# “Map of Sugar”: wearable non-invasive glucose monitoring and community data sharing

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# “Map of Sugar”: wearable non-invasive glucose monitoring and community data sharing

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## *Abstract*

**Background:** Diabetes mellitus is a global chronic disease with severe health implications, including retinopathy, neuropathy, and organ failure. In China, the rising incidence of diabetes and low public health literacy exacerbate the challenges in disease management. Traditional blood glucose monitoring methods are often invasive, painful, and costly, leading to insufficient monitoring frequency. Wearable non-invasive glucose monitoring devices and smart diet management applications have emerged as potential solutions, but many lack real-time feedback and community-driven data sharing.

**Objective:** This study introduces the "Map of Sugar" system, a wearable non-invasive glucose monitoring and community data-sharing platform, to address these gaps. The system aims to provide real-time blood glucose monitoring, dietary management alerts, and a community-driven "sugar map" to visualize the glycemic impact of restaurant dishes.

**Methods:** The system comprises a wearable bracelet using polarized light technology for non-invasive glucose monitoring, a mobile application for data visualization and alerts, and an online community for data sharing. A pilot study involving 20 participants with mild type 2 diabetes mellitus (T2DM) was conducted to evaluate the system’s accuracy, usability, and impact on dietary management. Participants were divided into experimental and control groups, with the former using the “Map of Sugar” system for 10 days. Blood glucose measurements from the wearable device were compared with traditional needle-tip methods, and user feedback was collected via the System Usability Scale (SUS) and interviews.

**Results:** The polarized light monitoring system demonstrated high accuracy, with an average error of 0.137 mmol/L compared to traditional methods. The experimental group exhibited significantly fewer instances of abnormal blood glucose levels (hyperglycemia or hypoglycemia) than the control group. User feedback indicated high satisfaction, with an average SUS score of 4.5 out of 5, highlighting the system’s ease of use and effectiveness in dietary management. Community data sharing was particularly well-received, enabling users to make informed dietary choices.

**Conclusions:** The "Map of Sugar" system offers an innovative, non-invasive solution for real-time glucose monitoring and dietary management. Its integration of wearable technology, mobile applications, and community data sharing effectively reduces blood glucose abnormalities and enhances user engagement. Future work will focus on expanding data sources, optimizing system functionality, and conducting larger-scale clinical trials to validate its long-term efficacy.

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# “Map of Sugar”: wearable non-invasive glucose monitoring and community data sharing

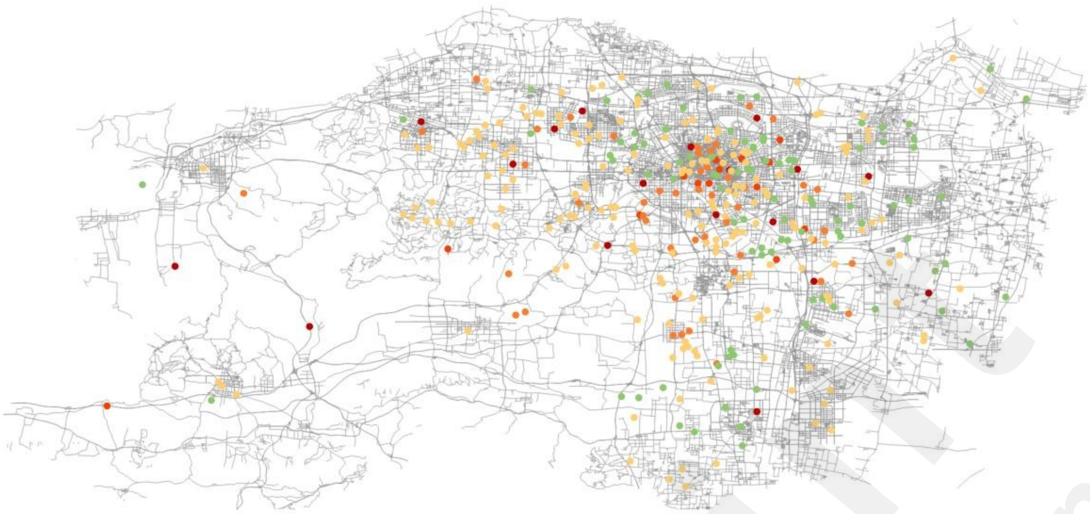

**Figure 1: The main interface diagram of Sugar's map system. The black lines of the map are the main urban streets of Zhengzhou City, and the origin of different colors is the visualization of the average blood glucose values after the restaurant users' meals, from dark red to green representing the postprandial blood glucose from the high to the bottom, where the dark red color represents the highest blood glucose, and the green color is the lowest.**


## Abstract

**Background:** Diabetes mellitus is a global chronic disease with severe health implications, including retinopathy, neuropathy, and organ failure. In China, the rising incidence of diabetes and low public health literacy exacerbate the challenges in disease management. Traditional blood glucose monitoring methods are often invasive, painful, and costly, leading to insufficient monitoring frequency. Wearable non-invasive glucose monitoring devices and smart diet management applications have emerged as potential solutions, but many lack real-time feedback and community-driven data sharing.

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**Conclusions:** The "Map of Sugar" system offers an innovative, non-invasive solution for real-time glucose monitoring and dietary management. Its integration of wearable technology, mobile applications, and community data sharing effectively reduces blood glucose abnormalities and enhances user engagement. Future work will focus on expanding data sources, optimizing system functionality, and conducting larger-scale clinical trials to validate its long-term efficacy.

Keywords: Non-invasive glucose monitoring, wearable devices, smart diet management, community data sharing, diabetes mellitus

# Introduction

## The Threat of Diabetes

Diabetes mellitus is a global chronic disease that poses serious health risks to the organism, including but not limited to: (1) blindness due to retinopathy caused by vasculopathy; (2) impaired urination caused by nerve damage; (3) ketoacidosis caused by metabolic disorders; and (4) organ failure such as foot ulcers [1].

In recent years, the incidence of diabetes mellitus in China has continued to rise [2], and there are about 140 million diabetic patients in China [2]. The rising incidence of diabetes is seriously jeopardizing the health of the Chinese public.

## Lack of Public Health Lliteracy

Data suggest that the Chinese public lacks adequate health literacy [3], which affects the behavior of diabetic patients in terms of proactive treatment, adherence to doctor's recommendations, and home rehabilitation management. The impact on diet and blood glucose management is particularly significant. Data suggest that

some groups do not begin treatment until the onset of diabetes or even at an advanced stage due to a lack of understanding of the concepts of "sugar" and "diabetes" [4], and during the treatment process they are unable to clearly identify the amount of sugar per unit of food and its possible impact on blood glucose [4].

Inadequate food intake often triggers the disease. Inappropriate food intake often leads to further deterioration of the disease [5].

## Lack of Public Health Lliteracy

As far as blood glucose monitoring is concerned, traditional methods of blood glucose monitoring have many inconveniences, such as pain, complexity of operation, and high cost, which leads to insufficient monitoring frequency for patients and affects the effectiveness of disease management [6]. For non-diabetic or pre- diabetic groups, the existing technologies and systems lack effective attraction in terms of leading them to take an active interest in their blood glucose status [8].

As far as smart diet management is concerned, there have been some studies focusing on the use of wearable devices and mobile apps to monitor and manage users' dietary health lacking real-time feedback of physiological data. For example, some apps provide personalized dietary advice by recording users' diet diaries and exercise [7]. However, most of these apps lack realtime blood glucose monitoring capabilities to accurately assess the immediate impact of food on users' blood glucose. There must be an inevitable error between the knowledge received by the user and the real blood glucose condition, while the purely intellectual transmission is not conducive to a deeper understanding by the user (especially for the low digital health literacy group) [9, 10].

## Solution Concept

The Sugar Map Smart Control APP introduced in this article is based on a non-invasive wearable blood glucose monitoring device using polarized light technology: the Sugar Map. The device is able to non-invasively, real-time and accurately monitor the user's blood glucose level, providing a scientific basis for dietary management. By sharing personal blood glucose data with the community, the APP builds a sugar map that helps users understand the impact of different restaurant dishes on their blood glucose, so they can make healthier dietary choices [11, 12].

## System Design

## Summarize

The system architecture of Sugar's Map consists of three main parts: a wearable bracelet, a mobile application and an online community. The wearable device is responsible for monitoring the user's blood glucose data in real-time and transmitting the data to the mobile app via Bluetooth. The mobile app processes and displays the data and allows users to upload the data to the online community. The online community is responsible for storing and managing all users' blood glucose data, building a map of sugar, and providing data query services.

## Functional Module

### *Real-Time Glucose Monitoring*

Sugar's map system utilizes the polarized light sensor built into the bracelet to monitor the user's blood glucose level in real time. When the user dines in a restaurant, the bracelet will automatically record the changes in blood glucose before and after the meal and synchronize the data to the APP, where the user can visualize the real-time curve of his/her blood glucose and understand the effect of different foods on blood glucose. The APP includes reminders for abnormal blood glucose. For example, when the blood glucose value is higher than 11.1mmol/L, the interface will change to dark red color, indicating that the user has not eaten properly, please stop eating immediately to observe the situation, and consult a doctor if necessary. When the blood glucose value is lower than 3.9mmol/L, the interface alert turns blue, suggesting that the user should supplement the food appropriately and give enough sugar.

### *Sugar's Map Construction*

After dining, users can select the restaurant where they dined and the dishes they ordered on the Sugar's Map APP, and upload the blood glucose data of this meal to the online community to share it with people around them. These data include the blood glucose value before and after the meal, the magnitude of blood glucose change, meal time and other information. Through the active participation of users, the online community will accumulate a large amount of restaurant blood glucose data, which will provide rich data support for the subsequent construction of the sugar map. As more and more users upload their data, the Sugar's

Map APP will utilize big data analysis technology to assess the blood glucose impact of each restaurant's dishes. By calculating the average magnitude of blood glucose increase of different dishes after dining, APP will generate a “Sugar Index” for each restaurant, which reflects the average impact of the restaurant's dishes on the user's blood glucose, and the higher the value, the greater the impact of the dishes on blood glucose. At the same time, the APP will display for the user the specific value of the blood glucose changes of all users under the name of the meal (all other information of the user from whom the data originated will be hidden automatically) [13].

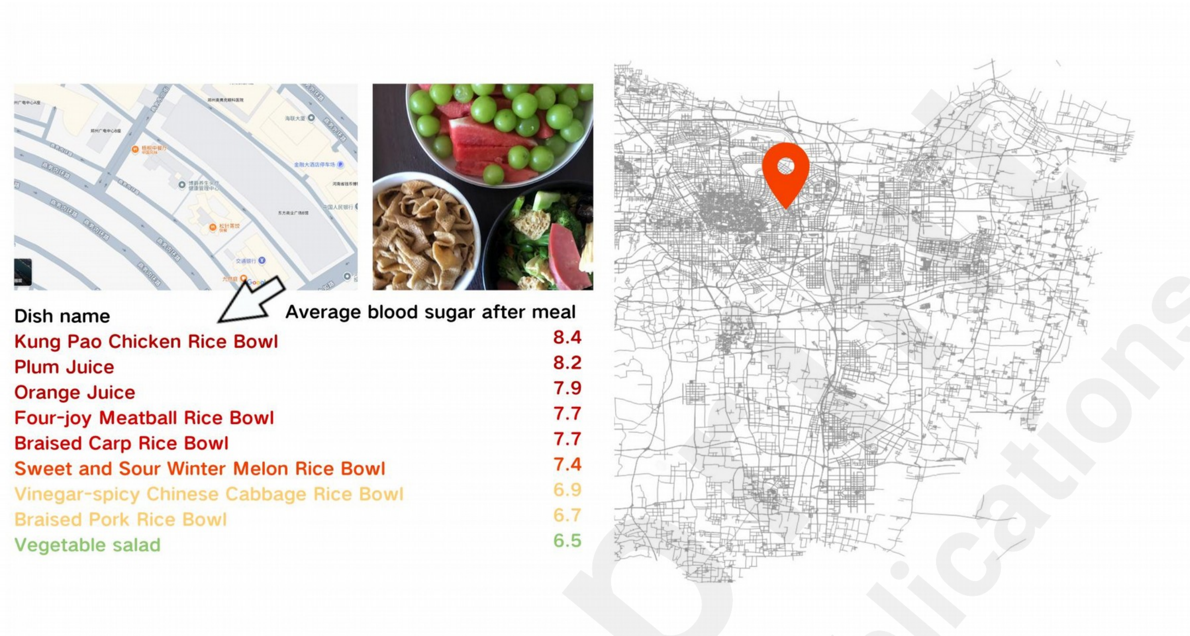


Figure 2:The map secondary interface of sugar. This figure shows the average value of blood glucose after dining for users of some meals in a restaurant in Zhengzhou.

### *Diet Management Alert*

New users can easily check the blood sugar information of any restaurant when using the Sugar Map Smart Control APP. On the map of the APP, users can see the distribution of the glycemic index of each restaurant and each dish. By clicking on a restaurant, you can view the detailed blood glucose data of the restaurant, including the rise in blood glucose of different dishes and the curve of blood glucose changes after the user has dined. This information will help users make more informed decisions when choosing restaurants and dishes, and avoid excessive blood glucose fluctuations due to improper diet. For old users, the system records their blood glucose defense curves after eating different dishes in different restaurants, reminding users of dietary management in the most intuitive way and giving advice on restaurant selection and meal choice.

## System Architecture

### *Wearable Device Layer*

The principle of the wearable bracelet using polarized light to detect blood glucose is as follows: when linearly polarized light passes through blood containing glucose, the plane of vibration of the polarized light is rotated by a certain angle. The angle of rotation and the glucose concentration satisfy the following relationship: A = [A]-C-l, where A represents the net optical rotation, [A] is the specific optical rotation of glucose (a constant), C represents the glucose concentration, and l is the depth of penetration of the light in the tissue.

For example, when the sensor monitors the sample information skin temperature T = 32°C, the measurement wavelength is 1650 nm, the optical range length is 0.5 dm, and the net optical rotation is 0.0474°, then we can substitute the formula [A]T = [A] 25°C + K (T-25), where 25°C glucose gets a specific rotation and the temperature coefficient K is a constant 52.7°- mL/dm/g, respectively. -0.014°-mL/dm/g/°C, so by substituting the value we can see that the specific optical rotation of glucose at 32°C is 52.602°-mL/dm/g, and by substituting the formula A = [A]-C-l we can get the concentration of glucose in the sample, C, equal to about 0.001802g/mL.

We used a non-invasive blood glucose monitoring bracelet based on polarized light technology, which has a built-in polarized light sensor to monitor the user's blood glucose level in real time. The sensor calculates the blood glucose concentration by emitting polarized light of a specific wavelength and detecting the change in the angle of rotation as the light travels through the tissue. The bracelet also features a Bluetooth communication module for transmitting the monitored blood glucose data to a mobile application. The specific hardware architecture data are as follows:(1) Optical system design. The main measurement wavelength is selected as the second near-infrared window of 1600-1750 nm, which has good skin penetration and can effectively detect glucose in interstitial fluid; meanwhile, a reference wavelength of 1300 nm is selected to compensate for skin moisture interference. In addition, the polarized optical path transmitter uses a vertically polarized VCSEL laser and a dynamic polarization modulator. The receiver end is equipped with a four-quadrant photodetector and Mueller matrix imaging module to detect depolarization effects for accurate polarized light signal measurement and processing. (2) Anti-interference design. We adopt a multimodal compensation strategy, including real-time calibration of the temperature sensor, pressure feedback module, and motion detection, and we use a 6-axis IMU to eliminate motion artifacts in order to minimize the influence of external factors on the monitoring results, and maximize the measurement accuracy and stability. (3) Mechanical structure. The wearable hardware adopts a bionic surface design to match the anatomical characteristics of Asian wrists to ensure a comfortable and snug fit [14].

## Mobile Application Layer

We use React Native cross- platform framework to realize the core function, and establish a low-power connection with the bracelet through Bluetooth 5.0 BLE protocol. The APP side receives data from the wearer in real time at 1Hz frequency through the GATT communication channel, which includes the raw optical data of several kinds of contacts: spin value, temperature, motion status, etc. The APP side receives data from the wearer in real time at 1Hz frequency through the GATT communication channel. After the mobile app receives the blood glucose data, the system first performs preliminary processing of the data, including data cleaning, outlier detection, etc., to ensure the accuracy and reliability of the data. Then the system uses Kalman filtering algorithm to reduce the noise of the original data, and calculates the instant blood glucose value through dynamic compensation model. A red alert interface is triggered when blood glucose >11.1mmol/L is detected and an emergency notification is pushed; a blue warning is displayed when blood glucose <3.9mmol/L, and sugar supplementation is recommended. Then according to the integration of the Gaode map API to realize the restaurant positioning, and the meal information uploaded by the user glyphs, the system application associates the processed data with the user's dining information and uploads it to the online community according to the preset data format. We receive the postprandial blood glucose data uploaded from the mobile terminal via a RESTful API, which contains the time stamp, restaurant ID, dish ID, blood glucose profile, and other online communities. After receiving the data, we further integrate and analyze the data, use machine learning algorithms to model the data, predict the degree of influence of different restaurant dishes on the user's blood glucose,

calculate the glycemic index (we use Spark-based real-time computation framework to aggregate the community data according to the formula GI = ∑
(ΔBG/t)/n, where ΔBG = Peak Blood Glucose - Pre-meal Blood Glucose, and t is the time interval), and update the map of sugar in real time (we use visualization in the form of D3.js to build dynamic blood glucose curve charts, and integrate Mapbox GL to achieve heat map rendering of the sugar index) [15]. The map takes the restaurant as the basic unit, and generates the restaurant's glycemic index by calculating the average degree of impact of all dishes in each restaurant on the user's blood glucose. At the same time, the map also displays information such as the specific value of each dish in terms of the rise in blood glucose after the user's meal, as well as the curve of blood glucose change after the user's meal. In the mobile application, the map of sugar is displayed to the user with an intuitive map interface. Users can view the distribution of the sugar index of restaurants in different regions by zooming, dragging and other operations. By clicking on a restaurant, detailed information about the restaurant can be viewed,
including the glycemic index, data on the glycemic impact of dishes, and the curve of glycemic changes after the user has dined. In addition, the application also provides a search function, which allows users to quickly find the blood glucose information of a specific restaurant or dish based on keywords such as restaurant name and dish name. Finally, we implement k- anonymization (k=10) and differential privacy processing to ensure user data desensitization [16].

### *User Interaction and Feedback*

The system of Sugar focuses on user interaction experience, providing a simple and clear operation interface and rich interaction functions. Users can easily view blood glucose data, upload dining information, check the map of Sugar, etc. in the application. At the same time, the application also has a user feedback module, users can give comments and suggestions on the system's functions, data accuracy, etc., to help us continuously optimize and improve the system.

## User Research

## Research Purpose

In order to protect the data security and health of our users, we conducted a small-scale basic evaluation to calibrate and optimize our system design prior to a full clinical wide-scale investigation of the system as follows: (1) Evaluate the accuracy of the system in monitoring blood glucose values (2) Evaluate the acceptance of the Sugar Map system by our users (3) Evaluate the impact of the Sugar Map on users' awareness of blood glucose management and behaviors.

## Experimental Design

### *Participants*

We recruited 20 patients with mild T2DM from online social media platforms (WeChat, Xiaohongshu, BILIBILI) to participate in this experiment, including 11 males and 9 females, with an age range of 25-56 years (MEAN=37.5, SD=10.34). All respondents were from the Zhengzhou area, which has a high prevalence of public diabetes.

## Procedure

1. T0 stage. All subjects filled out the basic T2DM knowledge questionnaire, and 20 subjects were assigned to the experimental group (10) and the control group (10) based on their scores, ensuring

that the mean scores of the two groups were essentially equal or similar. The questionnaire we used was the Diabetes Knowledge Test, DKT, from the University of Michigan, Ann Arbor, which is one of the authoritative questionnaires for monitoring diabetes knowledge [17].

2. T1 phase. Ten users in the experimental group measured blood glucose values from needle-tip blood collection and blood glucose values from polarized light system at ten different time points in a day, and recorded the data of both groups.

3. T2 phase. Both experimental and control groups wore 24h blood glucose monitoring probes. Ten users in the experimental group used Sugar's Map to assist in dietary management, and the control group had no intervention. It
lasted for 10 days.

## Data Analysis Methods

We used a combination of qualitative and quantitative methods. First, we ensured that in the initial state, the experimental group and the control group had baseline cognitive scores for diabetes that were basically the same, so as to minimize the interference of cognitive level differences in the experiment. Then we assessed the accuracy of the system in monitoring blood glucose by comparing and analyzing the needle glucose values and polarized light glucose values obtained in the T1 phase. Finally, we assessed the usefulness of the Sugar Map for users' dietary management by analyzing the time of blood glucose abnormality (more than 11.1 mmol/L or less than 3.9 mmol/L) in the experimental and control groups during the 10 days of the T2 phase. We invited users to complete the SUS scale [18]. In addition, as far as the qualitative study is concerned, we assessed users' acceptance of the APP by collecting their feedback on its functions, interface design, and ease of use through interviews [19].

## Ethical Approval

Ethical approval for this study was obtained from the (anonymized) University. All users participating in the study were informed about all research projects and experimental procedures and the purpose of the data. All data were kept strictly confidential and anonymized.

## Findings

We divided the users into two groups, the experimental group and the control group, based on the Diabetes Knowledge Test, DKT scale scores at stage T0. The average score of the users in the experimental group was 68.3, and that of the control group was 68.1, which was basically the same for both groups.

### *Accuracy of blood glucose measurement by polarized light*

The experimental data suggests that the polarized light system has high accuracy in measuring blood glucose, and the difference with the actual blood glucose value is between 0-0.49 mmol/L, details are shown in Table 1 below, and the average error is 0.137 mmol/L.

Table 1:Tip glucose values and polarized light glucose values measured at 10 time points by 10 users in the experimental group in $T^1$phase(tip measurements were recorded as N1,N2……N10,polarized light measurements are recorded as NI',N2……N10')

| ID | N1 | NI' | N2 | N2' | N3 | N3' | N4 | N4' | N5 | N5' | N6 | N6' | N7 | N7 | N8 | N8' | N9 | N9' | N10 | N10' |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 5.5 | 5.55 | 5.7 | 5.23 | 5.9 | 5.67 | 6.3 | 6.4 | 6.3 | 6.45 | 6.2 | 6.43 | 6.9 | 7.02 | 5.8 | 5.97 | 5.7 | 5.77 | 5.5 | 5.74 |
| 2 | 5. | 5.4 | 5. | 5.3 | 5. | 5.4 | 5. | 5.6 | 5. | 5.8 | 5. | 6.2 | 5. | 5. | 5. | 5.5 | 5. | 5. | 4. | 5.0 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 3 | 2 | 4 | 4 | 5 | 4 | 6 | 6 | 7 | 7 | 8 | 1 | 4 | 55 | 3 | 6 | 2 | 34 | 7 | 1 |
| 3 | 6.3 | 6.33 | 6.5 | 6.75 | 6.7 | 6.56 | 6.9 | 7.01 | 7.1 | 7.09 | 7.3 | 7.23 | 7.9 | 7.88 | 8.4 | 8.66 | 7.5 | 7.45 | 7.4 | 7.09 |
| 4 | 6.5 | 6.45 | 6.7 | 6.74 | 6.9 | 6.87 | 7.3 | 7.04 | 7.7 | 7.55 | 7 | 7.02 | 6.8 | 6.99 | 6.9 | 7.23 | 6.4 | 6.56 | 5.8 | 6.22 |
| 5 | 7.4 | 7.56 | 7.4 | 7.34 | 7.3 | 7.34 | 7.9 | 8.23 | 8.3 | 8.55 | 9.1 | 9.03 | 8.5 | 844 | 7.9 | 7.74 | 7.8 | 7.79 | 7.2 | 7.04 |
| 6 | 7.3 | 7.45 | 7.4 | 7.89 | 7.5 | 7.34 | 7.7 | 7.89 | 7.9 | 7.88 | 8.2 | 7.98 | 7.7 | 7.56 | 7.4 | 7.71 | 7.3 | 7.56 | 6.9 | 6.78 |
| 7 | 4.7 | 4.56 | 4.9 | 4.56 | 4.9 | 5.12 | 5.3 | 5.65 | 5.4 | 5.67 | 5.5 | 5.76 | 5.6 | 5.83 | 5.8 | 6.15 | 6.1 | 6.34 | 5.3 | 5.54 |
| 8 | 6.7 | 6.86 | 6.5 | 6.76 | 6.7 | 6.55 | 6.8 | 7.11 | 7.1 | 7.43 | 7.2 | 7.45 | 7.3 | 723 | 7.1 | 6.77 | 6.7 | 6.66 | 6.5 | 6.66 |
| 6 | 8.2 | 8.34 | 8.3 | 8.45 | 8.1 | 7.98 | 7.8 | 7.77 | 7.7 | 7.65 | 7.3 | 7.42 | 7.1 | 7.34 | 7.3 | 7.31 | 7.4 | 7.34 | 7.2 | 7.34 |
| 10 | 5.3 | 5.67 | 5.4 | 5.33 | 5.3 | 5.12 | 5.2 | 5.45 | 5.5 | 5.76 | 5.6 | 5.76 | 5.9 | 6.32 | 6.3 | 6.3 | 6.1 | 6.22 | 5.9 | 6.24 |

Table 2: Mean needle-tip blood glucose values and mean polarized light blood glucose values measured at 10 time points by 10 users in the experimental group in phase T1

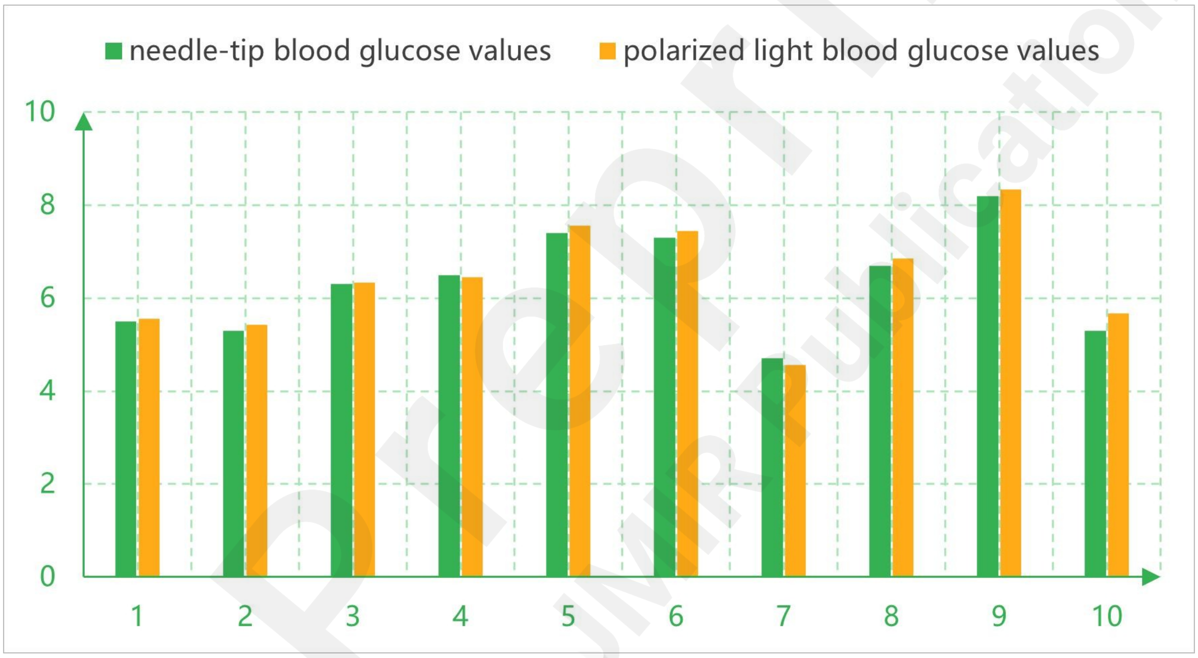


Table 3:Statistics on the time of blood glucose abnormality in the T2 stage for users in the experimental group (each line represents one user,the horizontal coordinate is the number of days in the experiment,and the vertical coordinate is the time of blood glucose abnormality)

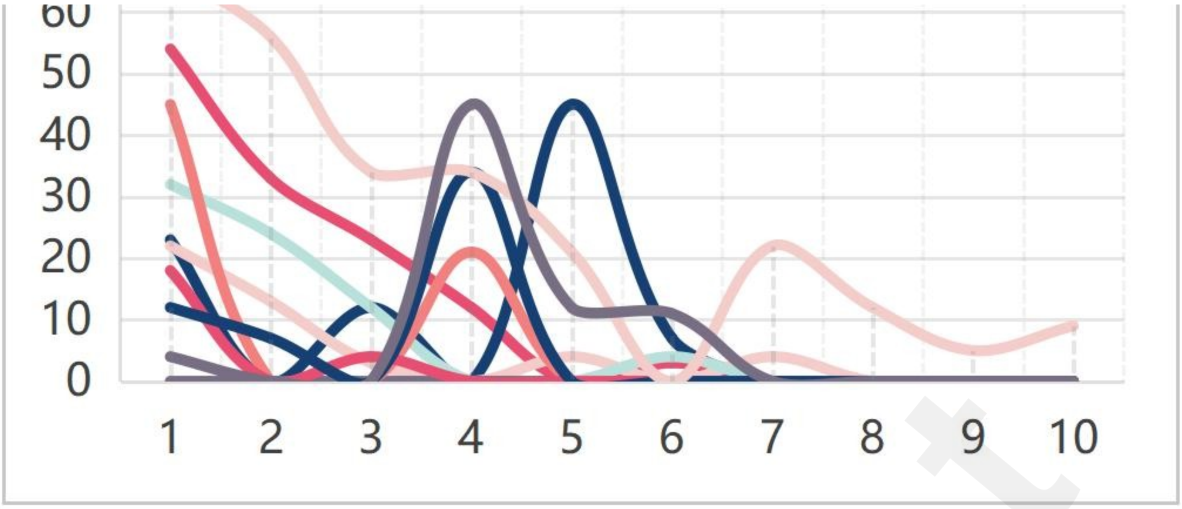


Table 4:Statistics on the time of blood glucose abnormality at T2 stage in control users(each line represents one user, horizontal coordinate is the number of days in the experiment, vertical coordinate is the time of blood glucose abnormality)

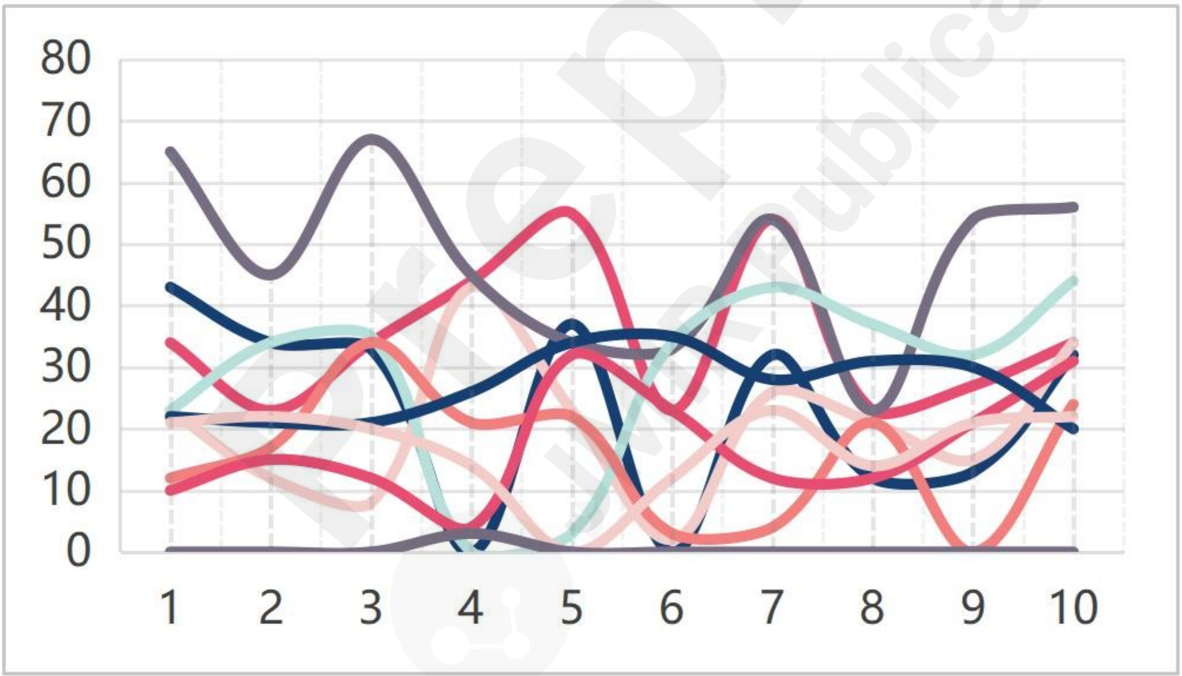


Table 5:SUS

| Title Number | Problem Statement | Average Rating |
|---|---|---|
| 1 | I think I'd like to use the Sugar Map system more often | 4.7 |
| 2 | I find the system overly complicated. | 1. 1 |
| 3 | I think this system is easy to use | 4.8 |

| | | |
|---|---|---|
| 4 | I need technical support to use this system | 1 |
| 5 | The functions in the system are well integrated | 4.5 |
| 6 | I found too many inconsistencies in the system | 1.3 |
| 7 | I can imagine most people would learn to use the system pretty quickly. | 5 |
| 8 | I find the system a pain in the ass to use | 1.2 |
| 9 | I feel confident using this system | 4.6 |
| 10 | I need to learn a lot about the operation before I can use it | 1 |

# Discussion

## Contributions

The data suggests that the system effectively and accurately measures the user's blood glucose, and on the basis of which it provides the user with warnings on blood glucose analysis and feeding management, effectively reducing the time of the user's blood glucose abnormality. Interview results show that the noninvasive monitoring method of the Sugar Map Smart Control APP significantly improves users' willingness to monitor blood glucose, and users generally consider the interface of the APP to be friendly and easy to operate. The community data sharing function was also welcomed by users, who indicated that by viewing other people's blood glucose data, they could better understand the impact of food on blood glucose and thus make healthier dietary choices. At the same time, users also put forward some suggestions for improvement, such as adding more restaurant menu data and optimizing the display of the glucose map.

## Limitations

The trial period was short, the number of trial participants was small, and the systematic clinical feasibility study has not yet been fully implemented. At the same time, users generally reflected that it is difficult to estimate the proportion of different dishes in cross-feeding (simultaneous intake of multiple dishes in a meal), which may lead to inaccurate estimation of glycemic glucose after individual dishes, which needs to be further optimized in order to be accurate.

# Conclusions

As a smart diet management application based on non-invasive wearable devices, Sugar Map Smart Control APP provides users with a brand-new diet management experience through real-time blood glucose monitoring, recording of meal data, and construction of sugar maps. User studies show that the APP can effectively reduce the rate of blood glucose abnormalities and help users make healthier dietary choices, which has a broad application prospect. In the future, we will further optimize the system functions, expand the data sources, improve the user experience, and promote the development of intelligent diet management technology.

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