Supporting Self-Management in Women with Gestational Diabetes: The Effect of eMOM Mobile Application on Self-Discovery and Psychological Factors – A Mixed-Methods Study

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Abstract

Background: Gestational diabetes (GDM) is a type of diabetes that develops during pregnancy and predisposes a mother to the later type 2 diabetes. The prevalence of GDM increases, that underscores the need to adopt more comprehensive treatment strategies, especially supporting maternal self-management. We showed recently that a mobile app (eMOM) where glucose, nutrition, and physical activity are combined within a single app improves significantly multiple clinical outcomes among women with gestational diabetes.

Objective: This study aims to explore the effects of the eMOM on maternal self-discovery, learning, autonomous motivation to manage GDM, and psychological well-being. We also examined the correlation between improved maternal clinical outcomes and change in autonomous motivation.

Methods: Building upon the original randomized controlled trial (RCT), in which the intervention arm used a mobile app (eMOM), we conducted a mixed-methods study which included semi-structured interviews on self-discovery, examination of eMOM log files, and questionnaires assessing motivation (TSRQ and PCS), technology usage and acceptance (UTAUT), usability (modified SUMI), and depression (EPDS). Additionally, we monitored participants' stress levels using wearable EKG devices (FirstBeat Bodyguard 2).

Results: A total of 148 women participated in the RCT study, with 76 in the intervention arm and 72 in the control arm. From the intervention arm, 18 participants were randomly selected for interviews. Results show that novel visualization supported self-discovery in women with GDM. The vast majority of participants (94%, 17 out of 18) indicated that the eMOM app helped to find the correlations between their daily activities and glucose levels. Especially having nutrition visualized together with glucose was highly appreciated. Participants also reported learning about the associations between physical activity and glucose levels. However, there weren´t any differences between intervention and control arm in autonomous motivation, depression, or stress. In addition, there were no correlations between improved clinical outcomes and changes in motivation.

Conclusions: The mobile application combining data from continuous glucose monitoring, food diary, and physical activity tracker supports maternal self-discovery regarding GDM. This encourages the utilization of such a mobile app into maternity care. Clinical Trial: ClinicalTrials.gov NCT04714762

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SH: Conceptualized the eMOM application, funding acquisition, planned the design of the study, review & editing
MK: Conceptualized the eMOM application, planned the design of the study, planned the analysis of the data, analyzed the data, wrote the original draft with SM & SK & HY, review & editing

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Keywords: self-discovery; self-management; motivation; self-determination theory; self-tracking; gestational diabetes; mobile application;

Introduction

Gestational diabetes (GDM) is an increasing issue in maternal health care as it affects approximately 14% of pregnant women globally [1]. GDM increases mother´s risk of developing type 2 diabetes and cardiovascular diseases [2,3], and also predisposes the child to adulthood obesity and type 2 diabetes [4].

In order to respond to increasing demand for treatment, digital health is a topic of growing interest, as it provides innovative approaches to support clinical management of various conditions. Mobile phone apps and wearable devices provide an opportunity to continuous tracking of numerous parameters for self-management of non-communicable diseases. Diabetes apps have been shown to improve patient self-management in type 1 and 2 diabetes [5–7], while also being cost-effective [8]. Recent studies have provided promising findings on telemedicine in the management of GDM [9–12], but the effective interventions have involved significant effort from healthcare professionals regularly, which is not an optimal use of digital tools. To tackle this and to support self-management in women with GDM, we developed an easy-to-use eMOM app that differs from the prior diabetes mobile applications in several aspects. First, it visualizes data from continuous glucose monitor, physical activity sensor, and digital food diary in real-time within the same app [13]. Second, the idea of eMOM is to teach a patient how their own lifestyle choices affect their glucose levels without extra help from healthcare personnel. Third, eMOM is used periodically, one week a month, to avoid getting tired of digital device. The recent results of our randomized controlled trial (RCT) demonstrated that the women with GDM and using eMOM improved their fasting glucose levels, enhanced physical activity, increased vegetables intake, and resulted in less weight gain during pregnancy [14]. Additionally, the incidence of newborns with macrosomia was lower among the women using eMOM [14]. Many of these improved clinical outcomes correlated with the usage of eMOM, suggesting that eMOM supported self-management of women with GDM.

The aim of this study is to continue from the RCT study and to evaluate the possible underlying maternal learning processes, i.e. self-discovery, and motivational factors that contributed to the observed improved clinical findings. Additionally, we examined the influence of autonomous motivation on the enhanced clinical outcomes observed in our original RCT study.

Materials and methods

Design

This study is a secondary analysis of eMOM GDM randomized controlled trial [13] where intervention arm used eMOM application with continuous glucose meter (CGM) and activity bracelet for one week per month and a digital food diary for 3 days of this week (referred as application week later in this article), from gestational weeks 24-28 to delivery. The eMOM GDM study was conducted between 02/2021 and 12/2022 in Helsinki, Finland. Patients were recruited from antenatal clinics in Helsinki metropolitan area by research nurses. Inclusion and exclusion criteria of participants are presented in Table 1. All participants gave written consent and were informed they were allowed to withdraw at any point. This study was approved by the Ethics Committee of the Helsinki University Hospital.

Table 1. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria

Age 18 to 45 years	Type 1 or type 2 diabetes
GDM[a] diagnosis at GW[b] 24-28	Use of medication that influences glucose metabolism (such as continuous therapy with oral corticosteroids or metformin)
	Multiple pregnancy
	Physical disability
	Current substance abuse
	Severe psychiatric disorder (that complicates participation to the study)
	significant difficulty in cooperating (e.g., inadequate Finnish language skills)

[a]GDM = gestational diabetes
[b]GW = gestational week

Participants were randomized 1:1 into intervention and control arm. The intervention arm received standard clinical antenatal care in addition to the eMOM app, while the control arm received only standard clinical care. Standard clinical care consisted of periodic visits with a nurse and a doctor in municipal maternal clinics, as offered for all pregnant women in Finland. A regular care protocol for low-risk pregnancies includes 9-10 visits with a nurse and two visits with a doctor. After being diagnosed with GDM, women receive guidance on diet, physical activity, and self-monitoring of blood glucose with electronic capillary glucose meters. [15]

eMOM application

The eMOM mobile app was developed to visually represent data from tissue continuous glucose meter (Medtronic Guardian connect with Enlite Sensor) and activity bracelet (Garmin Vivosmart 3) together with a digital food diary. The information from the sensors and food tracker is updated every 10 min to eMOM. In our previous study [16] physical activity was measured with three different devices (activity bracelet, hip-worn sensor and electrocardiography sensor). Most participants preferred the bracelet to hip sensor, so it was selected as an activity measurement tool for this study. Screenshots from the eMOM app are presented in Figure 1. For displaying the data, the eMOM GDM app has two main views, day view (see Figure 1A and 1D) and a week view (see Figure 1E). Nutrition intake from each energy yielding nutrient is visualized as stacked bars (see Figure 1A). More detailed information (recorded food items, nutrient intake in grams) can be accessed (see Figure 1B) by tapping the stacked bar (see Figure 1A). The eMOM GDM app shows detailed glucose values (see figure 1C) when tapping the glucose curve on the screen (see Figure 1A and Figure 1D).

Figure 1: Screenshots (A to E) from the eMOM (Copyright: Fujitsu Finland). A) Day view with nutrition and glucose filters selected, B) Detailed nutrition view, C) Detailed glucose view, D) Day view with physical activity (steps), and E) Week view with glucose and physical activity (minutes) selected. The following outcomes were visible to the user through the eMOM: 1. CGM glucose time in range (3.9-7.8 mmol/l) 2, Postprandial increase of continuous glucose in 2-hour –mmol/l, 3. Energy intake – kJ/day, 4. Intake of carbohydrate – g/day, 5. Intake of total fat – g/day, 6. Intake of saturated fat – g/day, 7. Intake of fiber – g/day, 8. Intake of protein – g/day, 9. Intake of sucrose – g/day, 10. Number of walking steps – steps/day, 11. Duration of physical activity – min/day.

Questionnaires and Interviews

Background questionnaire covered experience with self-tracking at baseline (gestational weeks 24-28). Other background information, such as age, BMI, parity and previous GDM status were collected from hospital registries.

Maternal learning and self-discovery were assessed through interviews conducted with randomly selected participants from the intervention arm. These interviews took place after participants had been using the app for approximately two months. Interviews were semi-structured and carried out remotely. They lasted from 30 to 56 minutes; mean duration was 40 minutes. Main interview questions are presented in Textbox 1.

Textbox 1. Main interview questions.

- Have you learned something while using the eMOM app? If yes, what?
- Has the eMOM helped you to make changes in your lifestyle? If yes, how?
- What features of the eMOM were most useful for you?
- How would you develop the app?

To assess maternal motivation, we used Treatment Self-Regulation Questionnaire (TSRQ) and Perceived Competence for Diabetes Scale (PCDS) [17] at baseline (gestational weeks 24-28) and at gestational weeks 35-37. TSRQ measures autonomous motivation versus controlled motivation. PCS measures feelings of competence.

The maternal depression was measured with Edinburgh Depression Postnatal Depression Scale [18] at baseline (gestational weeks 24-28) and at gestational weeks 35-37.

The acceptance of eMOM was measured with Unified Theory of Acceptance and Use of Technology (UTAUT)-questionnaire [19] after each application week (once a month), and Usability of eMOM was measured once, four weeks after taking the app into use with a questionnaire adapted from SUMI-questionnaire [20].

The timeline of the study is summarized in Table 2.

Interactions with eMOM

The interactions with eMOM were collected to log files to determine how the participants used eMOM during the study. Each row in the log file included pseudonymized user ID, timestamp, used view (day view, week view, detailed nutrition view, detailed glucose view, or info view,) and filter used in day view (glucose, nutrition, physical activity) or in week view (glucose, nutrition, physical activity, weight, and sleep).

Stress measurement

The Firstbeat Bodyguard 2, a chest-mounted sensor by Firstbeat Technologies in Jyväskylä, Finland, tracks heart rate variability (HRV) and physical activity using 3D acceleration over a continuous three-day period. It uses two clinical-grade ECG electrodes for attachment and boasts a high accuracy in HRV measurement, with less than 3 ms error and over 99.9% detection accuracy compared to standard ECGs [21]. Additionally, Firstbeat's Lifestyle Assessment software analyzes the HRV and motion data to evaluate stress and recovery levels, a methodology supported by extensive research validation [22,23].

Table 2. Timeline of the study measurements for intervention and control arms.

	Baseline GW 24-28	III trim GW 35-37
Measurements for intervention and control arm:		
Background questionnaires	x	
Questionnaires[a]	x	x
Heart rate variability	x[c]	x[c]

(Firstbeat Bodyguard 2)		
Measurements only for intervention arm:		
Data from sensors and apps: the eMOM GDM app, Garmin Vivosmart, Medtronic CGM, food tracker	One application week following 3 normal care weeks until delivery	
Semi-structured interview		x
Acceptance questionnaire (UTAUT)	x[b]	x[b]
Usability questionnaire (modified SUMI)	x[c]	

[a]Questionnaires: EPDS, TSRQ, PCDS
[b]Once a month, after each application week
[c]Four weeks after enrollment
[c]Firstbeat sensor was worn continuously for three days

Analysis

The interviews underwent transcription, and two researchers familiarized themselves with the content by reviewing the transcripts. The subsequent analysis followed the framework method, a recommended approach for multidisciplinary health research [24]. We used combination of deductive and inductive approaches, where we had a set of initial codes (self-tracking of glucose, self-tracking of nutrition, and self-tracking of physical activity) in the beginning of the coding and employed new codes when emerged from the gathered data. These codes were then combined into broader categories. Quotes featured in the results were translated into English using an intelligent verbatim technique, which involves the removal of filler words like “er” during the translation process.

The log files were examined by computing the frequency and timing of Interactions with the eMOM platform. Finally, we employed triangulation across these various data sources (interviews, questionnaires and log files, from eMOM) to gain a comprehensive understanding of how self-tracking with eMOM facilitated supported self-discovery.

For comparing the difference between the arms, we performed a two-sided t-test for continuous outcomes, setting the significance threshold at 5%. For binary outcomes, we applied a Chi-square test, resorting to Fisher’s exact test when expected frequencies fell below 10. The difference between application weeks in the acceptance of eMOM was evaluated using repeated-measures ANOVA.

In analyzing correlation between motivation and primary outcome from Kytö, et al. [14], we examined the linear relationship (Pearson correlation). For the binary outcomes, we employed logistic regression.

Results

Participants

In total, 148 women with GDM participated in the study. Out of 76 women in the intervention arm who used eMOM app, 63 women continued until delivery. The main reason for drop-out was the need to start GDM medication. In total, 18 participants from the intervention arm were randomly selected for user experience interviews for this study. The log files were collected from all the participants in the intervention arm. Baseline characteristics are presented in Table 3. Participants were familiar with using mobile apps and activity trackers and had a good conception on the significance on different nutrients for the diet, as shown in Table 3. No significant differences were observed between the arms at the baseline.

Table 3. Background characteristics. Regarding the statements, the Likert-scale was from 1 (=Strongly disagree) to 5 (= Strongly agree), and the responses are shown as mean values ± SD. The scale for TSRQ and PCS was from 1 (=low) to 7 (=high).

	Interviews (N = 18)	Invervention arm (N=76)	Control arm (N=72)	Difference between Intervention and Control arm, p-value
Mean Age ± SD	32.8 ± 3.7	34.2 ± 4.1	34.0 ± 3.9	0.2, *P*=.80

Mean BMI ± SD	27.5 ± 5.1	27.5 ± 5.5	26.7 ± 4.5	0.8, *P*=.34
Parity – Primiparous - % (No).	56% (10)	50% (38)	51% (37)	-1.4 *P*=.93
Early GDM – % (No).	38% (7)	49% (37)	49% (35)	0.0, *P*>.99
GDM Status (previous GDM) – % (No).	11% (2)	22% (17/76)	25% (18/71)	-3.1, *P*=.82
Mean GW at enrolment – Weeks ± SD	27.0 ± 1.8	26.5 ± 1.7	26.3 ± 1.7	0.2, *P*=.95
Weeks in the study at the interview – Weeks ± SD	9.3 ± 2.6	Not applicable.	Not applicable.	Not applicable.
"I am used to use mobile apps."	4.8 ± 0.4 (N=13)	4.8 ± 0.6 (N=64)	4.6 ± 1.1 (N=63)	0.2, *P*=.21
"I am used to use activity trackers (like Fitbit and Polar)"	4.3 ± 1.2 (N=13)	3.8 ± 1.5 (N=64)	3.8 ± 1.5 (N=63)	0.0, *P*=.99
"I am familiar with measuring my blood glucose"	3.2 ± 1.4 (N=13)	3.8 ± 1.4 (N=64)	4.2 ± 1.2 (N=63)	-0.4, *P*=.08
"I am familiar with keeping a food diary"	4.1 ± 1.0 (N=13)	3.6 ± 1.3 (N=64)	3.8 ± 1.2 (N=63)	-0.2. *P*=.22
"I know the significance of different nutrients, fiber, and fat for the diet."	4.5 ± 0.5 (N=13)	4.4 ± 0.8 (N=64)	4.3 ± 0.9 (N=63)	0.1. *P*=.78
Mean Autonomous motivation (TSRQ) ± SD	4.86 ± 0.51 (N=18)	4.85 ± 0.51 (N=75)	4,68 ± 0.52 (N=68)	0.17, *P*=.052
Mean Perceived Competence (PCS) ± SD	5.71 ± 1.18 (N=18)	5.60 ± 0.97 (N=75)	5.49 ± 1.18 (N=68)	0.11, *P*=.54
Incidence of	17% (3/18)	17% (12/71)	14% (10/72)	3.0, *P*=.62

EPDS (points > 10) (%)				
Stress percentage	52.8 ± 12.7 (N = 13)	56.3 ± 14.0 (N=49)	58.0 ± 14.0 (N=46)	-1.7, *P*=.52

eMOM usage

eMOM was mostly used in the mornings (0700 – 1000) and the evenings (1900 – 2200), see Figure 2a. The number of interactions with eMOM has been previously reported [14]. During the first application week, the users interacted with eMOM 18.7 times/day on average (see Figure 2b). In the following application weeks, the number of interactions was between 10-12 times/day. Between the application weeks participants interacted with eMOM 1-3 times/day.

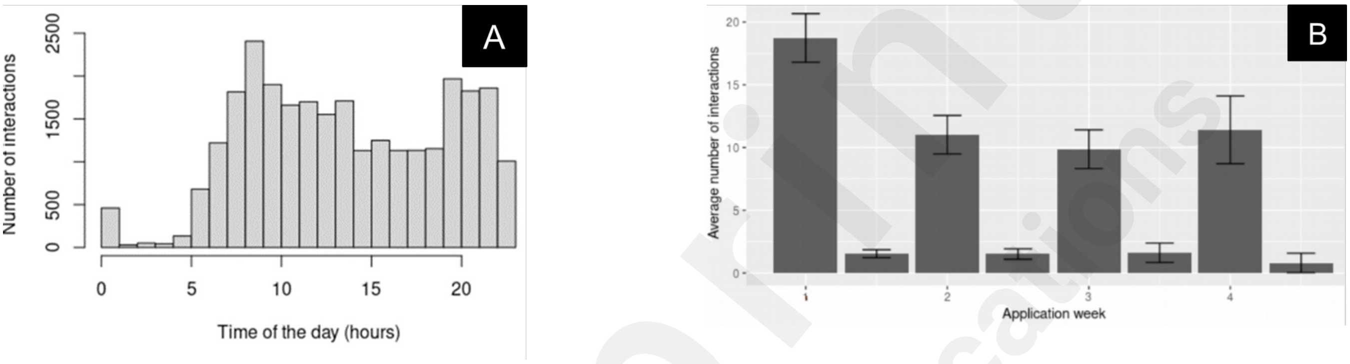

Figure 2: a) Histogram of the number of interactions at each hour within a day, b) The average number of interactions per day (error bars are for 95% confidence interval).

Day view was clearly the most popular view. It was used 65% of the times (see Figure 3a). For the viewed data, glucose filter was the most popular one, it was selected of 65 % of the times (see Figure 3b). Glucose was mostly viewed together with nutrition and physical activity, as shown in Figure 4.

Figure 3: A) Usage of different views, B) Usage of different filters.

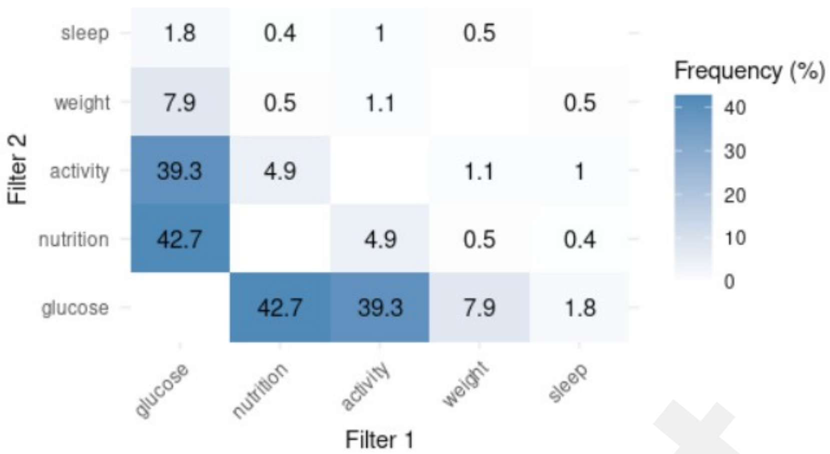

Figure 4. Parallel filter selections.

Self-discovery

Majority of interviewed participants (94%, 17 out of 18) reported that the eMOM app facilitated their understanding of the connections between their daily activities and glucose levels. Primarily, participants found their learning experiences centered around nutrition (83%, 15 out of 18) or physical activity (44%, 8 out of 18). Seven participants (39%) acknowledged the combined influence of both nutrition and activity on their glucose levels. The interviews highlighted various methods of learning, such as experimentation, comparison, and observation. For instance, one participant remarked, "During the application week, you could kind of try out how different foods affect the sugar level" (p8).
Regarding self-discovery, in total 335 codes emerged from the interview data and these codes were then combined into broader categories, which serve as subheadings below.

Learning between nutrition and glucose

Majority of the participants (n=15) discovered the patterns of association between nutrition and glucose. Nutrition information was presented through stacked bar charts, with a possibility to be integrated with the glucose curve, enabling direct comparisons of how various meals impacted glucose levels. Participants engaged in experimentation and comparison, evaluating different foods, mealtimes, and portion sizes. For example, one participant noted, "I have changed refined grains to whole grains. It [glucose] has stayed pretty good with them" (p15). Another participant reflected on meal timing, stating, "I hadn't understood that I had had way too long periods between meals. Like, you should eat more often. And by looking from the app I have noticed that if I don't eat regularly enough, it [glucose] starts to rise" (p10). Portion sizes also played a significant role, as evidenced by a participant's experience: "Some restaurant meals etc. are so big that the blood sugar rises very high for a very long time. It was a very useful fact for me, as I immediately quit eating those" (p12).

As shown in Figure 4, glucose was mainly viewed alongside the nutrition window (42,7% of time).

Learning between physical activity and glucose

Although the activity was viewed with similar frequency as nutrition (see Figure 3a) and nearly as frequently in parallel with glucose visualization (39.3% of the time, see Figure 4), it contributed less to self-discovery. However, almost half of the participants (n=8) noted a decrease in their glucose levels following exercise. For instance, one participant remarked, "I have noticed that when I'm more active, the glucose level decreases faster" (p16). Another stated, "I noticed that if I, for example, take a short walk after eating, the glucose curve starts decreasing more" (p8), while another participant shared, "I learned very concretely that if I take kids to football practice right after a meal, glucose starts to decrease even after a bigger meal. But if I sit at a brunch table with my friends, it [glucose] rises very high very easily. This was very useful information, I think" (p12).

Participants examined their activity levels across various days. As highlighted by one participant: "On February 19th, I've been quite active, so my blood sugar levels stay within their normal range. But then, for example, on February 20th, I haven't been very active, so they immediately jump above the threshold values. So, I've been comparing them like that" (p2).

Learning between sleep and glucose

Sleep data was found to be challenging to interpret, with a mere 3% viewing frequency (see Figure 3a). Four participants reported discrepancies between the sleep data provided by the device and their own assessments of sleep duration and quality. One participant observed a correlation between poorly slept nights and elevated morning glucose levels, stating, "Sometimes I was surprised at how high my glucose was in the morning. Then I started observing if there was something affecting it, and yes, there had been some nights when I had the flu and I had been awake for long periods at night" (p12).

Supporting features of learning in the eMOM app

The visual representation of measurements emerged as a pivotal aspect of the learning process. Through observing the glucose curve, participants noticed fluctuations in glucose levels. When various filters (nutrition, activity, sleep) were applied to the same graph alongside the glucose curve, participants could observe how different factors influenced glucose levels. One participant highlighted the advantage of the eMOM app's integrated approach, stating, "The eMOM app gathered both nutrition and food data in the same place, so if you wanted to do some kind of learning analysis about your nutrition or activity, the eMOM app was definitely better [versus only CGM/Medtronic] since it shows the combined data" (p3).

The ability to view nutrition information in a quantitative format was also valued. As one participant expressed, "I gained quite a good understanding of the number of calories in my meals and their variation. Since it is presented as bar graphs, it helps to get some insight into what changes I should make to my meal habits in the future" (p17).

Moreover, having a specific glucose target range was found to be important. Another participant noted, "Having target values on glucose helps to see how much you exceed the target" (p8). Participants found the eMOM app more informative than CGM/Medtronic in evaluating the overall picture of glucose balance. One participant explained, "CGM/Medtronic itself doesn't show the glucose target, like upper and lower bounds. I think that, for example, the variation in glucose level is more clearly presented in the eMOM app" (p6).

Table 4 summarizes the primary features utilized by women with GDM in the self-discovery process, their impact on glucose levels, and how the eMOM app supported the identification of associations between these features and glucose levels.

Table 4. Supporting features of EMOM.

	Effect on glucose levels	How eMOM supports
General physical activity level	More steps during the day keeps glucose levels lower.	Activity filter shows the number of steps and can be compared to the glucose curve.

Physical activity after the meal	Exercising right after a meal prevents high glucose peaks.	Activity filter and nutrition filter can be compared to glucose curve.
Meal rhythm	Irregular meal rhythm causes glucose peaks.	Nutrition filter shows meals as bar graphs together with glucose curve.
Portion size	Small breakfast keeps glucose levels more stable.	Nutrition filter shows the number of calories of every meal.
Evening snack	A substantial meal before going to sleep helps to prevent high fasting glucose in the morning.	Nutrition filter shows the number of calories, and glucose values from the morning are available.
Mealtimes	In the morning glucose level peaks easier.	Glucose curve visualizes the changes in glucose level throughout the day.
Carbohydrates	Having a high-carbohydrate breakfast results in a high peak in glucose levels.	Nutrition filter shows the number of carbohydrates in grams
Sleep	Poor sleeping quality results in higher glucose level in the morning.	eMOM app shows the amount of sleep.

Temporal progression of learning

In the evenings, eMOM served as a tool for obtaining a comprehensive overview of the day's events, as one participant described: "And then, at the end of the day, I looked at the eMOM application to see how the day had gone overall. I used it to get a summary" (p9). Conversely, during the day, participants tended to rely on Medtronic for checking glucose levels, as it offered easier and quicker measurements due to its lower latency, updating every 5 minutes compared to eMOM's 10-minute intervals.

For most participants (n=10), the first week of using the application was found to be the most significant in terms of learning. As one participant expressed, "The most useful was the first application week, then I learned the most" (p14), emphasizing their high interest in monitoring glucose levels during this period. Consequently, interactions with eMOM were most frequent during this initial learning phase, as illustrated in Figure 2b.

Periodic use of the eMOM app was found to be effective in maintaining motivation and sustaining interest in tracking activities. As one participant noted, "If it was available all the time, it probably wouldn't be used as much. Like, at the beginning, it is probably the most interesting, but when you learn to know how different things affect, then you no longer are interested in observing it" (p15).

Inhibiting features and improvement suggestions

Some participants (n=5) expressed a desire for enhanced informativeness by having all three filters (glucose, nutrition, and activity) integrated into the same graph.

A desire for additional support in interpreting data was expressed by 11 participants, particularly in understanding the impact of sleep data on glucose levels. Moreover, personalized recommendations regarding nutrition and more specific daily goals for macronutrients were requested. Preferences regarding support varied. While one participant mentioned seeking guidance from a nurse to interpret glucose data and two wished for assistance from healthcare personnel, others (8) would have been satisfied with suggestions or notifications from the app.

In this intervention, the activity bracelet tracked only steps and overall daily activity. Participants desired a broader range of sports tracking capabilities. For example, swimming is a preferred activity among pregnant women, but Vivosmart 3 was not able to track swimming. Issues with activity tracking, such as inaccurate step counting during activities like walking with a stroller or counting knitting as steps, led to a sense of distrust in the accuracy of activity data.

One participant expressed a desire for guidance on physical activity, including recommendations on duration and types of exercises to meet daily activity goals. Some also mentioned that motivation towards physical activity decreased as pregnancy progressed and exercise levels decreased.

Furthermore, some participants noted that when their glucose levels remained within target ranges, their motivation to use the app and adhere to a healthy diet diminished. As one participant articulated, "My glucose values have stayed quite good, but if I would have had more variation in glucose values it might have been easier to see associations between things. But since my glucose values have been on target, I haven't really made any changes to my diet or other things I otherwise might have done" (p14).

The effect of eMOM on Motivation, Depression, and Stress

Autonomous motivation (measured with TSRQ) was decreased in both arms: -0.11 ± 0.38 in control arm and –0.18 ± 0.32 in intervention arm between the baseline and gestational weeks 35-37. The between-arm difference was not statistically significant for the change of TSRQ (difference; -0.07; p = .37) nor for the change of Perceived competence (difference; -0.27; p = .23). There were no differences between the arms in the incidence of EPDS scores greater than 10 (5/52 in the control arm and 6/52 in the intervention arm). Results are presented in Table 5.

Table 5. The effect of eMOM on autonomous motivation, competence, EPDS and stress percentages.

	Control Arm		Intervention arm		Difference and p-value
	N	Mean ± SD	N	Mean ± SD	
Change in autonomous motivation (TSRQ)	48	-0.10 ± 0.41	51	-0.19 ± 0.36	-0.09; *P*=.25
Change in Perceived competence (PCS)	48	0.16 ± 1.03	51	-0.11 ± 1.17	-0.27; *P*=.23
Incidence of EPDS > 10	52	5 (10%)	52	6 (12%)	1 (2%); *P*>.99
Change in Stress percentage	34	0.2 ± 13.1	37	3.7 ± 12.0	3.5; *P*=.25

The acceptance and usability of eMOM

The acceptance of eMOM and wearable sensors was considered to be high over the whole intervention (see Table 6 for a subset of statements, responses to all the statements are in Appendix 1). For example, participants found the eMOM and the sensors useful for supporting lifestyle changes and they perceived eMOM easy to use.

Table 6. Responses to a subset of statements in UTAUT-questionnaire. Participants responded to each statement in UTAUT-questionnaire with a scale 1=Totally disagree, and 7=Totally agree.

	Application week 1 (N=67)	Application week 2 (N=47)	Application week 3 (N=26)	Application week 4 (N=10)
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD
Perceived Usefulness				
I find the eMOM and eMOM and sensors useful for supporting healthier lifestyle.	6,0 ± 1,1	6,0 ± 1,0	6,0 ± 0,8	6,3 ± 0,9
Using the eMOM and sensors enables me to improve my lifestyle more quickly.	5,9 ± 1,2	5,9 ± 1,1	5,8 ± 1,0	5,9 ± 0,9
If I use the sensor, I will increase my chances of getting a concrete lifestyle improvement.	6,0 ± 1,1	5,9 ± 1,1	5,7 ± 1,0	6,3 ± 0,8
Perceived Ease of Use				
My interaction with the sensor is clear and understandable.	5,6[a] ± 1,1	5,8 ± 1,0	6,2[a] ± 0,8	6,1 ± 0,9
I find the eMOM and sensors easy to use.	5,8[a] ± 1,1	6,0 ± 1,0	6,2 ± 1,0	6,6[a] ± 0,5
Attitude towards behavior and use				
Using the eMOM and sensors is a good idea.	6,3 ± 0,8	6,3 ± 0,8	6,2 ± 1,0	6,4 ± 0,8
The eMOM and sensors make changing lifestyle more interesting.	6,3 ± 0,9	6,1 ± 0,9	6,3 ± 0,8	6,3 ± 0,8
Intrinsic motivation				
Using the eMOM and sensors is fun.	5,3 ± 1,3	5,1 ± 1,3	5,4 ± 1,3	5,3 ± 0,9
I like using the eMOM and sensors.	5,6 ± 1,4	5,5 ± 1,1	5,7 ± 1,3	5,7 ± 1,2
Extrinsic motivation				
People who influence my behavior think that I should use the eMOM and sensors.	3,7 ± 1,5	3,9 ± 1,3	4,1 ± 1,3	4,0 ± 1,3
Facilitation				
I have the resources necessary to	6,3 ± 1,0	6,3 ± 1,1	6,6 ± 0,6	6,9 ± 0,3

use the eMOM and sensors.				
I have the knowledge necessary to use the eMOM and sensors.	6,4 ± 0,9	6,4 ± 0,9	6,7 ± 0,6	6,9 ± 0,3
I could improve my lifestyle using the eMOM and sensors If there was no one around to help me with eMOM and sensors.	5,4 ± 1,4	5,6 ± 1,4	5,5 ± 1,3	6,2 ± 0,9
Anxiety				
I feel apprehensive about using the system.	1,4 ± 1,1	1,4 ± 1,0	1,3 ± 1,1	1,5 ± 1,3
The eMOM and sensors are somewhat intimidating to me.	1,2 ± 0,7	1,1 ± 0,4	1,2 ± 0,7	1,3 ± 0,5

[a]=values on the same row are statistically significant different from each other at significance level (p < .05)

Responses to usability questionnaire (modified from SUMI) were in line with responses to UTAUT. For example, 86% (38/44) of participants disagreed with the statement "Learning the functions of the eMOM GDM application takes too long" and 66% (29/44) agreed with the statement "I understand and know how to act based on the information provided by the application." 59% (26/44) of participants agreed with the statement "eMOM answers too slowly to inputs", which may have influenced the preference for Medtronic, which updates more quickly, during the day and eMOM more frequently in the evening. Please see Appendix 2 for all the results on usability questionnaire.

Correlations between motivation and improved clinical outcomes

Correlations between autonomous motivation (TSRQ) and perceived competence (PCS) and improved primary and secondary clinical outcomes [14] in the intervention arm are shown in Table 7. No significant correlations were found in change of motivational factors and improved clinical outcomes.

Table 7. Correlations between autonomous motivation (TSRQ) and perceived competence (PCS) on clinical outcomes.

	Change in autonomous motivation	Change in perceived competetence
Outcome where the effect of the intervention was observed in Kytö [14]		
Primary outcome: Change in fasting glucose from the baseline to 35–37 gestational weeks – mmol/L	-0.02, *P*=.88, N = 50	-0.05, *P*=.75, N = 50
Mean morning capillary fasting glucose – mmol/L	-0.11, *P*=.52, N = 36	0.26, *P*=.12, N = 36
Timing of medication start[a]	-0.20, *P*=.54, N = 11*	0.25, *P*=.43, N = 11*

Gestational weight gain from the baseline to delivery – kg	0.07, *P*=.61, N = 50	0.06, *P*=.67, N = 50
Change in intake of vegetables (g/MJ)	-0.04, *P*=.79, N = 37	0.24. *P*=.15, N = 37
Change in duration of sedentary behavior (min/day)	-0.09, *P*=.54, N = 47	-0.14, *P*=.35, N = 47
Change in duration of light-physical-activity (min/day)	0.05, *P*=.74, N = 47	0.06, *P*=.67, N = 47
Macrosomia (> 4 kg)[b]	1.26, *P*=.44, N = 50	-0.35, *P*=.48, N = 50

[a] Only the baseline measurement of motivation available.
[b] Logistic regression.

Discussion

This study is the first to investigate the role of comprehensive self-tracking in the self-discovery and motivation to manage GDM. We found that a mobile app combining glucose monitoring, nutrition, and physical activity within the same app supported self-discovery among women with gestational diabetes. Providing mothers with the opportunity to compare the effects of nutrition and physical activity on glucose levels facilitated their understanding of cause and effect. Almost all participants using mobile app discovered associations between either nutrition or physical activity, and glucose levels. Majority found associations between nutrition and glucose and nearly half of the participants between physical activity and glucose. There were no differences between the intervention and control arms in the change of perceived competence to manage GDM, autonomous motivation, depression, or stress scores. Additionally, autonomous motivation did not have an effect on the improved clinical outcomes observed in our previous randomized controlled trial [14].

Self-discovery

The concept of personal discovery through self-tracking data has gained attention in human-computer interaction [25–32]. In the context of diabetes self-discovery, there has been a notable focus on how to effectively present and visualize glucose data in recent research [30,33–35]. Findings of this study also support that associations between nutrition and glucose emerge as the most important way of learning. Real-time feedback on a meal's impact on glucose levels, coupled with detailed nutritional information, empowers individuals to make dietary choices conducive to better glucose balance [14]. Additionally, in this study the simultaneous display of the glucose curve and nutrition data in a single window facilitates the interpretation of temporal connections between eating and glucose levels, aiding in the regulation of meal rhythms. Glucose was mainly viewed alongside the nutrition window, emphasizing the value of parallel visualization. Participants also mentioned comparing different foods and portion sizes. This underscores the importance of having a comprehensive portrayal of nutrition than merely recording the quantity of carbohydrates. The associations between nutrition and glucose observed in this study are consistent with our previous work with various sensors but without eMOM app [16], where participants noted causal relationships between nutrition and glucose levels.

Learning the associations between physical activity and glucose proved to be a little bit more challenging than understanding the associations between nutrition and glucose. However, in this study, the associations between physical activity and glucose were more prominent compared to our study without eMOM app [16]. The availability of parallel visualization of activity and glucose may explain the better results observed in the present study, where participants had access to the eMOM app.

The eMOM app also provided data on sleep patterns, although interpreting this information proved challenging. Only one participant reported observing a potential connection between sleep and glucose levels, noting that during a flu accompanied by poor sleep, her glucose levels were higher. However, this association remains uncertain, as the flu itself can affect glucose levels. These results highlight the difficulty in finding associations between sleep patterns and glucose levels. Additionally, there is limited evidence on the effectiveness of wearable sensors on sleep during pregnancy [36]. Further investigation is needed in this area.

Previous studies indicate that trial-and-error learning is prevalent among women with GDM [37–42]. In a recent study by Ibrahim et al. [37], women diagnosed with GDM expressed a desire to have all their self-monitoring tools (such as phone apps, paper-based journals, spreadsheets) gathered in one place to aid in sense-making. The eMOM's capability to visualize data from continuous glucose monitors, physical activity sensors, and digital food diaries in a single view supports this trial-and-error approach by assisting in understanding the effects of dietary and physical activity changes on glucose levels.

Motivation

While previous studies indicate a strong motivation among women with GDM to manage their condition [39,42–44], our study aimed to understand how eMOM influences motivation, particularly in terms of autonomous motivation. Contrary to the findings of Williams et al. [45], who demonstrated a significant correlation between improved glucose levels and autonomous motivation among Type 2 diabetes patients, our findings suggest that the eMOM application did not lead to improved clinical outcomes through increased motivation. The women using eMOM did not either perceive higher competence to manage GDM than women in control arm. These findings suggest that the improved maternal clinical outcomes reported earlier [14] are primarily attributed to self-discovery rather than increased motivation. Thus, motivational interventions which are effective in Type 2 Diabetes management may not directly apply to GDM. Instead, educational approaches, such as the eMOM app, play a crucial role in helping women with GDM learn how to manage their condition effectively.

Strengths and limitations

The eMOM app offers a novel approach to GDM self-management by integrating continuous glucose monitoring, nutrition tracking, and physical activity monitoring real-time within a single application, without guidance from health care personnel, thus addressing a gap in previous GDM apps [46]. This integrated approach was also requested in our previous study, where participants used the same variable sensors and meters (CGM, physical activity, food diary, sleep) as in this study, but separately in different apps and devices [16] Although continuous glucose monitors (CGMs) have been found to be acceptable among women with GDM [47–50], their use alone may not lead to improved glycemic control [49,51] or a reduction in macrosomia (birthweight > 4kg) [50]. One contributing factor is the lack of clarity regarding the cause-and-effect relationships between lifestyle choices and glucose levels among women diagnosed with GDM [29,39,40,44,52]. eMOM provides a tool for observing these causal relationships, thus enhancing the self-discovery process in managing GDM.

As reported in the RCT study [14], eMOM usage was consistently high. Most of the learning occurred, however, during the first application week. In the following application weeks eMOM was mainly used to check if the glucose stayed within the limits. As noted by the participants, continuous availability of the sensors might lead to decreased motivation for tracking. Due to this periodicity, engagement with eMOM remained high during the application weeks, in contrast to the declining engagement observed in automatic self-tracking among people with type 2 diabetes and type 1 diabetes [53]. Participants continued to interact with eMOM even outside the designated application weeks, even when they did not have access to the activity bracelet or CGM. However, these interactions were significantly less compared to the application weeks. Throughout this study, the acceptance of eMOM and wearable sensors remained high, as indicated by usability questionnaires.

Previous research has suggested that extensive self-monitoring could lead to adverse psychological outcomes [54,55]. We found no evidence of an effect on depression or stress, as measured by EPDS questionnaires and Firstbeat stress scores. This suggests that comprehensive tracking does not have a detrimental effect on maternal psychological well-being.

The most significant limitation concerning the self-discovery process was the inability to display nutrition, physical activity, and glucose data together in one graph. Participants expressed a need for more support in interpreting data and making informed choices. For example, the app could send notifications when glucose values exceed the target range and instruct users to review their recent meals.

Self-discovery's impact on clinical outcomes couldn't be objectively measured, as there is currently no effective method for measuring learning. However, the results of the interviews suggest that self-discovery had a positive effect on clinical outcomes. Another limitation is that women who required medication for GDM were excluded from the study. This may have introduced bias into the results of motivation, depression, and stress levels, as the analyses only included patients whose condition was managed well enough to avoid medication.

Selecting features related to physical activity is challenging during pregnancy, as it complicates activity tracking. Activity bracelets typically track activity based on heart rate, which physiologically increases during pregnancy [56]. Currently, there are no activity bracelets designed specifically for pregnancy, which would account for these physical changes. While walking is a common form of physical activity during pregnancy [57,58], it may become difficult in the later stages. Swimming, water running, and weightlifting are preferred alternatives among pregnant women [57]. Therefore, it is essential to be able to track these alternative forms of physical activity. It´s also worth noting that as pregnancy progresses, there is a general decline in physical activity levels [59,60]. Consequently, the relevance of physical activity in the management of GDM diminishes as pregnancy approaches its later stages. Similar challenges in physical activity tracking emerged in a study by Årsand et al. [61] on type 2 diabetes, where patients expressed a desire for a broader range of trackable sports beyond just counting steps.

Insights, recommendations, and future directions

Implementing digital tools in clinical care requires patients to have health literacy. Low health literacy in patients with type 2 diabetes has been linked to lower engagement with mobile-based health interventions [62]. To be effective, information provided by these apps should be tailored to the health literacy levels of the target population [63]. In future research, eMOM should be evaluated in populations with varying levels of health literacy. Artificial intelligence-based solutions could assist users in understanding lifestyle improvements based on their health data.

Our findings suggest that an application presenting features in a quantifiable format is well-suited for the self-discovery process in GDM. Additionally, the limited number of features in GDM and the clear causal relationships between glucose and these features make this process easier to learn. Self-discovery in GDM exemplifies goal-driven tracking [64], particularly for monitoring nutrition and physical activity to maintain glucose levels within the recommended limits set by healthcare providers. We believe that our approach of integrating data from various sources in real-time could be beneficial for other non-communicable diseases, such as type 2 diabetes, where the relationships between features and outcomes are relatively clear and learnable. Especially after diagnosis, when individuals are still in the learning phase of managing their condition, patients could benefit from a solution like ours.

Conclusion

By visualizing continuous glucose monitoring, nutrition and activity in a single app in real time, the eMOM app provides a promising tool to enhance self-discovery in GDM, without additional support from healthcare personnel. In order to support learning further, future work involves visualization of more than one feature impacting glucose at the same time and utilization of AI-based recommendations. In addition to GDM, this kind of mHealth solution could be utilized to support learning in other non-communicable diseases, such as type 2 diabetes.

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Conflicts of Interest

None declared

Abbreviations

GDM: gestational diabetes mellitus
CGM: continuous glucose monitoring
RCT: randomized controlled trial

Multimedia Appendix 1

Responses to UTAUT questionnaire

Multimedia Appendix 2

Responses to modified SUMI questionnaire

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Supplementary Files

Multimedia Appendixes

Responses to UTAUT questionnaire.
URL: http://asset.jmir.pub/assets/e8b79f801f85f5fb8cad6630f19c46b5.xlsx

Responses to modified SUMI questionnaire.
URL: http://asset.jmir.pub/assets/b5022fc3ce0b58e47ec8027812c04fcc.docx