Original Paper

Associations Between Technology Attitudes, App Use, and Health Outcomes in a Diabetes Self-Management Education and Support Intervention: Secondary Analysis of a Randomized Controlled Trial

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Abstract

Background: Mobile health (mHealth) apps are increasingly incorporated into diabetes self-management education and support (DSMES) programs to improve access to behavioral and clinical support. Although digital DSMES interventions have demonstrated benefits for self-management and glycemic control, considerable variability exists in app use, and less is known about whether preintervention technology attitudes are associated with subsequent app use and related outcomes.

Objective: This study examined whether baseline technology attitudes are associated with app use and whether app use is associated with diabetes self-care and hemoglobin A_{1c} (HbA_{1c}) among adults participating in a digital DSMES intervention.

Methods: We conducted a secondary analysis of the Living Healthier with Diabetes randomized controlled trial (RCT) in Texas (2020-2022). The RCT included 3 study arms: virtual DSMES, smartphone app–based DSMES, and a combined intervention. Analyses were restricted to the 2 intervention arms with app access. Baseline technology attitude was assessed using a 4-item composite scale. App use was measured using 2 indices: a primary app use index derived from days per week, minutes per day, and overall 3-month usage, and a feature-use index summing use across 10 app functions. Outcomes included HbA_{1c} and diabetes self-care. Multivariable linear regression and linear mixed-effects models were used to evaluate associations after adjustment for intervention arm, age, gender, past month financial situation, and baseline outcome values.

Results: Of the 189 participants enrolled in the primary trial, 129 randomized to the intervention arms with smartphone app access were included. Follow-up HbA_{1c} and diabetes self-care data were available for 116 (89.9%) and 114 (88.4%) participants at 3 months and 117 (90.7%) and 116 (89.9%) participants at 6 months, respectively. More positive baseline technology attitudes

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were associated with greater app use at both 3 months (β=0.64, 95% CI 0.29 to 0.99; *P*<.001) and 6 months (β=0.78, 95% CI 0.39 to 1.17; *P*<.001) but were not associated with feature use. App use was not associated with HbA_{1c} at 3 months but was associated with lower HbA_{1c} at 6 months (β=−0.04, 95% CI −0.074 to −0.013; *P*=.005) and in longitudinal models (β=−0.04, 95% CI −0.074 to −0.006; *P*=.02). Greater app use was associated with higher self-care at 3 months (β=0.56, 95% CI 0.29 to 0.82; *P*<.001) and 6 months (β=0.38, 95% CI 0.14 to 0.62; *P*=.002) and remained associated with self-care in longitudinal analyses (β=0.44, 95% CI 0.21 to 0.68; *P*<.001). App and feature use did not change significantly between 3 and 6 months (*P*=.14 and *P*=.11, respectively).

Conclusions: These findings suggest that preintervention technology attitudes are associated with greater app use within digital DSMES programs and that greater use of the app may represent an important pathway linking mHealth interventions with behavioral and clinical outcomes in adults with type 2 diabetes.

Trial Registration: ClinicalTrials.gov NCT06370494; http://clinicaltrials.gov/ct2/show/NCT06370494

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KEYWORDS

type 2 diabetes; diabetes self-management education and support; mHealth; mobile apps; technology attitudes; app use; self-care; hemoglobin A1c; mobile health; mobile phone

Introduction

The number of people with diabetes (diagnosed and undiagnosed) in the United States surpassed 40 million as of recent estimates [1], with an increase in the age-adjusted prevalence rates (diagnosed and undiagnosed) for adults from 11.2% (2001-2004) to 13.5% (2021-2023). When considering diagnosed diabetes among adults during 2021-2023, the most recent data reveal marked geographic variations [1]. For example, higher rates were identified in nonmetropolitan areas as compared to metropolitan areas (10% vs 8.3%), for those with less than 100% of the federal poverty level (FPL) as compared to those at 500% or more of the FPL (13% vs 5.5%), and for those with less than a high school education vs those with more than high school (13.3 vs 7%) [1]. Beyond its rising prevalence, type 2 diabetes mellitus (T2D) is a complex, chronic illness that, when inadequately managed, confers substantial microvascular and macrovascular complications, which impair health-related quality of life and contribute to excess morbidity and mortality [2]. The economic burden is substantial; recent analyses provide estimates of the growing economic costs for diagnosed diabetes at US $412.9 billion in 2022 alone, of which US $306.6 billion was attributed to direct medical costs while another US $106.3 billion was attributed to indirect costs [3,4]. This represents a major financial burden to the US economy and to the millions of Americans impacted by this major public health issue. As such, there are several opportunities for potential interventions aimed at specific aspects of diabetes-related self-care.

Diabetes self-management education and support (DSMES) is a foundational component of type 2 diabetes care, facilitating the knowledge, skills, and behaviors required for effective self-management [5,6]. Evidence from a network meta-analysis of 108 randomized trials involving 17,735 participants demonstrated that DSMES significantly improves glycemic outcomes, reducing hemoglobin A_{1c} (HbA_{1c}) by an average of 0.61% compared with usual care [7]. Additional benefits include improvements in diabetes knowledge, self-efficacy, and weight-related outcomes, with effects sustained beyond the intervention period in some studies [8]. Despite its established effectiveness, DSMES remains substantially underused [9]. Referral, participation, and completion rates remain low, with disparities observed among individuals with lower income, lower educational attainment, and historically underserved populations [10,11].

Additionally, national evidence suggests that individuals experiencing lower socioeconomic status (SES) or who are Black or Hispanic may experience gaps in access to the internet at home [12]. The authors suggest that this link between lower access and potential for lags in access to health promotion may further worsen existing disparities [12]. Therefore, action must be taken to increase access and ameliorate both existing and potentially further disparities into the future as this cohort ages into adulthood [12,13]. Regardless of age, there is increased recognition of internet access as a social determinant of health [13,14], especially with more services being delivered through telehealth and patient portals that require access to the internet [14]. As such, this is a critical resource that warrants further investigation and widespread recognition to eliminate persistent disparities. These barriers have prompted increasing interest in alternative delivery approaches. In particular, digital and mobile health (mHealth)–based DSMES models have emerged as strategies that extend access to evidence-based DSMES beyond traditional in-person settings [15,16].

In 2018, a global review identified over 1000 apps focused on diabetes management alone [17]. The use of mHealth apps for T2D management has garnered significant research attention in recent years, with studies examining both clinical outcomes and self-management behaviors. Smartphone apps pose an alternative option that can help people with T2D improve HbA_{1c} levels by optimizing insulin management [18]. The proliferation of mHealth apps designed for T2D management has prompted researchers to evaluate their clinical effectiveness and impact on patient self-management. People living with T2D who use diabetes management apps demonstrated modest improvements in glycemic control and enhanced self-care behaviors [19-22]. Key factors linked to better outcomes included sustained app use, app features that support active self-monitoring, and

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integration of feedback mechanisms [19-23]. A recent scoping review concluded that mobile apps for people living with diabetes allowed for convenient user experiences and contributed to improved blood glucose levels, with significant HbA_{1c} reductions [24]. Mobile apps have demonstrated potential for clinically meaningful reductions in HbA_{1c} levels, though results vary based on participants, intervention duration, and app use frequency [24].

While mobile apps offer an additional avenue for providing health-related interventions, technology attitudes may be associated with adoption and sustained use of mHealth apps, particularly in chronic disease self-management. A systematic review has demonstrated that attrition rates in mHealth interventions for chronic disease average approximately 43%, with real-world engagement often far lower [25]. Individual orientation toward technology has been described through related constructs such as personal innovativeness in IT and technology readiness. Personal innovativeness refers to an individual's willingness to try new information technologies [26], while technology readiness reflects a person's propensity to embrace and use new technologies [27]. These concepts provide a basis for considering technology attitudes as a person's general orientation toward new technologies. Prior research has linked technology readiness with technology adoption and use [28].

Although diabetes mobile apps and digital DSMES programs have been associated with improvements in self-care and HbA_{1c}, app use remains uneven and is influenced by multiple patient and implementation factors [23,29,30]. Moreover, even among those who initially adopt a diabetes app, a discrepancy has been observed between early uptake and sustained long-term use, with many individuals substantially reducing or discontinuing engagement over time [25,31]. Such variability in app use may help explain differences in behavioral and clinical outcomes observed across participants. Despite evidence that more positive attitudes toward technology are associated with willingness to use digital health tools, less is known about whether baseline technology attitudes predict subsequent app use within DSMES programs [32,33]. Consequently, an important gap remains in understanding whether preintervention technology attitudes are associated with subsequent app use within DSMES programs and whether app use is associated with diabetes self-management behaviors and glycemic outcomes.

To address these gaps, we used data from the Living Healthier with Diabetes trial, a 3-arm randomized controlled DSMES trial conducted in Texas to examine patterns of app use over time and their associations with outcomes [34]. Specifically, we aimed to (1) examine differences in sociodemographic factors between groups with high and low attitudes toward technology at baseline, (2) examine whether baseline technology attitudes were associated with app use at 3 and 6 months, (3) evaluate the association between app use and diabetes self-care and HbA_{1c}, and (4) assess whether app use declined between 3 and 6 months. We hypothesized that more positive baseline technology attitudes would be associated with greater app use at follow-up. We further expected that higher levels of app use would be associated with better self-care behaviors, given the proximal role of behavior change in DSMES, and with lower HbA_{1c}. Finally, given the structured support embedded within the intervention (eg, blood glucose tracking, health coaching), we expected that app use would not decline between 3- and 6-month assessments.

Methods

Study Design and Setting

We conducted a secondary analysis of data from a 3-arm randomized controlled trial (RCT) designed to assess the relative effectiveness of DSMES interventions in adults with T2D in Texas [34]. Participants were recruited and enrolled between November 2020 and March 2022. The three arms of the intervention were (1) a virtual asynchronous DSMES program with individualized follow-up support, called Virtual Making Moves With Diabetes (vMMWD); (2) a technology-based education and support delivered through a smartphone app (TBES); and (3) a combined modality where participants received vMMWD followed by TBES. Participants completed a web-based survey on sociodemographic, behavioral, and health data and HbA_{1c} assessment at 3 time points: baseline, 3 months, and 6 months. Details of the study design, participant recruitment, and primary findings related to HbA_{1c} outcomes have been previously reported [34].

Ory et al [34] evaluated the effectiveness of the 3 intervention approaches and reported significant improvements across all intervention arms. The present secondary analysis focused on technology attitudes, app use, and diabetes-related outcomes among participants with access to the smartphone app. We therefore restricted the sample to participants in the TBES-only and combined arms. Specifically, we examined whether baseline technology attitude was associated with app use at 3- and 6-month follow-up assessments and whether app use was associated with better self-care behaviors and glycemic outcomes. The combined arm provided app use data during the TBES exposure period, which occurred after the vMMWD component was completed.

Participants

The inclusion criteria for the trial were being aged ≥25 years, self-reporting as T2D, having baseline HbA_{1c} ≥7.5%, living in Texas, having a smartphone with internet access, and being able to read and speak English. Pregnant individuals and individuals who previously had conditions known to invalidate HbA_{1c} values (eg, liver failure, kidney dialysis, or organ transplant) were excluded from participation. Participants were recruited through community partnerships, provider referrals, social media, and radio ads [34].

Of the 189 participants enrolled in the trial, those assigned to the vMMWD-only arm (n=60) were excluded because participants in this arm did not have access to the mobile app. Our analytic sample at baseline (N=129) included participants from the TBES-only (n=68) and combined arms (n=61). Analyses were conducted using available case data.

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Intervention

Participants randomized to TBES were given access to a smartphone app designed to support diabetes self-management [34]. The intervention was delivered over 3 months; however, participants continued to have access to the app thereafter and used the app at their own pace. The app included features for tracking blood glucose, meals, physical activity, and medications, as well as medication reminders, health coaching, and access to diabetes-related information (Table S1 in Multimedia Appendix 1). Participants could also communicate through the app with a diabetes coach, who provided text-based support several times per week, including encouragement, recipe ideas, and support related to blood glucose and other health tracking. Participants in the combined arm received both interventions sequentially, completing the vMMWD DSMES program before receiving access to the TBES mobile app. Compared to TBES, vMMWD included more structured education and counseling support through 8 hours of online diabetes education and periodic 1:1 virtual education and counseling with a clinical diabetes educator (eg, a registered nurse or registered dietitian nutritionist).

Variables

Primary Exposure: App Use

App use was assessed using an index score based on 3 self-reported items representing the intensity and frequency of app use over the past 3 months. App use was assessed at the 3- and 6-month follow-up surveys. The three items were (1) the number of times participants used the app for diabetes management over the preceding 3 months (10-point scale, 1 [never] to 10 [all the time]), (2) days per week of app use (0 to 7 days per week), and (3) average minutes per day of app use (7-point ordinal scale, 1 through 7 corresponded to 0-10 minutes, 11-20 minutes, 21-30 minutes, 31-40 minutes, 41-50 minutes, 51-60 minutes, and more than 60 minutes per day, respectively). Due to the heterogeneity of these scales, we rescaled each component to a common 0-10 metric using the transformation:

$$\text{rescaled score} = \left(\frac{X - X_{min}}{X_{range}}\right) \times n$$

where X is the original observed value, X_{min} is the lowest possible value of the scale, X_{range} denotes the span of possible values of the scale (calculated as the maximum minus the minimum), and n sets the upper limit of the rescaled scale (here, n=10). The app use variable was created by summing the 3 rescaled components. Scores on the app use index ranged from 0 to 30, with higher values indicating more overall use of the app (Table S2 in Multimedia Appendix 1).

Secondary Exposure: Feature Use

Additionally, at 3- and 6-month follow-up assessments, participants rated the frequency with which they used 10 specific app features over the preceding 3 months. Responses were captured using a 10-point scale ranging from 1 (never) to 10 (all the time). The assessed features are summarized in Table S1 in Multimedia Appendix 1. To capture the overall use of the features in the app, a feature use index was calculated as the sum of responses across the 10 features. Possible scores ranged from 10 to 100, where a score of 10 indicates no reported feature use, and higher scores reflect more frequent use of individual features, broader use across multiple features, or both.

Baseline Technology Attitude

In this study, technology attitude refers to a person's general orientation toward new technologies. We assessed baseline technology attitude using 4 items. Study participants indicated their level of agreement with the following items on a 5-point Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree): (1) I usually try new technologies before others do, (2) I generally avoid using new equipment or technology, (3) I enjoy using new equipment or technology, and (4) my friends come to me to learn about new technologies. The 3 positively worded items (1, 3, and 4) were reverse-coded so that higher scores across all 4 items reflected a more positive attitude toward technology (Table S3 in Multimedia Appendix 1). Baseline technology attitude score was computed by summing responses across the 4 items; scores therefore ranged from 4 to 20, with higher scores indicating a more positive attitude toward technology. The 4 items were adapted for this study. Internal consistency of the technology attitude measure was acceptable (Cronbach α=0.798).

Outcomes

The primary clinical outcome was HbA_{1c}. Given the statewide reach of the trial and restrictions on routine health care access during the COVID-19 pandemic, we chose a home-based testing approach using self-administered A_{1c}Now+ kits (PTS Diagnostics). This method has been used in previous diabetes self-management research [35]. Study personnel provided standardized testing instructions to supplement the manufacturer's instructions. Participants assessed their HbA_{1c} at baseline, 3 months, and 6 months and reported their results to the study team. HbA_{1c} was treated as a continuous outcome with possible values ranging from 4% to 14%. Higher scores represent poorer glycemic control.

Diabetes self-care was the secondary outcome and was measured using a 9-item modified Summary of Diabetes Self-Care Activities [36]. Items included assessing diet, physical activity, blood glucose monitoring, and foot care in the past 7 days using a scale ranging from 0 to 7 (Table S4 in Multimedia Appendix 1). The items were harmonized and summed up, creating a possible score ranging from 0 to 63. Higher scores represent greater performance of diabetes self-care activities. Cronbach α at baseline, 3 months, and 6 months were 0.81, 0.75, and 0.79, respectively.

Covariates

Additional variables considered important were selected based on existing literature [34], including intervention arm (TBES-only vs combined), age (years), gender (male or female), and self-reported financial situation over the past month (categorized as having money left over, just enough, or not enough). Race or ethnicity (non-Hispanic White, Hispanic, or other) and marital status (married or partnered, or other) were also collected and are reported to describe the study sample.

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Ethical Considerations

The RCT was approved by the Texas A&M Institutional Review Board (IRB; #2019-0804D) and registered at ClinicalTrials.gov (NCT06370494). All participants provided written informed consent before enrollment, and participation was voluntary. Participants could withdraw from the study at any time without a penalty. Study data were deidentified and deposited in the Texas A&M institutional data repository, with access restricted to members of the study team. Participants could receive up to US $375 in compensation based on completion of study assessments. This secondary analysis used deidentified data collected under the original study approval.

Sample Size

The RCT used an a priori sample-size calculation based on its primary outcome, HbA_{1c}. Assuming a moderate effect size (Cohen *d*=0.5), 34 participants with baseline and postintervention measurements were required to provide 80% power at a 2-sided α=.05 [34]. The present study is a secondary analysis restricted to participants in the 2 intervention arms with access to the mobile app, with 129 participants available at baseline. Because this analysis used the available sample from the primary trial, no new prospective sample-size calculation was performed. For transparency, we conducted a sensitivity analysis for the multivariable linear regression models using the analytic sample available for each model (n=106-113). At 80% power and a 2-sided α=.05, the minimum detectable effect size for the focal predictor (Cohen f^2) ranged from 0.074 to 0.080 across the primary regression models. At 90% power, the corresponding minimum detectable effect size ranged from 0.099 to 0.107. These values indicate the analysis was sensitive to small-to-medium standardized effects.

Statistical Analysis

Baseline characteristics of participants were summarized using means with SDs for continuous variables and frequencies with percentages for categorical variables. Median splits of baseline technology attitude and app use at 3-month follow-up were used to separately stratify the participants' characteristics at baseline. Group differences were compared using a 2-sided Welch *t* test for continuous variables and Pearson chi-square test for categorical variables.

Separate multivariable linear regression models were fitted to investigate the association between baseline technology attitude and app use at 3- and 6-month follow-ups. Two outcomes were considered: app use and feature use. All models were adjusted for the intervention arm, age, gender, and the participant's baseline past-month financial situation.

Multivariable linear regression models were then used to investigate the cross-sectional associations between app use and health and behavioral outcomes at each of the follow-up time points. The primary predictor was app use measured at 3 and 6 months, and outcomes included HbA_{1c} and self-care assessed at the respective time points. The models were adjusted for baseline values of the respective outcome variables, intervention arm, age, gender, and past month's financial situation. The same model specifications were subsequently applied using feature use as an alternate predictor. The regression analyses used complete cases for each model. To assess the potential impact of missing data, we conducted sensitivity analyses using multiple imputation by chained equations (50 imputed datasets) with the *mice* package in R (R Foundation). Estimates were pooled using Rubin rules. These analyses yielded comparable estimates for the primary app-use associations.

Linear mixed-effects models with random participant intercepts were used to evaluate the association between app use and outcomes (HbA_{1c} and self-care) over time. In these models, app use at 3 months was included as a predictor of longitudinal outcomes measured at 3 and 6 months. Models were adjusted for baseline values of outcomes, intervention arm, age, gender, and past month's financial situation. The same model specifications were then applied using feature use as an alternate predictor.

To assess whether use of the app was sustained during the 3- to 6-month assessments, paired *t* tests were performed on the app use and on the feature use. Within-subject differences were calculated as 6-month minus 3-month, and the mean changes were reported with a 95% CI.

We assessed model assumptions by visually examining residual plots for linearity, homoscedasticity, and normality. Multicollinearity was assessed using variance inflation factor (VIF) and tolerance values (VIF range 1.00-1.47; tolerance range 0.68-1.00). Influential observations were assessed using Cook distance, with all values below 1 (maximum 0.37). All statistical analyses were conducted in R software, version 4.5.2. A 2-sided α of .05 was used as the threshold for statistical significance.

Results

Participant Characteristics

Figure 1 illustrates the participant selection process and data availability for the secondary analysis. At baseline, the analytic sample included 129 participants with access to the mobile app. Follow-up data were available for 116 (89.9%) participants for HbA_{1c} and 114 (88.4%) for self-care at 3 months and for 117 (90.7%) and 116 (89.9%), respectively, at 6 months.

Table 1 shows baseline characteristics stratified by median split of baseline technology attitude. Participants with an above-median technology attitude were younger (mean 49.2, SD 11.8) compared with those at or below the median (mean 53.5, SD 9.6; *P*=.03). No other significant differences were observed across attitude groups for gender, race and ethnicity, marital status, financial situation, baseline HbA_{1c}, or baseline self-care (all *P*>.05).

Baseline characteristics of participants with available app use data at 3 months (n=116) stratified by median split of 3-month app use are presented in Table S1 in Multimedia Appendix 2. A significantly greater proportion of participants in the combined arm fell into the lower app use group (36/58, 62.1%) compared to the proportion in the app-only arm (*P*=.02). Baseline technology attitude was higher among those with above-median app use (mean 14.6, SD 3.2) compared to those

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at or below the median (mean 13.3, SD 3.7; *P*=.04). No other significant differences were observed.

Figure 1. Flow diagram showing participant selection and availability of HbA_{1c} and diabetes self-care data at 3- and 6-month follow-up. HbA_{1c}: hemoglobin A_{1c}; vMMWD: Virtual Making Moves With Diabetes.

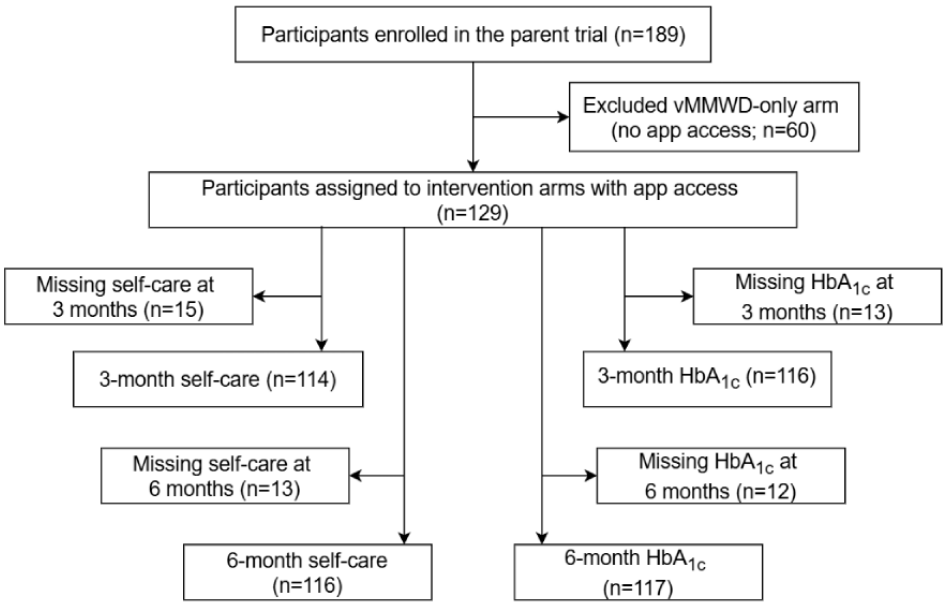


Table 1. Participant characteristics at baseline, stratified by baseline technology attitude (median 14, IQR 12-16).

Participant characteristics and baseline measures	Overall (N=129)	Technology attitude ≤14 (n=79)	Technology attitude >14 (n=50)	*P* value
Intervention arm, n (%)				.50
App only	68 (52.7)	44 (55.7)	24 (48.0)	
Combined	61 (47.3)	35 (44.3)	26 (52.0)	
Age (years), mean (SD)	51.9 (10.7)	53.5 (9.6)	49.2 (11.8)	.03
Gender, n (%)				.63
Female	99 (76.7)	59 (74.7)	40 (80.0)	
Male	30 (23.3)	20 (25.3)	10 (20.0)	
Race or ethnicity, n (%)				.28
Non-Hispanic White	66 (51.2)	39 (49.4)	27 (54.0)	
Hispanic	48 (37.2)	28 (35.4)	20 (40.0)	
Other	15 (11.6)	12 (15.2)	3 (6.0)	
Marital status, n (%)				.87
Married or partnered	85 (65.9)	53 (67.1)	32 (64.0)	
Other marital status	44 (34.1)	26 (32.9)	18 (36.0)	
Financial situation over the past month, n (%)				.18
Money left over	49 (38.9)	30 (39.0)	19 (38.7)	
Just enough	58 (46.0)	32 (41.5)	26 (53.1)	
Not enough	19 (15.1)	15 (19.5)	4 (8.2)	
Baseline HbA_{1c}[a] (%), mean (SD)	9.5 (1.6)	9.4 (1.6)	9.6 (1.7)	.59
Baseline self-care, mean (SD)	27.5 (13.5)	26.3 (13.5)	29.2 (13.4)	.23

[a]HbA_{1c}: hemoglobin A_{1c}.

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Association of Baseline Technology Attitude With App Use

Higher baseline technology attitude was significantly associated with greater app use at both 3 months (β=0.64, 95% CI 0.29 to 0.99; *P*<.001) and 6 months (β=0.78, 95% CI 0.39 to 1.17; *P*<.001; Table S2 in Multimedia Appendix 2). Participants randomized to the combined arm had significantly lower app use at 3 months compared with participants randomized to the app-only arm (β=–2.90, 95% CI –5.17 to –0.62; *P*=.01). On the other hand, higher baseline technology attitude was not significantly associated with feature use at 3 months (β=0.72, 95% CI –0.23 to 1.67; *P*=.14) or 6 months (β=0.67, 95% CI –0.35 to 1.68; *P*=.20) after adjustment for covariates (Table S3 in Multimedia Appendix 2).

Association of App Use With HbA1c

The complete-case cross-sectional regression models for HbA_{1c} included 112 participants at 3 months and 113 at 6 months. At 3 months, app use was not associated with HbA_{1c} following adjustment (β=–0.04, 95% CI –0.08 to 0.00; *P*=.08; Table 2). However, at 6-month follow-up, higher app use was associated with lower HbA_{1c} (β=–0.04, 95% CI –0.074 to –0.013; *P*=.005; Table 2). In the longitudinal analysis, app use was associated with lower Hb A_{1c} (β=–0.04, 95% CI –0.074 to –0.006; *P*=.02; Table 3). Time was not significantly associated with HbA_{1c} across follow-up (*P*=.18).

Table 2. Multivariable linear regression analyses examining the association of app use with HbA_{1c}[a]. Analyses were restricted to participants with complete data on all variables included in each regression model.

Variables and factors	Beta value (95% CI)	*P* value
Cross-sectional analysis at the 3-month follow-up (N=112)		
App use at 3 months	–0.04 (–0.08 to 0.00)	.08
Baseline HbA_{1c}	0.39 (0.21 to 0.57)	<.001
Intervention arm (combined; reference: app only)	0.21 (–0.34 to 0.76)	.45
Age (years)	–0.01 (–0.04 to 0.02)	.41
Gender (reference: female)	–0.06 (–0.75 to 0.64)	.87
Financial situation over the past month		
Money left over	—[b]	—
Just enough	–0.16 (–0.78 to 0.46)	.61
Not enough	0.87 (–0.02 to 1.76)	.05
Cross-sectional analysis at the 6-month follow-up (N=113)		
App use at 6 months	–0.04 (–0.074 to –0.013)	.005
Baseline HbA_{1c}	0.38 (0.23 to 0.52)	<.001
Intervention arm (combined; reference: app only)	–0.06 (–0.49 to 0.37)	.79
Age (years)	–0.03 (–0.05 to –0.01)	.01
Gender (reference: female)	–0.50 (–1.06 to 0.05)	.08
Financial situation over the past month		
Money left over	—	—
Just enough	–0.33 (–0.84 to 0.18)	.20
Not enough	0.89 (0.16 to 1.62)	.02

[a]HbA_{1c}: hemoglobin A_{1c}.

[b]Reference group.

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Table 3. Linear mixed-effects model examining the longitudinal association of app use with HbA_{1c}[a] across follow-up.

Variables and factors	Beta value (95% CI)	*P* value
Time	–0.17 (–0.41 to 0.08)	.18
App use at 3 months	–0.04 (–0.074 to –0.006)	.02
Baseline HbA_{1c}	0.39 (0.25 to 0.53)	<.001
Intervention arm (combined; reference: app only)	0.10 (–0.32 to 0.53)	.63
Age (years)	–0.02 (–0.04 to 0.00)	.08
Gender (reference: female)	–0.35 (–0.89 to 0.19)	.20
Financial situation over the past month		
Money left over	—[b]	—
Just enough	–0.23 (–0.71 to 0.25)	.34
Not enough	0.83 (0.14 to 1.53)	.02

[a]HbA_{1c}: hemoglobin A_{1c}.

[b]Reference group.

Association of App Use With Diabetes Self-Care

For self-care, the complete-case cross-sectional regression models included 108 participants at 3 months and 111 at 6 months. Greater app use was associated with better self-care at 3 months (β=0.56, 95% CI 0.29 to 0.82; *P*<.001; Table 4). Similarly, at 6 months, app use continued to show an association with self-care (β=0.38, 95% CI 0.14 to 0.62; *P*=.002; Table 4). In longitudinal analysis, app use was associated with higher self-care across follow-up (β=0.44, 95% CI 0.21 to 0.68; *P*<.001; Table 5). The main effect of time was not significantly associated with self-care changes (*P*=.79).

Table 4. Multivariable linear regression analyses examining the association of app use with diabetes self-care. Analyses were restricted to participants with complete data on all variables included in each regression model.

Variables and factors	Beta value (95% CI)	*P* value
Cross-sectional analysis at the 3-month follow-up (N=108)		
App use at 3 months	0.56 (0.29 to 0.82)	<.001
Baseline self-care	0.44 (0.32 to 0.57)	<.001
Intervention arm (combined; reference: app only)	1.14 (–2.24 to 4.52)	.51
Age (years)	0.05 (–0.11 to 0.21)	.53
Gender (reference: female)	2.34 (–1.73 to 6.41)	.26
Financial situation over the past month		
Money left over	—[a]	—
Just enough	2.20 (–1.59 to 5.98)	.25
Not enough	6.81 (1.64 to 11.98)	.01
Cross-sectional analysis at the 6-month follow-up (N=111)		
App use at 6 months	0.38 (0.14 to 0.62)	.002
Baseline self-care	0.54 (0.41 to 0.67)	<.001
Intervention arm (combined; reference: app only)	2.97 (–0.43 to 6.36)	.09
Age (years)	0.16 (–0.01 to 0.33)	.07
Gender (reference: female)	5.16 (0.83 to 9.50)	.02
Financial situation over the past month		
Money left over	—	—
Just enough	4.51 (0.56 to 8.46)	.03
Not enough	6.84 (1.16 to 12.53)	.02

[a]Reference group.

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Table 5. Linear mixed-effects model examining the longitudinal association of app use with diabetes self-care across follow-up.

Variables and factors	Beta value (95% CI)	*P* value
Time	–0.24 (–2.01 to 1.54)	.79
App use at 3 months	0.44 (0.21 to 0.68)	<.001
Baseline self-care	0.51 (0.40 to 0.62)	<.001
Intervention arm (combined; reference: app only)	2.18 (–0.78 to 5.14)	.15
Age (years)	0.10 (–0.04 to 0.24)	.18
Gender (reference: female)	3.50 (–0.13 to 7.13)	.06
Financial situation over the past month		
Money left over	—[a]	—
Just enough	3.22 (–0.10 to 6.54)	.06
Not enough	6.02 (1.36 to 10.67)	.01

[a]Reference group.

Association of Feature Use and Outcomes

Feature use was not associated with HbA_{1c} at 3 months (β=0.00, 95% CI –0.02 to 0.02; *P*=.82). At 6 months, feature use was associated with lower HbA_{1c} (β=–0.01, 95% CI –0.03 to 0.00; *P*=.02; Table S4 in Multimedia Appendix 2). In the longitudinal model, the association between feature use at 3 months and HbA_{1c} across follow-up did not reach statistical significance (Table S5 in Multimedia Appendix 2). Turning to self-care, feature use was associated with self-care at both 3 months (β=0.18, 95% CI 0.07 to 0.29; *P*=.002) and 6 months (β=0.16, 95% CI 0.06 to 0.27; *P*=.002; Table S6 in Multimedia Appendix 2). The association remained statistically significant in the longitudinal analysis (β=0.14, 95% CI 0.04 to 0.23; *P*=.005; Table S7 in Multimedia Appendix 2).

Change in App Use Between 3- and 6-Month Follow-Up

Paired *t* tests showed no significant decline in use between the 3- and 6-month assessments. App use was not significantly different between 3 months (mean 9.13, SD 6.48) and 6 months (mean 8.49, SD 7.13), with a mean change of –0.64 (SD 4.52, 95% CI –1.49 to 0.21; *P*=.14). Similarly, feature use was not significantly different between 3 months (mean 24.45, SD 16.49) and 6 months (mean 27, SD 18.77), with a mean change of 2.55 (SD 16.45, 95% CI –0.56 to 5.65; *P*=.11; Tables S8 in Multimedia Appendix 2).

Sensitivity Analysis

Sensitivity analyses using multiple imputation yielded estimates comparable to the complete-case analyses. The association between app use and HbA_{1c} at 6 months remained statistically significant, whereas the association at 3 months remained nonsignificant. Positive associations between app use and self-care were maintained at both follow-up assessments (Table S9 in Multimedia Appendix 2).

Discussion

Principal Results and Interpretations

This study examined the association between baseline technology attitude, app use, and diabetes outcomes within a digital DSMES intervention. Baseline technology attitude was associated with greater app use at both 3 and 6 months, with stronger estimates observed at 6 months. No clear association was observed with feature use. Higher app use, in turn, was associated with better diabetes self-care at both 3 and 6 months. In contrast, the association between app use and HbA_{1c} at 3 months was not statistically significant, but higher app use was associated with lower HbA_{1c} at 6 months. In longitudinal analyses, app use at 3 months remained associated with both self-care and HbA_{1c} across follow-up. Finally, app use did not decline significantly between 3 and 6 months.

In this study, higher baseline technology attitude was associated with greater app use at both 3 and 6 months, independent of age, gender, financial situation, and intervention arm. The larger estimate at 6 months suggests that technology attitudes may remain relevant as participants transition from early exposure to longer-term app use. This finding is consistent with previous research showing that individuals with greater personal innovativeness toward new technologies used a health promotion app more frequently [37]. Similar findings have been reported among adults with T2D, where participants who continued using a diabetes management app had more positive baseline attitudes toward technology, and more positive attitudes were associated with greater frequency and intensity of app use among noninsulin users [38]. In contrast, baseline technology attitude was not associated with feature use. This divergence suggests that general attitudes toward technology may shape willingness to incorporate an app into self-management routines, whereas use of individual features may depend on perceived relevance, usability, and personal need. Similar heterogeneity in module use has been reported in real-world diabetes app studies, where most users used only a single app component, a pattern the authors attributed to the highly heterogeneous self-management needs of patients with diabetes [32].

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The pattern of findings for HbA_{1c} suggests that the association between mHealth app use and glycemic control may differ across follow-up assessments. Although app use was not associated with HbA_{1c} at 3 months, higher use was associated with lower HbA_{1c} at 6 months, and 3-month use was associated with HbA_{1c} in the longitudinal analysis. This temporal pattern is consistent with evidence indicating that clinically meaningful glycemic improvements often require sustained exposure to digital self-management interventions. Studies of diabetes apps and digital therapeutics have reported greater HbA_{1c} reductions among participants with higher levels of app use, including dose-response patterns across engagement groups [39] and stronger clinical effects after 6 months of continued use [40]. However, findings across the mHealth literature are not entirely consistent. Vehi et al [41] observed improvements in glycemic outcomes regardless of use frequency, suggesting that frequency alone may not fully explain clinical benefit. Collectively, these findings suggest that the association between app use and glycemic outcomes may extend beyond frequency of use alone and may involve the quality, consistency, and behavioral context of use.

The clinical significance of these findings warrants consideration. Although the adjusted association between app use and HbA_{1c} at 6 months was modest ($\beta=-0.04$ per point), the observed IQR of the app-use index (1.43-14.19) corresponds to an estimated 0.51 percentage-point lower HbA_{1c} at the higher level of app use, based on the fitted regression model. This magnitude is comparable to the pooled HbA_{1c} improvement of approximately 0.2-0.4 percentage points reported across intervention categories in a systematic review and meta-analysis of randomized trials of mHealth-delivered DSMES, which the authors characterized as clinically relevant [16]. However, unlike intervention effects reported in randomized trials, our estimate reflects an observational association between self-reported app use and HbA_{1c}. Thus, the observed association may be clinically relevant across meaningful differences in app use, but its causal interpretation remains uncertain.

Greater app use demonstrated a consistent association with diabetes self-care at both 3 and 6 months and remained significant in longitudinal analyses. This finding is consistent with prior mHealth research showing that diabetes app users report higher levels of self-management behaviors than nonusers [21]. The feature-use findings further support this interpretation, as greater use of app features was also associated with higher self-care scores. Prior research suggests that diabetes apps support self-management through functions such as blood glucose monitoring, dietary recording, medication management and reminders, physical activity tracking, and tailored education or real-time feedback, which are intended to reinforce adherence to self-care regimens [42,43]. Real-world evidence from the myDiabetes app similarly suggests that use of digital education and self-monitoring functions can support structured diabetes education and ongoing self-management activities [44]. Taken together, these findings suggest that digital DSMES apps may support self-care by facilitating ongoing self-monitoring, feedback, and behavioral reinforcement.

App and feature use did not significantly decline between the 3- and 6-month assessments. This finding contrasts with the pattern reported in mHealth interventions, where app use declines commonly after an initial adoption period. Large-scale evaluations of digital diabetes prevention programs have documented progressive reductions in use over time, with many participants disengaging from intervention features within the first several months of enrollment [45]. The stability observed in the present study may reflect the structured nature of DSMES delivery and the continued support provided within the intervention. Similar observations have been reported in studies showing that sustained retention and continued app use are associated with more favorable long-term glycemic outcomes [46].

Significance and Strengths

This study contributes to digital DSMES literature in 3 ways. First, previous research linking technology attitudes to mHealth use has been conducted within acceptance-based frameworks, which primarily model behavioral intention rather than directly measured usage [47,48]. In this study, we assessed technology attitude before exposure to the app and then examined its association with reported app use at 3 and 6 months. This allowed us to evaluate whether baseline disposition toward technology was associated with subsequent app use. Second, many mHealth studies characterize app use using single measures, such as logins or time-based indicators [49,50]. We assessed app use using an app-use index capturing frequency, regularity, and duration, alongside a separate index of use across specific app features. This provided complementary measures of how participants used the app. Third, app use is not often evaluated over time in mHealth research. In a systematic review, only one-third of studies assessed change in engagement over time [50]. By measuring app and feature use at 3 and 6 months within a randomized DSMES trial, our study adds temporal depth to a literature that often relies on a single time point.

Limitations

This study has several limitations. App use was determined using self-report, rather than objective app-use logging data, which, while common in community-based research, may be subject to recall and social desirability biases. Despite this, self-reported app use can capture dimensions of engagement that may not be fully captured by objective usage metrics alone [51]. Additionally, diabetes self-care was self-reported and may therefore be subject to recall and social desirability bias. HbA_{1c} was measured using self-administered home testing kits, with participants reporting their results to the study team. This approach may be less precise than laboratory-based measurement [52] and may introduce reporting errors.

The feature-use index combines frequency of use across 10 app features into a single score. Similar scores could therefore represent different patterns of use, such as frequent use of a small number of features or less frequent use across several features. The index should be interpreted as a measure of overall feature use and does not distinguish the breadth and frequency of feature use. Residual confounding is also possible because some potentially relevant factors were not measured and so were not included in the adjusted models. These include

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medication regimen or insulin use, digital literacy, and other factors that could be related to both app use and study outcomes. Additionally, participants in the combined arm received structured DSMES before app access. Although the regression models adjusted for the intervention arm, differences in prior structured DSMES exposure, self-management knowledge, and confidence between the intervention arms could still have contributed to the observed associations.

Restricting the analysis to the 2 intervention arms with app access was necessary because app use was only defined for participants assigned to receive the mobile app. Because app access was determined by randomized treatment assignment, this restriction is less likely to introduce collider bias through self-selection into app use. Nevertheless, trial eligibility required smartphone and internet access, and the analyses relied on available follow-up data. These factors may introduce selection bias and limit the generalizability of the findings to populations with lower digital access or different patterns of follow-up participation. Lastly, recruitment and data collection for the parent trial occurred during the COVID-19 pandemic [34]. The pandemic may have influenced participants' willingness to enroll in a digital DSMES intervention as well as their technology attitudes, access to digital resources, and patterns of app engagement. Consequently, the observed associations may not fully reflect technology use and engagement under usual, nonpandemic conditions.

Research and Policy Implications

Future mHealth research should move beyond evaluating app use through single, isolated metrics such as login counts or session duration [50]. Our parallel analysis of app and feature use indices demonstrated that each may capture distinct dimensions of participant interaction with digital interventions; for example, baseline technology attitude was associated with the app use index but not feature use. Researchers should adopt multidimensional, longitudinal approaches to better understand how technology attitudes influence different patterns of app use and how these patterns relate to behavioral and clinical outcomes over time [50].

From a policy perspective, the absence of a significant decline in app use between 3 and 6 months suggests that engagement with digital DSMES may be sustained over short-term follow-up. However, the present study did not assess costs, cost-effectiveness, health care use, reimbursement, or implementation economics. Future studies should examine the resources required to assess technology-related factors and support digital DSMES uptake, including whether such implementation strategies are cost-effective and whether reimbursement approaches can facilitate equitable access.

Conclusions

This study provides new evidence on the relationship between technology attitudes, app use, and diabetes outcomes within a digital DSMES intervention. More positive baseline technology attitudes were associated with greater app use, while higher app use was associated with better diabetes self-care and lower HbA_{1c} over follow-up. App use did not significantly decline between 3 and 6 months, contrasting with the declining use patterns commonly reported in mHealth interventions. These findings suggest that technology attitudes may influence how individuals interact with digital DSMES programs and highlight the importance of considering technology-related factors when designing, implementing, and evaluating mHealth interventions for adults with type 2 diabetes.

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Data Availability

The datasets generated or analyzed during this study are not publicly available due to restrictions enforced by Blue Cross Blue Shield of Texas. Requests to access the datasets should be directed to the Texas A&M point of contact for all data (Mr Jim Colson, MS, Texas A&M Associate Vice President, Digital Health, jim.colson@tamu.edu).

Generative AI Use

The authors declare that generative AI was not used in the preparation of this manuscript.

Authors' Contributions

Conceptualization: KDO, GH, MLS, MGO
Formal analysis: KDO

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Funding acquisition: MLS, MGO
Project administration: MLS, MGO
Supervision: GH, MLS, MGO
Writing – original draft: KDO, SDCTJ, CE, SA, SL
Writing – review & editing: KDO, GH, SDCTJ, CE, SA, SL, MLS, MGO
MLS and MGO served as senior authors, reflecting their roles as coprincipal investigators and joint scientific directors for this project.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Definitions and scoring of study measures.
[DOCX File , 19 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Additional statistical results.
[DOCX File , 41 KB-Multimedia Appendix 2]

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Abbreviations

DSMES: diabetes self-management education and support
FPL: federal poverty level
HbA1c: hemoglobin A1c
IRB: Institutional Review Board
mHealth: mobile health

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RCT: randomized controlled trial
SES: socioeconomic status
T2D: type 2 diabetes mellitus
TBES: technology-based education and support delivered through a smartphone app
VIF: variance inflation factor
vMMWD: Virtual Making Moves With Diabetes

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