; an insulin absorption simulation study [34]; and a study for predicting diabetes [35], which is useful in several approaches.

This study had some limitations. First, because we used publicly available data, other data such as detailed patient background data (height, weight) collected during a clinical study but not made publicly available, were not included in the analysis. Second, Empatica, a wearable device, continuously collects a vast amount of data on physiological indicators, whereas the Dexcom G6, which measures glucose, collects data at 5-min intervals. For the analysis of the physiological indicator, data were extracted according to the glucose measurement interval, and data that were not extracted could not be considered. Third, because the data were from 16 participants, which is a small population, the calculation of correlation coefficients and multiple regression analysis were conducted; however, only exploratory studies were possible. Fourth, while data at the beginning of the meal were available for all cases, data at the end of the meal were only available for some cases. Therefore, in analyzing the relationship between the upward and downward slopes of postprandial glucose to the peak and the nutritional index of the meal, the nutritional index immediately before the peak was added together. Therefore, the effect of the length of mealtime may not have been considered

Conclusions

Existing data from clinical studies on wearable-type devices (Dexcom 6 CGM and Empatica) from PhysioNet, a public open data set, were used secondarily to examine the association of blood glucose with physiological and nutritional indices in 16 patients with borderline diabetes. The results showed that physiological indices associated with blood glucose were physical activity, HR, TEMP, and EDA, a stress indicator. In addition, physiological indices that were associated with the slope of the peak of the rise and fall of blood glucose were TEMP, physical activity, HR, and EDA. Nutritional measures associated with the slope of the peak rise and fall of blood glucose were carbohydrates, dietary fiber, and sugars. For the three analyses, the physiological measures associated with blood glucose were similar and consistent with previous reports.

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The use of the wearable-type device dataset allowed the examination of the relationship of blood glucose with physiological and nutritional indicators. Research using existing data is expected to increase in the future as open data sets of wearable device data become more readily accessible through data sharing, and as it becomes possible to perform statistical analysis from various angles using such data.

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Conflicts of Interest

None declared.

Ethical statement

An ethics statement is not applicable because this study is based exclusively on published literature.

Abbreviations

ACC: acceleration
ANOVA: analysis of variance
BVP: blood volume pulse
Carbon: carbohydrate
CGM: continuous glucose monitor
EDA: electrodermal activity
ECG: Electrocardiogram
Fat: total fat
HbA1c: glycated hemoglobin
HF: heart failure
HR: heart rate
IBI: inter-beat interval
IEEE: Institute of Electrical and Electronics Engineers
N: number of data
OWEAR: Open Wearables Initiative
P: p-value
PPG: photoelectric volumetric pulse wave
R: correlation coefficient
SCG: seismocardiogram
SD: standard deviation
TEMP: temperature

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Supplementary Files

Figures

Lag data before data collection time shift at eight time points(?120, ?105, ?90, ?75, ?60, ?45, ?30, and ?15 min).

Time-shifted as lag data in 15 minutes increments up to -120 minutes

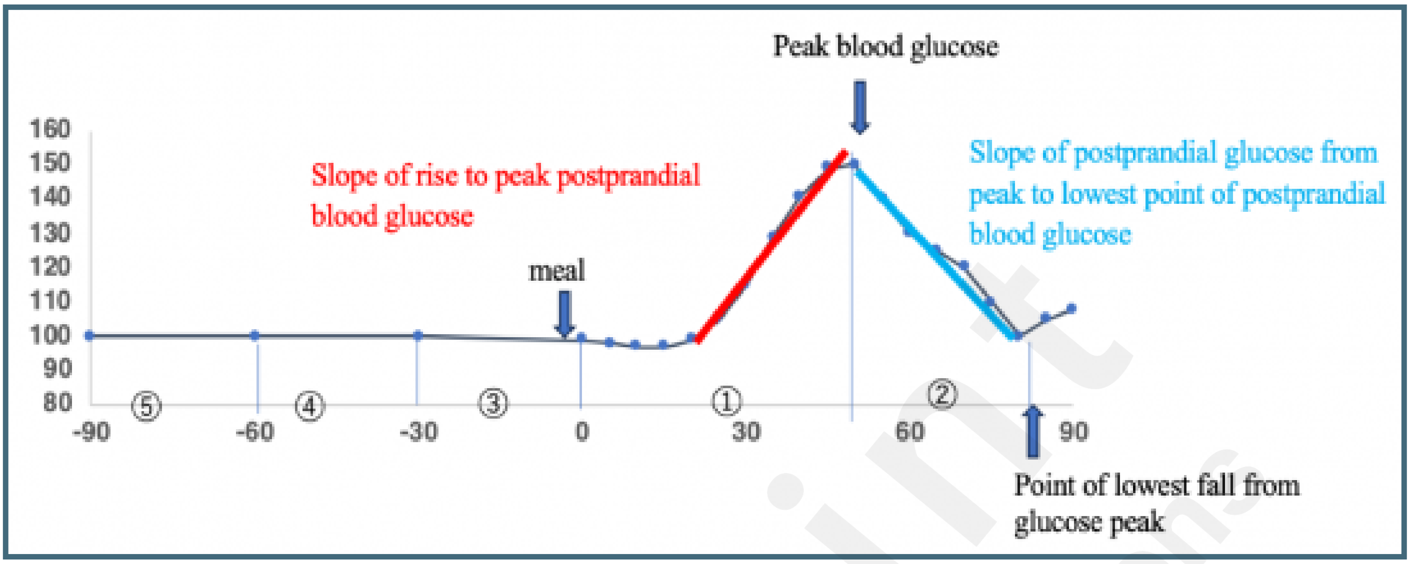
No	Time min	N_Rows	Mean_ Glucose_	Mean_ acc_	MEAN_ ACC_lag1	MEAN_ ACC_lag 2	MEAN_ ACC_la g3	MEAN_ ACC_lag 4	MEAN_ ACC_lag 5	MEAN_ ACC_lag6	MEAN_ ACC_lag7	MEAN_ ACC_lag8
				0	-15	-30	-45	-60	-75	-90	-105	-120
1	0	3	59.33	67.61								
2	15	3	63.00	61.86	67.61							
3	30	3.	63.33	60.47	61.86	67.61						
4	45	3	72.00	67.04	60.47	61.86	67.61					
5	60	3.	116.67	64.01	67.04	60.47	61.86	67.61				
6	75	3	138.33	62.70	64.01	67.04	60.47	61.86	67.61			
7	90	3	131.67	65.15	62.70	64.01	67.04	60.47	61.86	67.61		
8	105	3	114.33	68.29	65.15	62.70	64.01	67.04	60.47	61.86	67.61	
9	120	3	110.33	64.34	68.29	65.15	62.70	64.01	67.04	60.47	61.86	67.61
10	135	3	119.00	59.84	64.34	68.29	65.15	62.70	64.01	67.04	60.47	61.86
11.	150	3	123.33	62.82	59.84	64.34	68.29	65.15	62.70	64.01	67.04	60.47
12	165	3	120.00	60.81	62.82	59.84	64.34	68.29	65.15	62.70	64.01	67.04
13.	180	3	108.33	65.97	60.81	62.82	59.84	64.34	68.29	65.15	62.70	64.01
14	195	3	104.67	62.96	65.97	60.81	62.82	59.84	64.34	68.29	65.15	62.70
15	210	3	97.67	58.23	62.96	65.97	60.81	62.82	59.84	64.34	68.29	65.15

Lag data after data collection time shift at eight time points (120, 105, 90, 75, 60, 45, 30, and 15 min).

ID	No	Time	N_Rows	Mean_Glucose_	MEAN_GLU_lag1	MEAN_GLU_lag2	MEAN_GLU_lag3	MEAN_GLU_lag4	MEAN_GLU_lag5	MEAN_GLU_lag6	MEAN_GLU_lag7	MEAN_GLU_lag8	Mean_acc_
A001	1	0	3	59.33									67.61
A001	2	15	3	63.00	59.33								61.86
A001	3	30	3	63.33	63.00	59.33							60.47
A001	4	45	3	72.00	63.33	63.00	59.33						67.04
A001	5	60	3	116.67	72.00	63.33	63.00	59.33					64.01
A001	6	75	3	138.33	116.67	72.00	63.33	63.00	59.33				62.70
A001	7	90	3	131.67	138.33	116.67	72.00	63.33	63.00	59.33			65.15
A001	8	105	3	114.33	131.67	138.33	116.67	72.00	63.33	63.00	59.33		68.29
A001	9	120	3	110.33	114.33	131.67	138.33	116.67	72.00	63.33	63.00	59.33	64.34

Time-shifted as lag data in 15 minutes increments up to 120 minutes

Collection times for the objective (blood glucose slope) and explanatory (physiological indices) variables used in the multiple regression analysis.



Multimedia Appendixes

Supplementary_data.
URL: http://asset.jmir.pub/assets/f5df8cad1f09b495a00a4d535e08b397.docx