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Decoding heterogeneity in data-driven self-monitoring adherence trajectories in digital lifestyle interventions for weight loss: a qualitative study

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Abstract

Background Data-driven trajectory modeling approaches have been used to identify participant subgroups with differing responses to digital lifestyle interventions. Identifying contributing factors to different participant subgroups can inform tailored strategies to early "rescue" intervention non-responders. Self-monitoring (SM) is a central mechanism in lifestyle interventions for driving behavior change and can serve as an early indicator for later intervention response. This qualitative study aimed to compare SM experiences between intervention response subgroups and to identify contributing factors to intervention response subgroups in a 6-month digital lifestyle intervention for adults with overweight or obesity.

Results Participants were middle-aged (52.9 ± 10.2 years), mostly female (65%), and of Hispanic ethnicity (55%). Four major themes with emerged from the thematic analysis: Acceptance towards SM Technologies, Perceived SM Benefits, Perceived SM Barriers, and Responses When Facing SM Barriers. Participants across both subgroups perceived SM as positive feedback, aiding in diet and physical activity behavior changes. Both groups cited individual and technical barriers to SM, including forgetfulness, the burdensome SM process, and inaccuracy. The Responder Group displayed positive problem-solving skills that helped them overcome the SM barriers. In contrast, some in the Non-responder Group felt discouraged from SM. Both subgroups found diet SM particularly challenging, especially due to technical issues such as the inaccurate food database, the time-consuming food entry process in the Fitbit app.

Conclusions Our study indicates that qualitative analysis is valuable for translating data-driven findings to actionable intervention improvement strategies. Our findings may inform the development of practical SM improvement strategies in future digital lifestyle interventions for weight loss. Notably, building problem solving skills emerge as a key approach to prevent potential non-responders from intervention disengagement.

Keywords Data science, Qualitative research, Lifestyle interventions, Obesity, Self-monitoring, Adherence

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Background

More than 40% of American adults are obese [1]. Obesity is associated with a range of major comorbidities and imposes a significant economic burden on the society. In 2018, the total direct medical cost of obesity among adults in the United States exceeded $260 billion [2]. Behavioral lifestyle interventions have been recommended as front-line treatment strategies for adults with overweight or obesity [3]. Self-monitoring (SM) is a major component in these lifestyle interventions to support diet and physical activity (PA) behavior improvements [4, 5]. However, SM adherence declines over time [6].

Declined SM adherence, especially during the early phase of the intervention, was consistently reported to be predictive of later behavior change and weight loss unsuccess [7, 8]. Recent evidence suggests that to effectively support weight loss and its maintenance, SM adherence must remain consistently above a specific threshold (e.g., diet SM for at least 3 days/week) [9]. However, only a small proportion of participants could meet this threshold over the long run. With previous attempts failing to re-engage in SM after initial disengagement [10], developing effective SM improvement strategies to prevent non-response is of urgent need.

Data-driven statistical models have been employed to identify intervention response subgroups based on various SM adherence trajectories. Our recent study employed data-driven models to categorize participants into intervention response subgroups based on their adherence trajectories to SM of diet, PA, and weight [11]. We identified a "Lower SM Group" with consistently low adherence to all SM targets, showing no significant weight or glycemic control improvements over 6 months (Non-responders). In contrast, the 'Higher SM Group' demonstrated high adherence to physical activity SM, moderate adherence to diet and weight SM, and achieved significant weight loss while maintaining glycemic control (Responders). Notably, these subgroups exhibited significantly different SM adherence levels across all SM targets since week two. Thus, understanding the specific SM challenges faced by non-responders could be crucial in developing tailored SM improvement strategies to prevent non-response.

Previous studies on improving SM has largely focused on logistic improvements, such as reducing the burden of SM [12]. However, various factors could lead to declined SM. For example, a recent systematic review reported a range of factors for decreased use of fitness trackers, including concerns about data accuracy, privacy, the inconvenience of use, and a loss of SM motivation [13]. These findings suggested that the *one-size-fits-all* solution to sustaining long-term SM engagement is insufficient and that understanding the unique situations faced by intervention non-responders is necessary for developing tailored SM improvement strategies to prevent non-response.

Taken together, to effectively translate insights from data-driven models on intervention response subgroups into actionable strategies for preventing intervention non-response, we analyzed qualitative data on SM experiences and perceptions across different intervention response subgroups. Qualitative data is invaluable as it offers deep insights into individual behaviors, experiences, perspectives, and surrounding contexts [14]. By exploring factors that facilitated or hindered SM adherence, we aimed to inform SM improvement strategies in future digital lifestyle interventions to prevent intervention non-response.

Methods

Study design and sample

This study used data collected from participants in a pilot randomized controlled trial (RCT). The pilot RCT was a 6-month trial examining the effect of a digital lifestyle intervention in overweight/obese adults. Enrolled participants were adults (≥ 18 years of age) who were overweight or obese (Body Mass Index ≥ 25 kg/m^2), with or without diagnosis of type 2 diabetes, and with or without evidence of chronic kidney diseases. Participants were randomly assigned to either a low-fat low-calorie diet or a ketogenic diet. Digital lifestyle interventions were offered during the trial, including digital education, individual counseling sessions, and personalized feedback. All participants were encouraged to SM diet, physical activity, and weight daily over 6 months. Table 1 shows the SM protocol and tools during the RCT. All study procedures were approved by the Institutional Review Board of The University of Texas Health Science Center at San Antonio. Further details of the pilot RCT have been reported elsewhere and only study procedures of relevance to this study's aim are reported here [15].

During the pilot RCT trial, we measured daily adherence to SM of diet, PA, and weight using binary outcomes, which were aggregated biweekly to calculate the percentage of days each individual being adherent to SM. Days without SM data were marked as zero, indicating non-adherence.

To identify participant response subgroups based on SM adherence, we conducted a secondary data analysis on study completers ($n = 50$) that used GBMM to model the longitudinal trajectories of adherence to SM of diet, PA, and weight. Using GBMM within a larger sample allows for the identification of participant subgroups within the sample. GBMM assumed that individuals within a subgroup share similar SM adherence levels across all targets.

Table 1 Self-monitoring instructions and adherence criteria.

Self-monitoring Target	Self-monitoring Device/App	Frequency Recommendation	Daily Adherence Criteria
Diet	Fitbit App	Log Daily	Caloric intake ≥800kcal logged
Physical Activity	Fitbit Inspire 2	Log Daily	Steps ≥ 500 logged
Weight	Withings Body Scale	Log Daily	At least one valid weight readings logged

We modeled SM adherence trajectories over 6 months using GBMM and evaluated model fit against pre-defined criteria. We tested number of participant subgroups from two to five. The two-group model with linear terms emerged as the optimal choice. We then named the trajectory subgroups based on the clinical interpretation of the SM adherence trajectories: *the Higher SM Group, and the Lower SM Group.* Notably, only the Higher SM group showed significant weight loss and glycemic control, suggesting it to be the Responder group (Figs. 1, 2). Additionally, these subgroups also started showing significantly different levels of SM adherence starting from week two. Detailed GBMM procedures and quantitative findings are reported elsewhere [11]

Data collection

All participants were invited for a three-month individual interview. For this qualitative study, we aimed for equal sample sizes for each of two participant subgroups (Fig. 3).

A semi-structured interview guide consisting of five open-ended questions with optional probing was developed by members of our research team (SL, YD, CM, JW) (Table 2). The team was composed of nursing scientists with extensive experience in digital health and qualitative research, research coordinators experienced in patient communication and qualitative research, and a registered dietitian. The guide was developed to explore SM perceptions and experiences, facilitators and barriers to SM, and suggestions for SM strategies.

Each interview lasted for 15 to 30 minutes. For the ketogenic diet group, a dietitian conducted the interviews, and a research coordinator took detailed notes during the interview. For the low-fat low-calorie diet group, a research coordinator conducted the interviews, and a research assistant took detailed notes. Notetakers transcribed statements from the interviewees as much as possible rather than summarizing answers. All interviews were conducted virtually on Zoom (Zoom Video Communications Inc., USA). All interview notes were deidentified and imported into Microsoft Excel (Microsoft Corporation, USA) for analysis.

Data analysis

Thematic analysis, with no predetermined theory, structure, or framework, was conducted across participant subgroups "identify, explore, explain, and compare" themes expressed by subgroups about SM [16]. We followed a deductive approach in which themes were derived from the dataset itself [17]. First, two researchers

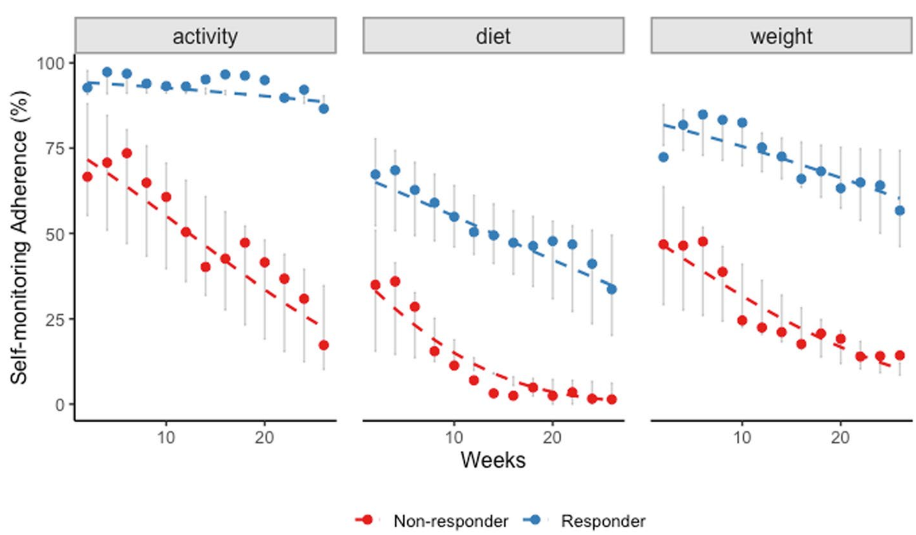

Fig. 1 Self-monitoring adherence levels by response subgroups

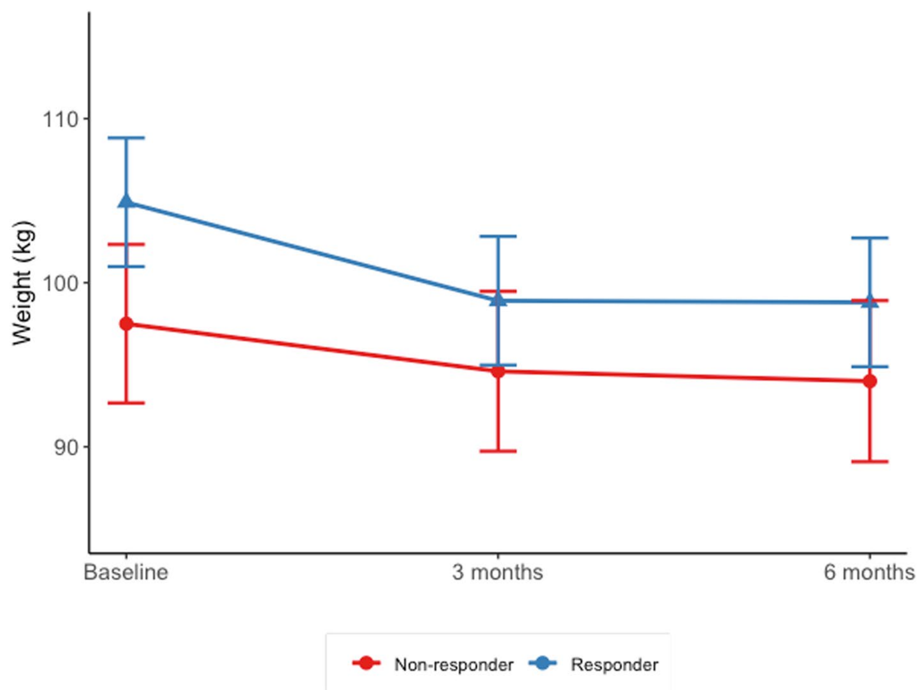

Fig. 2 Changes in body weight over 6 months by intervention response subgroups

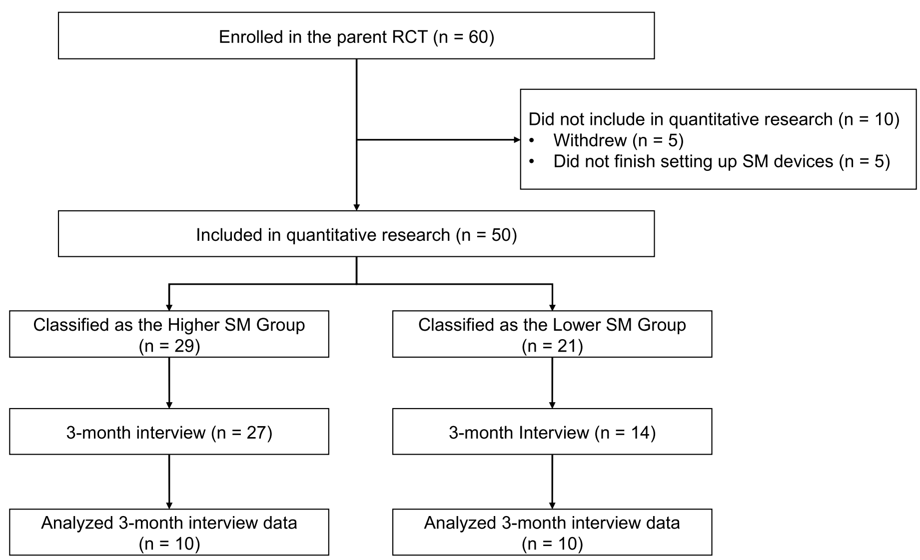

Fig. 3 Sampling for the qualitative study. (RCT: randomized controlled trial; SM: self-monitoring)

(SL and DS) familiarized with the data through reading the interview notes multiple times. Second, two researchers each inductively coded data to generate a codebook and grouped codes into themes across trajectory subgroups. Frequent repetition of codes occurred after analyzing around 10 interview notes for each trajectory group. The research team decided data saturation was achieved, and thus, a total of 20 interview notes were used to generate codebooks and themes. Third, SL and DS gathered to compare codebooks, coded texts, and themes. Discrepancies were reconciled through discussion between the two researchers until a consensus was reached. This consensus was then reviewed by the study team, consisting of nursing and public health scientists.

Table 2 Semi-structured interview questions.

1. How has your experience been in using SM devices in general?
2. How has your experience been with food logging (i.e., any difficulties, inaccuracies, pros of food logging observed)? If no self-monitoring of food logging - do you know why you need to monitor food?
3. At what time/ when do you enter your food logs?
4. What suggestions you can give to improve the food logging process?
5. How has your experience been with using the Fitbit as an activity tracker?

Table 3 Baseline characteristics of the qualitative sample (n = 20)

	Total (n = 20)	**Lower SM (Non-responder) (n = 10)**	**Higher SM (Responder) (n = 10)**
Age	52.9 ± 10.2	51.2 ± 11.1	54.5 ± 9.5
Female	13 (65%)	7 (70%)	6 (60%)
Hispanic	11 (55%)	5 (50%)	6 (60%)
Annual Household Income $80,000 or Higher	7 (35%)	4 (40%)	3 (30%)
College Degree or Higher	9 (45%)	4 (40%)	5 (50%)
Type 2 Diabetes	7 (35%)	2 (20%)	5 (50%)
Body Weight (kg)	95.3 ± 19.0	90.1 ± 14.6	100.5 ± 22.1
BMI (kg/m^2)	34.6 ± 4.9	33.3 ± 3.9	35.9 ± 7.8
HbA1c (%)	5.7 ± 0.8	5.6 ± 0.5	5.8 ± 0.9

A nursing scientist (YD) provided consultation as necessary throughout the process.

Results

Baseline characteristics of the sample are presented in Table 3, stratified by SM trajectory subgroup. Participants were middle-aged (52.9 ± 10.2 years), mostly female (65%), and of Hispanic ethnicity (55%). No differences were found in the baseline characteristics among the sample for the qualitative analysis the sample for identifying intervention subgroups.

Qualitative analysis of individual interview notes revealed the following major themes that were consistently reported by both intervention response subgroups: (1) Acceptance towards SM Technologies, (2) Perceived SM Benefits, (3) Perceived SM Barriers, and (4) Responses When Facing SM Barriers. However, the specific codes within each theme were subtly different (Fig. 4), suggesting unique experience within each intervention response subgroup.

Theme 1. Acceptance towards SM Technologies

This theme comprises the features and functionalities of SM technologies that were deemed acceptable for participants in both subgroups. The codes listed under this theme represent enabling factors that could encourage diligent recording of diet, PA, and weight, which is the critical first step for achieving successful behavioral self-regulation through successful SM.

Participants in both groups (Lower SM: 2, Higher SM: 4) expressed their acceptance towards SM technologies in terms of their accuracy.

> *"Has compared with an exercise activity app that he has been using for a long time now, and finds that the Fitbit is similar to the results from the app." [Higher SM,40-49 years old]*

	Acceptance towards SM Technologies	**Perceived SM Benefits**	**Perceived SM Barriers**	**Responses when facing SM Barriers**
Codes unique to the Responder	• Preference of non-study related SM functionalities	• SM become a habit • SM was enjoyable	• None	• Positive problem solving • Action planning
Shared codes between groups	• Accuracy • Ease of Use	• SM as a positive feedback • SM facilitated behavior change	• Forgetfulness • Technical barriers • Burden • Inaccuracy • Lack of customization	• None
Codes unique to the Non-responder	• None	• None	• Busyness • Lack of SM knowledge • Preference for personally owned SM devices	• Changes in attitude from positive to negative

Fig. 4 Themes and codes by intervention response subgroup

> *"Finds it (Fitbit food log) to be accurate compared to the MyFitnessPal app. Finds the apps to be the same." [Lower SM, 40-49 years old]*

> *"Scale works well and is accurate" [Lower SM, 40-49 years old]*

Each SM subgroup had one participant who mentioned the ease of use associated with the automatic syncing function of the weight scale.

> *"Scale – simple and easy to use and syncs to phone very easily" [Higher SM, 50-59 years old]*

> *"Weight scale – likes it, automatically connects over and finds it to be the easiest one" [Lower SM, 50-59 years old]*

Two individuals in the Higher SM group also stated a preference for non-study-related features of SM technology, such as body fat percentage, daily temperature readings on the weight scale, and sleep pattern monitoring.

Theme 2 Perceived SM Benefits

This theme captures positive factors that participants associated with SM daily practices. These factors could serve as crucial motivators for participants to initiate the necessary behavioral adjustments for behavioral goal achievement.

Participants in both subgroups (Lower SM: 4, Higher SM: 2) perceived the fitness tracker and the weight scale as sources of positive feedback, motivating participants to stay committed and continue their efforts.

> *"It tells the steps she has been taking, likes to see it during exercise. Is working good, no problems with it" [Lower SM, 50-59 years old]*

> *"Weight scale – easy to use, will show you how much you have lost which is a good incentive. Finds it to be efficient." [Higher SM, 60-69 years old]*

Participants in both subgroups (Lower SM: 1, Higher SM: 4) also recognized the facilitating role of diet SM for diet adherence.

> *"The fitbit food logs has helped the most (on following the diet), seeing if it was higher or lower in calories in general. Also helped to prepare her own portions (grams and oz and serving size). Understanding sizes and what that means calorically, and then putting it in on the Fitbit." [Lower SM, 40-49 years old]*

> *"Using the Fitbit has helped a lot (on following the diet), being able to see and track foods and choices." [Higher SM, 50-59 years old]*

In addition to perceiving SM as positive feedback, a subset of participants in the Higher SM group (n = 3) underlined the sense of enjoyment they experienced from observing SM results.

> *"Likes using it, can see progress throughout the day, can see the 10,000 step goal" [Higher SM, 50-59 years old]*

> *"loves the scale, thinks it is amazing, likes the tracking of ups and downs. [Higher SM, 60-69 years old]*

Furthermore, SM has become part of the daily habit for some participants (n = 3) in the higher SM group.

Theme 3. Perceived SM barriers

This theme included factors that participants identify as barriers to engaging with SM effectively. These perceived barriers could hinder participants from SM at any stages of behavioral self-regulation and can be classified into individual-level and technical-level barriers. At individual-level, both subgroups (Lower SM: 1, High SM: 2) reported occasions forgetting to SM.

> *"Forgets to do it a lot. Does not like to do it before in case gets distracted or called for work and doesn't end up eating." [Lower SM, 40-49 years old]*

> *"(Self-monitoring) has been challenging, forgets sometimes." [Higher SM, 40-49 years old]*

Some (n = 2) in the Lower SM group also attributed their lack of SM to a busy schedule.

> *"gets busy with work. Then much time had passed and continued to get busy and not log any food." [Lower SM, 30-39 years old]*

Individual-level barriers to SM that are specific to the Lower SM group include a lack of knowledge about how to SM (n = 4).

> *"Has not been tracking food. (Hope for the study team to) do a video of the food logging and give out. [Lower SM, 60-69 years old]*

Technical level barriers that hindered both subgroups from SM included inaccuracy, burden of diet SM, lack of customization, preference for non-study provided SM technologies, and lack of data integration

Inaccuracy emerged as a major concern for participants in both subgroups (Lower SM: 3, Higher SM: 8) that might discourage them from continuing with SM.

> *"When putting in foods like salads, shows much more carbs than is in the food actually." [Higher SM, 50-59 years old]*

> *"Too much walking logged for what is actually happening. Couple hundred steps off usually. Does autotrack, but makes it seem like it is sprinting occasionally. Hits steps when driving sometimes." [Lower SM, 40-49 years old]*

Diet SM was regarded as time-consuming and burdensome by participants in both subgroups (Lower SM: 6, Higher SM: 3).

> *"takes up a lot of time to input all of the food. Has not put in for about two weeks." [Lower SM, 50-59 years old]*

> *"Does not like using the app. Has to manually input a lot of things in there, especially if going out to eat. Has to ask the place for nutrients and then manually input it." [Higher SM, 40-49 years old]*

Many participants also mentioned the lack of customization in SM devices (Lower SM: 6, Higher SM: 5), particularly the Fitbit food logging feature and its extensive and confusing food database.

> *"Two of the same products (strawberries) will come up as different calories depending on the store buying from in Fitbit, even though the product is the same." [Higher SM, 40-49 years old]*

> *"the calorie range varies even within food item." [Lower SM, 50-59 years old]*

Participants in both subgroups emphasized that logging homemade foods on Fitbit was particularly challenging, noting that it was generally more cumbersome to log homemade meals compared to eating out.

> *"Many random foods that come up and fast-foods come up first. When doing home made foods, it is hard to know for example: if meatloaf made at home is similar to a meatloaf out to eat. When a food item does come up, there are several options which are not the basic food and rather from a restaurant which may not be accurate." [Lower SM, 40-49 years old]*

> *"Is simple when doing or scanning a barcode, but when making meals has to enter each item individually which is more difficult." [Higher SM, 50-59 years old]*

Participants in both groups (Lower SM: 1, Higher SM: 2) expressed a desire for an "all-in-one" platform to reduce their burden associated with using multiple SM technologies and mobile applications.

> *"Thinks some of it should be condensed. Feels like you have to bounce from app to app. One device or app to do everything." [Higher SM, 40-49 years old]*
> *"Switching to a new app like MyFitness pal, and integrating apps together like the apple phones can sometimes do." [Lower SM, 40-49 years old]*

Additionally, participants in the Lower SM ($n = 3$) emphasized their preference for personally owned SM devices over study-provided ones, citing reasons related to usability and functionalities.

> *"MyFitnessPal is more user friendly. Hard to find things in Fitbit and log them." [LowerSM, 40-49 years old]*

Theme 4. Responses When Facing SM Barriers

This theme highlights how individuals from different subgroups navigate SM barriers. A major difference between the two subgroups was how they reacted to SM barriers. Notably, due to above-mentioned barriers, some participants ($n = 3$) in the Lower SM group reported a shift in their attitude from initially positive to negative after SM for a few weeks.

> *"It was good at first, it was exciting in the beginning. After the first few weeks, it was hard to keep up with and often forgets to log food or do the blood sugar readings." [Lower SM, 50-59 years old]*

However, in the Higher SM group, most participants ($n = 8$) self-initiated positive problem-solving strategies and action planning skills to overcome barriers and continue with SM.

> *"Scale is connected to Wi-Fi, so whenever the Wi-Fi is changed (every few days depending on if staying with significant other), the Wi-Fi needs to be changed again. Has found a way around this by adding it as a new item in the app and it keeps the old data in there." [Higher SM, 40-49 years old]*

For example, many participants in the Higher SM Group ($n = 8$) described writing things down as a good approach for recalling their daily meals and found it improved adherence to diet SM.

> *"Carries a written log and then goes back and puts them in later into the Fitbit" [Higher SM, 50-59 years old]*

Planning and logging all meals at the beginning of the day before eating was also mentioned as an effective strategy to promote adherence to diet SM ($n = 2$).

"(Logging foods) At the beginning of the day if knowing what will be eaten during the day, and then will add other items right away to not forget." [Higher SM, 40-49 years old]

Discussion

By analyzing and comparing SM perceptions and experiences across intervention response subgroups that were identified by data-driven trajectory modeling approach, we aimed to explore practical SM improvement strategies to prevent intervention non-response. We found similarities across both subgroups on perceived SM benefits, barriers, and acceptance. There were also key differences especially in terms of responses after facing SM barriers. Findings from this study revealed factors that led to differences in SM experiences and behaviors among the subgroups. Notably, participants in the Higher SM Group commonly described their adoption of positive problem-solving strategies to overcome SM barriers. On the other hand, participant from both subgroups consistently reported technical difficulties, especially with the burdensome diet SM component. This emphasizes the necessity of refining the technical aspects of diet SM. Taken together, our findings highlight the potential of translating data-drive findings into actionable SM improvement strategies to prevent intervention non-response in future digital lifestyle interventions for obesity management.

Participants from both groups expressed positive perceptions of SM tools, noting their ease of use and accuracy. However, only participants in the Responder group reported feeling sense of enjoyment from SM. Perceived ease of use was recognized as a critical factor in the initial adoption of digital health tool usage; however, its influence is limited in sustaining long-term engagement. For example, Ma et al. examined the association between perceived ease of use and online SM behavior in a 15-month coach-led weight loss intervention [18]. They found that perceived ease of use was significantly associated with initial SM during the first 3 months. However, this association did not persist between months 3 and 15. In contrast, feeling a sense of enjoyment indicates an intrinsic, self-determined autonomous motivation toward SM. Autonomous motivation has been consistently reported for its predictive role in maintaining long-term health behaviors [19]. Taken together, our findings suggested that while current SM tools could encourage initial SM usage, there is a crucial need for future research to encourage enjoyment of SM activities to re-engage potential non-responders.

Despite facing similar barriers to SM, the Responder group used more problem-solving skills to overcome these barriers effectively, whereas the Non-responder group tended to feel discouraged. Problem solving is a core skill to support chronic disease self-management [20]. Previous research found that individuals with stronger problem-solving skills had better adherence to diet SM and weight loss in a 6-month behavioral lifestyle intervention [21]. However, behavioral lifestyle interventions alone are insufficient to impact one's problem-solving ability. According to Yu et al., the problem-solving ability of individuals participating a behavioral lifestyle intervention for weight loss remained stable over 12 months [22]. Thus, our findings suggested that providing supplemental problem-solving therapy to address SM barriers for participants with lower level of SM adherence during the early phase of an intervention could be beneficial.

Our findings revealed several technical aspects that can be improved to reduce the burden associated with diet SM. One major source of burden was the time-consuming manual entry process for homemade meals compared to restaurant meals. Embedding computer-vision algorithms into diet SM apps holds great promise in simplifying the process of adding new homemade meals to the food database [23]. Another commonly reported burden of diet SM was the extensive yet confusing built-in food database. Similar to previous research, common issues associated with the food database include the inaccurate nutritional information, the presence of multiple entries for the same food item, and the requirement for precise search terms to locate desired food products [24–26]. Thus, additional effort is required on the part of app developers to improve the food database and assure the quality and accuracy of information in the food database. Another source of burden was the need to bounce back and forth between different apps to complete SM. Our findings, similar to previous studies, emphasized the necessity for all-in-one SM apps to reduce SM burden [27].

Interestingly, many in the Non-responder group favored certain SM technology brands over those provided by the study team due to perceived advantages in accuracy, usability, ease of use, and aesthetics. Traditionally, SM technologies are often grouped together in the relevant literature under terms such as "digital food diary," "fitness tracker," and "smart scale" [6]. Given that these SM technologies shared similar characteristics (e.g., SM, positive feedback, goal setting), future study should investigate the potential moderating role of SM technology brands on SM adherence [28]. Furthermore, our findings also suggest that a lower level of adherence to SM may not always imply disengagement from SM. Instead, it could be the result of an individual switching to alternate SM technologies after being dissatisfied with the ones offered by the study team. In such situations, it is important for the interventionist to assess the individual's needs for app features and assist him/her in selecting SM technologies that fit best with their needs and preferences in order to prevent him/her from disengagement [29].

There are several limitations to be noted. First, the qualitative data was collected at 3 months, which was a relatively short period of time given that weight loss and maintenance require long-term commitment. This time-frame was chosen because significant differences in weight loss among intervention response subgroups had already emerged at 3month, suggesting that insights into early SM experiences could inform strategies to enhance SM adherence and improve overall intervention response. Future studies are needed to explore how perceptions of SM change over time to gain a comprehensive understanding of SM behavior. Second, the sample was derived from a subset of the pilot RCT who sustained engagement for 3 months. Consequently, our findings might reflect a biased population with greater commitment to SM and may not be generalizable to the entire population. Additionally, we relied on interview notes in the qualitative data analysis. Although the research coordinators made efforts to transcribe the conversations accurately, there could be missing or potentially biased information in these notes.

Conclusion

This study aimed to translate data-drive findings into actionable intervention improvement strategies. Through a qualitative approach, we gained a comprehensive understanding of SM experiences across intervention response subgroups. We identified key SM facilitators and barriers shared by both subgroups. Specifically, we found that problem-solving to be a unique factor distinguishing intervention response subgroups. Taken together, findings from our study can aid in the development of practical SM improvement strategies in future digital lifestyle interventions for obesity management.

Abbreviations

PA	Physical Activity
SM	Self-monitoring
RCT	Randomized Controlled Trial

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Authors' contributions

SL: conceptualization, methodology, validation, formal analysis, writing-original draft; YD: resources, data curation, supervision, writing-review & drafting, funding acquisition; CM: data curation, writing-review & drafting, project administration; DS: methodology, software, formal analysis, validation, writing-review & editing; KS: resources, writing-review & drafting, supervision, funding acquisition; ZY: writing-review & editing; BB: writing-review & editing; JW: conceptualization, resources, writing - review & editing, supervision, funding acquisition.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

This study was approved by the Institutional Review Board of The University of Texas Health Science Center at San Antonio (#20190528HU) and conducted in accordance with the Declaration of Helsinki. Written informed consent for participation were obtained prior to study procedures

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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