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Weight loss in a digital app-based diabetes prevention program powered by artificial intelligence

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Abstract

Objective: The National Diabetes Prevention Program (DPP) reduces diabetes incidence and associated medical costs but is typically staffing-intensive, limiting scalability. We evaluated an alternative delivery method with 3933 members of a program powered by conversational Artificial Intelligence (AI) called *Lark DPP* that has full recognition from the Centers for Disease Control and Prevention (CDC).

Methods: We compared weight loss maintenance at 12 months between two groups: 1) CDC qualifiers who completed ≥4 educational lessons over 9 months (n = 191) and 2) non-qualifiers who did not complete the required CDC lessons but provided weigh-ins at 12 months (n = 223). For a secondary aim, we removed the requirement for a 12-month weight and used logistic regression to investigate predictors of weight nadir in 3148 members.

Results: CDC qualifiers maintained greater weight loss at 12 months than non-qualifiers (M = 5.3%, SE = .8 vs. M = 3.3%, SE = .8; p = .015), with 40% achieving ≥5%. The weight nadir of 3148 members was 4.2% (SE = .1), with 35% achieving ≥5%. Male sex ($\beta = .11$; $P = .009$), weeks with ≥2 weigh-ins ($\beta = .68$; $P < .0001$), and days with an AI-powered coaching exchange ($\beta = .43$; $P < .0001$) were associated with a greater likelihood of achieving ≥5% weight loss.

Conclusions: An AI-powered DPP facilitated weight loss and maintenance commensurate with outcomes of other digital and in-person programs not powered by AI. Beyond CDC lesson completion, engaging with AI coaching and frequent weighing increased the likelihood of achieving ≥5% weight loss. An AI-powered program is an effective method to deliver the DPP in a scalable, resource-efficient manner to keep pace with the prediabetes epidemic.

Keywords

Preventive healthcare, prediabetes, chronic disease management, mobile health (mHealth), lifestyle behavior change, obesity, type 2 diabetes

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Introduction

More than 88 million Americans have prediabetes,[1] and three-quarters of individuals with prediabetes at age 45 will eventually progress to having type 2 diabetes (T2D).[2] The American Diabetes Association (ADA) reported a $327 billion total cost of diagnosed diabetes in 2017, representing a 26% inflation-adjusted increase from 2012 due to a growing prevalence of T2D and cost of care.[3] Individuals diagnosed with T2D have a $9601/year estimated excess in medical expenses compared to those who are not diabetic.[3]

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The ADA recommends that individuals with prediabetes join a CDC-recognized diabetes prevention program (DPP) focused on lifestyle changes because such programs can cut the risk of progression to T2D in half.[4]

Being overweight or obese has been shown to be the single most important predictor of T2D.[5] In a widely recognized lifestyle intervention study by Hamman et al., [6] the dominant predictor of reduced diabetes risk was weight loss, with each kilogram of weight loss associated with a 16% reduction in the risk of T2D. In a large meta-analysis of randomized clinical trials, the effects of lifestyle modifications on diabetes risk reduction were sustained long-term, while the effects of medications were not sustained after discontinued use.[7] The effects of lifestyle interventions continue to provide benefits 30 years later, delaying diabetes, decreasing cardiovascular disease events, and increasing life expectancy.[8] Even in the short term, there is a positive return on investment. Individuals who completed the DPP had significantly lower medical expenditures, fewer emergency hospital visits, and reduced work absenteeism in the year after the intervention.[9,10] A large and growing number of health plans, including Medicare, offer DPPs to eligible members at no out-of-pocket cost.[11]

Traditional in-person DPPs are effective for weight loss, with a pooled estimate of 3.99% (2.83 to 5.16) weight loss maintenance at 12 months.[12] In contrast, individuals not enrolled in a weight loss program tend to gain weight over the course of a year.[13,14] A critical component of successful DPPs is helping members to develop skills required to overcome barriers to weight loss.[15] This role is typically fulfilled by expert healthcare professionals; thus, the original DPP was resource-intensive, with annual direct costs of approximately $1400/person largely due to staffing.[16] In-person DPPs also present barriers for members, including scheduling, work, transportation, and childcare,[17] and are increasingly challenging to implement due to new restrictions related to COVID-19 and the post-pandemic era.[18] Digital DPPs are pragmatic alternatives that offer more affordable, convenient, and scalable care.[19] A key aspect of digital programs is the ability to deliver continuous, on-demand care between both physician visits and educational lessons of the DPP. Digital DPPs are equally effective for weight loss maintenance, with a pooled estimate of 3.98% (3.46 to 4.49) at 12 months.[20] However, most digital programs should be considered "hybrid-digital" as they involve multiple human coaching components, limiting their scalability (e.g..[21–23])

Automated digital health programs offer flexible and cost-effective alternatives to in-person or hybrid-digital programs.[24] Automated programs can deliver personalized support via web-based or mobile apps and have been used to address several chronic conditions, including depression, heart disease, Alzheimer's Disease, arthritis, and diabetes glaucoma.[25] Interpersonal contact is an important element of successful chronic disease management.[26] Automated programs may address the need for interpersonal contact by using artificial intelligence (AI)-enabled conversational agents to deliver personalized coaching. Despite the promise of AI agents for chronic disease management, there are few studies demonstrating the effectiveness of DPPs powered by AI for facilitating weight loss. Thus, there is an urgent need to evaluate automated approaches, such as conversational AI, to deploy the DPP in a scalable, resource-efficient, and effective manner.

In this study, we investigated 12-month weight-loss maintenance and predictors of peak weight loss in a program called *Lark DPP* that is powered by conversational AI. The program is delivered via a mobile application and has full CDC recognition (organization # 4358176). The Lark DPP provides coaching powered by conversational AI that emulates human coaching and is monitored by human lifestyle coaches who are trained in the CDC curriculum. Early work in a small sample of members enrolled in the beta version of the Lark application demonstrated the potential of an AI program for promoting weight loss.[27] The program has since been updated, certified by CDC, and used as a commercially available diabetes prevention health intervention.

Our primary hypothesis was that members of an AI-powered program who met CDC qualifying criteria would maintain a greater magnitude of weight loss at 12 months than members who did not achieve this engagement benchmark. CDC qualifying criteria involve completing ≥3 educational lessons in months 1–6 and having ≥1 lesson after 9 months in the program (≥4 total). Comparing CDC qualifiers and non-qualifiers is a standard approach for evaluating outcomes in the National DPP.[28] We further expected that higher levels of engagement with the AI coach and other application features would be associated with a greater likelihood of achieving the National DPP goal of ≥5% weight loss during the program.

Methods

Study design

This study received exemption status from Advarra (Protocol #Pro00047181) Institutional Review Board for retrospective analyses of previously collected and de-identified data. We conducted a retrospective, longitudinal study of members of the Lark DPP who enrolled between May 2019 and April 2020, provided a starting weight, and completed at least one educational lesson, demonstrating minimal intent to engage in the program. These individuals agreed to Lark's privacy policy, which included permission to use their de-identified data for research. We selected this date range to reduce time-dependent variations in coaching content and available member-coach interactions.

Participants and recruitment

Members enroll in the Lark DPP as a covered service under their health insurance plans or employer. Digital advertising (e.g. Facebook) and/or outreach from their health plan, employer, or Lark helps facilitate awareness of this covered service. Eligible members who opted into the program received a link via text message to download the program to their iOS or Android smartphones. Inclusion criteria for this study were based on CDC requirements [29]: 1) over 18 years old; 2) no previous diagnosis of type 1 or 2 diabetes; 3) initial body mass index (BMI) ≥ 25 kg/m^2; and had to meet at least one of the following items 4 or 5: 4) blood test result (within past year) of either fasting plasma glucose between 100–125 mg/dl, two-hour plasma glucose after 75-gram glucose load between 140–199 mg/dl, or hemoglobin A1c 5.7–6.4%; or 5) a risk score indicating high risk for T2D.[30] Thus, all members had either been diagnosed with prediabetes or were at high risk based on CDC criteria. Members self-reported these inclusion criteria (e.g. demographics, blood test results).

Inclusion and exclusion criteria for this study were consistent with CDC reporting guidelines to ensure comparability with other related studies. Per 2018 reporting guidelines [29] (the current guidelines when this cohort completed the program), only those members who completed ≥3 educational lessons in months 1–6 and had ≥9 months between their first and last lessons (≥4 total) were eligible for the CDC analysis of weight loss maintenance at 12 months. These criteria demonstrate at least minimal involvement in the DPP curriculum, enabling clinical outcomes to be attributed to program participation. However, in addition to these criteria, other key DPP outcomes studies have also analyzed individuals who completed ≥1 educational lesson,[28,31] referring to these individuals as those "not meeting the reporting threshold," and compared them to those who did meet reporting thresholds. Thus, to be consistent with the literature, we divided members in this study into two groups: 1) Those who met CDC reporting criteria, termed "CDC qualifiers," and 2) Those who did not meet CDC reporting criteria, termed "non-qualifiers." For the flow of members through study aims 1 and 2, see Figure 1.

Description of the AI-powered DPP

For a detailed overview of the Lark DPP see Supplement 1. Briefly, the program is available to members 24/7 through their smartphones, where members receive the CDC PreventT2 curriculum lessons.[32] The conversational AI interface is a critical component of the program because it delivers all educational content and is the primary method of coaching (tips, feedback, encouragement) provided to participating members. The curriculum is delivered over 26 educational lessons that emphasize losing weight, engaging in daily activity, managing stress, and healthy eating habits. Consistent with the National DPP, the primary goal of the Lark DPP is weight loss. All members receive a digitally connected scale that automatically uploads their weights to the digital platform and are encouraged to weigh weekly. AI coaching conversations are developed by human coaches and experts using strategies such as cognitive behavioral therapy [33] and positive psychology [34] that help members increase healthy lifestyle habits and reduce health risks. Members receive personalized feedback and daily and weekly summaries of weight loss, dietary habits, and other trends.

Primary outcome of weight loss maintenance at 12 months

CDC's DPP curriculum is structured over a year such that the whole second half of the program (months 7–12) is considered the "maintenance phase." In-person DPPs and the CDC use first and last weights taken at the time of the weekly lessons to calculate percent weight loss maintenance at 12 months.[29] In contrast, the AI-powered DPP in this study collects many more weigh-ins, facilitated by AI coaching and the digitally connected scale. Given the larger number of weight measurements available, we used an average of weights at the start and end of the program to calculate first and last weights to provide a robust and conservative estimate.

Starting weight was the average of the first three weights provided in the first 10 days of the program. Final weight was the average of the last three weights provided in the last month (prior to day 365) of the program. As a quality control, abnormal weigh-ins are flagged for review by identifying a weight loss rate of >7lbs/week. This criterion is stricter than those in other publications of digital DPPs.[31] Additionally, members receive an immediate message from the AI coach with personalized feedback about their weigh-in and weight trajectory. The AI coach will periodically ask the member to confirm that weigh-ins indeed belong to them. Finally, we analyzed all data to ensure that there were no suspect weight trajectories over longer time frames (e.g. in the case of large gaps between weight measurements) as described by Turicchi and colleagues.[35] If a member exhibited a suspect weight trajectory, we removed them from final analyses (see Figure 1 for removed members).

The primary outcome was percent weight loss maintenance at 12 months (starting weight - final weight)/starting weight. We assessed percent weight loss maintenance for all members who had weigh-ins at 12 months (N = 414) and compared weight loss maintenance between two groups: members who met CDC qualifying criteria (n = 191) versus those who did not (n = 223). The CDC

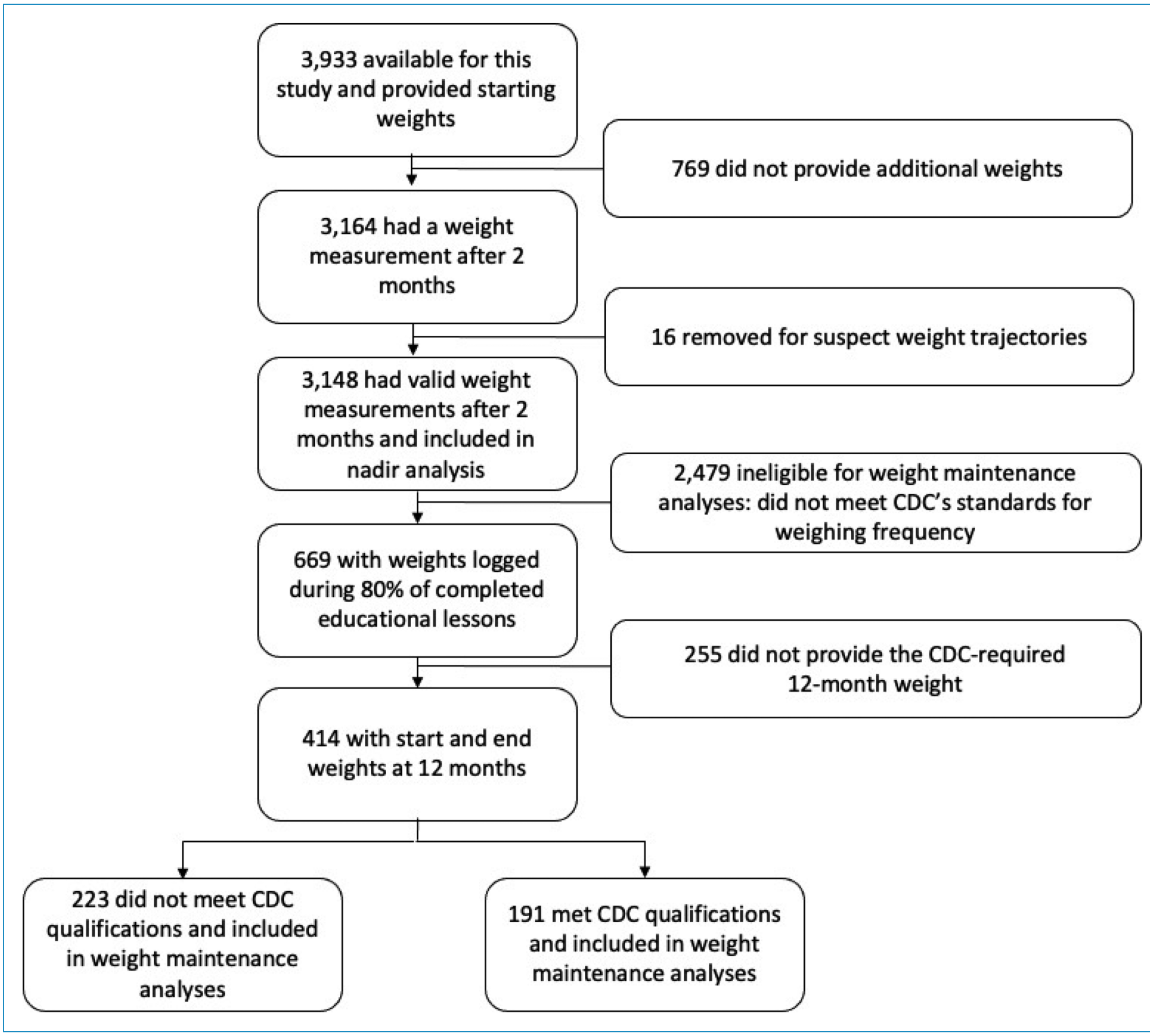

Figure 1. Flow chart for members included in both primary and secondary weight loss calculations. The primary analysis was weight loss maintenance at 12 months. The secondary analysis was identifying predictors of weight nadir that occurred any time after 2 months in the program. Selection criteria were consistent with CDC reporting standards and analyzed in the same manner that CDC analyzes data biannually. CDC qualifying criteria involved completing ≥4 educational lessons over ≥9 months. Suspect weight trajectories described in methods.

assesses weight loss outcomes for only those individuals who meaningfully engage in the program. Qualifiers must complete ≥3 lessons in months 1–6 and have ≥1 lesson after 9 months (total of ≥4 lessons).[29] The CDC independently analyzes the weight data from the Lark DPP every 6 months to ensure compliance with all benchmarks.

Predictors of peak weight loss

In addition to CDC lessons, Lark DPP members engage in other coaching and activities that could be related to weight loss before the maintenance phase. In a secondary analysis, we examined predictors of peak weight loss (called weight nadir) in the program using logistic regression. Weight nadir is a common metric used in long-term weight loss and DPP studies because peak weight loss often occurs prior to program completion.[31,35,36] Additionally, per Medicare DPP standards, the lowest recorded program weight is used to evaluate achievement of the ≥5% goal.[37] Since the weight nadir did not have to occur at 12 months, we removed the requirement of having a 12-month weight and had N = 3148 members for this analysis (Figure 1). We calculated weight nadir as the peak percent weight loss that occurred after at least 8 weeks in the program and starting weight as described above in the Weight Loss Maintenance at 12 Months section.

Table 1. Description and rationale for independent variables entered in the primary and secondary analyses.

Independent variable	Description	Rationale
Gender	0 if female, 1 if male	Weight loss may differ by gender with some evidence that men may lose more weight in lifestyle interventions [54].
Age	Age calculated at program start date	Older and younger members may differ in program engagement, affecting weight loss [40].
Starting BMI	Based on initial weight and height	Members with higher initial BMI have greater potential to lose weight [55].
Median income	Median income within a member's zip code. Taken from the 2020 American Community Survey (5-year estimate) which is run by the United States Census Bureau. Downloaded from the Simple Maps Interactive Maps & Data (United States Cities Database).[57]	Neighborhood socioeconomic status is associated with excessive weight gain or loss [58].
Education	Percent of members within a zip code with a college education or above. Taken from the 2020 American Community Survey (5-year estimate) which is run by the United States Census Bureau. Downloaded from the Simple Maps Interactive Maps & Data (United States Cities Database).[57]	Neighborhood socioeconomic status is associated with excessive weight gain or loss [58].
Health Professional Shortage Area (HPSA) Designation	Defined by the Health Resources and Services Administration (HRSA) as areas and population groups within the US that have a shortage of healthcare professionals [59]. HPSAs can be geographic areas, populations, or facilities. Geographic and Population HPSAs have a population to physician ratio of at least 3500 to 1 and are built from either county, county subdivisions, or census tracts. If an entire county is classified as having a shortage, the county is designated as a "whole-county" shortage area [60]. If only specific subdivisions or census tracts have a shortage, then the county is considered a "partial-county" shortage area.	Previous research has shown that individuals living in HPSAs had a lower likelihood of success in a chronic disease self-management program [61].
Rural vs. Urban Locale	HRSA's Federal Office of Rural Health Policy defines urbanized areas and clusters and considers anything not falling into these urban designations as rural.	Members living in rural areas experience barriers to quality health care and have lower engagement in health-promoting behaviors compared to urban counterparts [62].
Met CDC qualifications (completed $\geq$3 lessons in months 1–6 with $\geq$9 months between first and last = 4 total)	0 if no, 1 if yes	CDC only assesses weight loss maintenance outcomes for those who meaningfully engage with program content [29].
Weeks with 2 or more weigh-ins	The number of weeks that a member	

(continued)

Table 1. Continued.

Independent variable	Description	Rationale
	weighed-in two or more times (normalized by length in program)	Greater frequency of weight tracking is related to weight loss [56].
Days with a coaching exchange	The number of days a member had an exchange with the AI coach (normalized by length in program). These coaching exchanges included topics such as diet, daily movement, and other healthy lifestyle behaviors	Interactions with coaches and personalized feedback are related to weight loss [43].

The binary dependent variable in the regression was attaining ≥5% weight loss (yes/no). Independent variables (IVs) included member age, gender, starting body mass index (BMI), and program engagement metrics normalized to time within the program (see Table 1 for details regarding each selected IV for primary and secondary analyses). Exploring engagement predictors of weight loss enabled us to include CDC qualifying status along with other program engagement metrics. We did not separately include meal logging as an IV due to the way the AI-powered program facilitates meal logging. All members have an exchange with the AI coach upon entering meals; therefore, inclusion of both variables would cause issues of collinearity. We also did not include physical activity as an IV because although all members had data for daily "movement minutes" obtained from their mobile phone, these data did not distinguish the intensity of the activity. Some members chose to log exercise sessions within the mobile app and others synced a wearable fitness tracker.

Statistical analyses

We performed all analyses in R version 4.0.5. Members self-reported their age, gender, race, and height upon enrollment. We calculated BMI (kg/m^2) from height and starting weight. We performed t tests or Chi-square tests to compare demographics and characteristics between members with weights at 12 months who did and did not meet CDC qualifying criteria (Table 2). For the primary hypothesis regarding weight loss maintenance at 12 months, we conducted a multivariate linear regression including age, starting BMI, sex, income, education, Health Professional Shortage Area (HPSA) designation (none of county, part of county, or whole county), and rural/urban designation as covariates. We report the adjusted group means for percent weight loss. For a definition and justification of each covariate, please see Table 1. We further tested for heterogeneity of treatment effects across subgroups for age (below or above median), starting BMI (below or above median), and sex (male vs. female). We report the adjusted means for each subgroup and the Bonferroni-corrected contrasts (Table 3).

For the secondary analysis of predictors of weight nadir, we conducted a multiple logistic regression (N = 3148) to assess the effects of member characteristics and engagement with the AI coach on members' likelihood of achieving a ≥5% weight nadir during the program (Table 4). We used standardized regression coefficients (β) and odds ratios to describe the effects of each IV. Our sample size was appropriate for logistic regression.[38] We carefully constructed the engagement metrics to ensure that there were no issues of multicollinearity among variables. All variables entered in the final model had a variance inflation factor of <3 with values of 1.0–1.7. We used an *a* priori alpha≤.05 for all statistical tests.

Results

Member demographics and characteristics

We observed differences in weight loss maintenance between members who met CDC qualifications and those who did not (Table 2). CDC qualifiers were older than those who did not meet CDC criteria.

Percent weight loss maintenance at 12 months

There were 191/414 members who met CDC qualifications (46.1% of the sample with weigh-ins at 12 months). CDC qualifiers did not differ from non-qualifiers in starting BMI but completed more educational lessons than non-qualifiers and experienced significantly greater weight loss maintenance at 12 months (Table 2). When controlling for the covariates Age, Starting BMI, Income, Education, Sex, HPSA designation, and Rural/Urban designation, CDC qualifying status was still a statistically significant predictor of percent weight loss, $t = 2.5$, $p = 0.015$. The adjusted mean for CDC qualifiers was 5.3% (SE = .8) and for non-qualifiers was 3.3% (SE = .8).

Subgroup effects on percent weight loss (age, starting BMI, and sex) are shown in Table 3.

Table 2. Member demographics and characteristics at baseline and means for program outcomes and engagement metrics following one year.

	All members (N = 414)	CDC qualifying (n = 191)	Non-qualifying (n = 223)	CDC qualifying vs. non-qualifying
Demographics/characteristics	Mean (SE)	Mean (SE)	Mean (SE)	*t* stat; *P* value
Age (years)	53.2 (.5)	55.4 (.7)	51.3 (.7)	4.0; <.001*
Starting BMI (kg/m^2)	36.2 (.3)	35.9 (.6)	36.5 (.4)	−1.0; .328
	n (%)	n (%)	n (%)	χ^2; *P* value
Gender (% female)	273 (66%)	127 (66%)	146 (65%)	0.0; .909
Race (% white)	282 (68%)	122 (64%)	160 (72%)	2.6; .108
Members who hit 5%	145 (35%)	76 (40%)	69 (31%)	3.2; .075
Primary outcome at 12 months	Mean (SE)	Adjusted mean (SE)	Adjusted mean (SE)	*t* stat; *P* value
Percent weight loss maintenance (%)	4.1 (.4)	5.3 (.8)	3.3 (.8)	2.5; .015*
Other outcomes at 12 months	Mean (SE)	Mean (SE)	Mean (SE)	*t* stat; *P* value
Weight loss maintenance (kg)	4.4 (.4)	5.3 (.7)	3.6 (.6)	1.9; .050*
BMI change (kg/m^2)	1.2 (.2)	1.5 (.2)	0.9 (.2)	2.1; .041*
Lessons completed	15.1 (.4)	22.3 (.4)	9.0 (.4)	23.5; <.0001*
Number of coaching exchanges	443.6 (21.4)	708.6 (35.7)	216.6 (11.8)	−13.9; <.0001*
Number of weigh-ins	195.0 (6.0)	179.2 (9.1)	208.5 (7.9)	2.4; .015*

Note: CDC qualifiers completed ≥3 lessons in months 1–6 and had ≥1 lesson after 9 months (≥4 total). Non-qualifiers did not meet this lesson completion criteria. Significant between-group differences highlighted by *.

Predictors of peak weight loss

The weight nadir occurred, on average, at day 150 (SE = 1.6) in the program and was 4.2%, SE = .1 (4.4 kg, SE = .1) for the 3148 members included in the regression, with 35% achieving a weight nadir of ≥5% weight loss. The average weight nadir for the subset of CDC qualifiers was 7.0%, SE = .3 (7.3 kg, SE = .4). In the regression model, meeting the lesson criteria to be a CDC qualifier did not significantly predict the likelihood of achieving a ≥5% weight loss nadir. Member age and starting BMI were also not associated with the likelihood of achieving ≥5% (all $P >$ .05).

The regression results (Table 4) revealed that over the course of the program, men were 27.3% more likely than women to attain ≥5% weight loss (odds ratio 1.273). There were two engagement variables that were significantly associated with weight loss, independent of other variables in the regression model: weigh-ins and coaching exchanges. For every additional week with two or more weigh-ins, members were 7.7% more likely to achieve ≥5% weight loss (odds ratio 1.077). For each additional day that members had an exchange with the AI coach, they were 0.8% more likely to achieve ≥5% (odds ratio 1.008). To compare the significant engagement variables on the same time scale, we translated the odds ratios for coaching exchanges to the scale of a week by multiplying by 7 days (.008*7). Thus, a week with two or more weigh-ins and at least seven coaching exchanges (one per day) had a 7.7% and 5.6% (odds ratio 1.056) greater likelihood of achieving ≥5%, respectively.

Discussion

The primary aim of this study was to compare weight loss maintenance at 12 months for members of an AI-powered DPP who met CDC qualifying criteria versus those who did not. We further assessed member characteristics and program engagement metrics to identify significant

Table 3. Subgroup analyses of the difference in percent weight loss between CDC qualifiers and non-qualifiers at 12 months.

Subgroup	# of members	CDC qualifiers Mean % (SE)	Non-qualifiers Mean % (SE)	P value for contrasts
Age below median	191	6.3 (1.4)	3.4 (1.2)	.03
Age above median	205	4.6 (.9)	3.6 (1.1)	.35
BMI below median	199	4.9 (.9)	3.2 (.9)	.08
BMI above median	197	5.4 (1.3)	3.2 (1.3)	.10
Female	259	5.3 (1.0)	2.4 (1.0)	.01
Male	137	4.8 (1.1)	4.5 (1.2)	.85

Notes: Adjusted means provided for each subgroup. Median age = 53 years; median BMI = 35.1 kg/m^2.

Table 4. Regression results for the likelihood of achieving ≥5% weight loss (n = 3148).

Variable	Standardized coefficient (β)	Standard error	Z value	*P* Value
Constant	-.67	.04	−16.43	≤.0001
Age	-.07	.04	−1.69	.09
Sex (is male)	.11	.04	2.63	.009
Starting BMI	.01	.04	.34	.74
CDC Qualifier (yes)	.08	.05	1.76	.08
Weeks with 2 or more weigh-in days	.68	.05	14.23	≤.0001
Days with a coaching exchange	.43	.05	7.97	≤.0001

Note: weeks with 2 or more weigh-ins and days with a coaching exchange normalized to time within program until weight nadir occurred.

associations with achieving the National DPP benchmark of ≥5% weight loss during the program.[29] We found that members who met CDC qualifying criteria achieved an average weight nadir of 7.0% during the program and had an average adjusted weight loss maintenance of 5.3% at 12 months. This level of success in the National DPP is expected using in-person or hybrid-digital deployment [12,20,28,31]; the difference in this study was that the program was delivered via conversational AI.

Weight loss maintenance at 12 months

The primary outcome of this study was the CDC-defined weight loss maintenance measured at 12 months during the maintenance phase because this is the clinical endpoint of interest for the National DPP.[11] Maintaining weight loss over time is important for reaping the long-term benefits of diabetes risk reduction.[7,8] The intensity and sustained engagement of the PreventT2 curriculum enable CDC to promote 5% weight loss as their benchmark. This magnitude of weight loss is associated with multiple improved clinical outcomes related to cardiometabolic risk reduction.[39] We observed that 40% of CDC qualifiers and 35% of all members who provided weights at 12 months achieved ≥5% weight loss maintenance. To place these percentages in context, in a review of 435 CDC-recognized DPPs (most in-person), 35.5% of members completing at least one lesson achieved ≥5% weight loss maintenance at 12 months,[28] and in a review of online DPPs (most hybrid-digital deployment) 28% of members initiating CDC lessons and 41% of those meeting CDC qualifications achieved ≥5% weight loss maintenance at 12 months.[31] The average weight loss maintenance at 12 months was 4.1% for all members in this study with a 12-month weight, which is consistent with the pooled estimates of 3.98% at 12 months observed in predominantly hybrid-digital programs [20] and 3.99% observed for in-person programs.[12]

Prior studies, most of which focus on in-person DPPs, show that the minimum lesson requirement to meet CDC qualifying criteria is an important key predictor of achieving ≥5% weight loss at 12 months.[28] Therefore, the percentage of members who meet the CDC qualifying criteria is an important outcome to measure in digital DPPs. We observed that 46.1% of members with 12-month weights in this study met CDC qualifying criteria and completed 22 of 26 available lessons. Thus, an AI-powered DPP delivered the CDC curriculum and encouraged long-term program engagement. The high engagement of CDC qualifiers in this study might be attributable to the AI platform being able to present additional coaching and feedback within and between CDC lessons.

Achieving CDC qualifier status appeared to have a greater impact on weight loss maintenance at 12 months for some subgroups of members compared to others. For example, we observed that younger members who were CDC qualifiers lost significantly more weight at 12 months than those who were not qualifiers, but the same was not true for older members. Females who were CDC qualifiers lost significantly more weight than non-qualifiers, but we did not observe this relationship for males. We previously demonstrated that older adult members of a commercially available, fully digital health platform exhibited greater engagement than younger adults in application features including AI coaching exchanges, meal logging, and device measurements.[40] This higher level of engagement across application features may be one reason why completing CDC lessons did not have the same level of impact for older members.

Although 5% weight loss maintenance was set as the standard for the DPP, there are also clinical benefits associated with achieving smaller magnitudes of weight loss. For example, individuals losing more than 2%, but less than 5%, may see improvements in fasting glucose and hemoglobin A1c [39] and other cardiovascular risk factors [41]—key indicators of T2D risk. All members who provided weights at 12 months in this study averaged 4.1% weight loss maintenance. This magnitude of weight loss is an important step toward reducing the risk of T2D. Hitting the 5% benchmark is an important goal, but there are clear clinical and lifestyle benefits to completing the DPP besides weight loss, and the CDC has recently added other achievement benchmarks (e.g. physical activity).[42]

Associations of increased likelihood of 5% weight loss

Predictors of successful weight loss in traditional in-person and hybrid-digital programs include interactions with coaches, social support, personalized feedback, and adherence to self-monitoring behaviors (e.g. tracking weight).[43,44] We are aware of two other AI-powered programs [45,46]; however, neither has reported on predictors of weight loss. This paper adds to the body of knowledge on AI-powered programs by investigating aspects of program engagement other than lesson completion that were associated with a greater likelihood of achieving ≥5% weight loss.

The results of our regression demonstrated that frequent exchanges with the AI coach and weigh-ins kept these members engaged in the program and promoted weight loss independent of whether a member completed the lessons required to be a "CDC qualifier." The regression model considered predictors of losing ≥ 5% even if this nadir did not occur at 12 months. AI coaching exchanges, weigh-ins, and other app engagements were not restricted to the prescribed and paced timeline of the CDC PreventT2 lessons.

Members who engaged more frequently with the AI coach were more likely to achieve ≥5% weight loss. Every day with a coaching exchange was associated with a 0.8% increased likelihood of achieving this weight loss benchmark. Patient-centered coaching, involving triggering self-reflections and tailoring suggestions to an individual's preferences, is particularly important for helping individuals make and sustain healthy behavior changes.[47] Exchanges with an AI coach may be salient because an AI coach is available 24/7 and responds immediately to member actions, offering "just-in-time" or synchronous support. Immediate and relevant feedback offers a timely reward and can overcome limitations of asynchronously delivered feedback provided by other hybrid-digital programs.[48] An AI coach is further able to continuously improve the personalization of coaching and feedback as it interacts with a member and learns their patterns and preferences.

Members with more frequent weigh-ins were also more likely to achieve ≥5% weight loss. Every week with two or more weigh-ins was associated with a 7.7% increased likelihood (1.077 odds) of achieving this weight loss benchmark. However, the frequency of weigh-ins did not appear to be associated with being a CDC qualifier. This finding is consistent with our prior work that discovered Engagement Personas, or distinctive longitudinal engagement patterns in a digital DPP.[49] We described one of the observed Engagement Personas as "Data-Driven Members" who weighed more frequently than the sample average but had lower engagement in educational lessons. In contrast, another Engagement Persona coined "Learners" engaged frequently in educational lessons and AI coaching exchanges but only had an average weigh-in frequency. These findings demonstrate that there are multiple ways to engage with a digital DPP. For Data-Driven members, objective tracking coupled with personalized feedback can help to promote greater awareness of one's lifestyle behaviors.[50] A digital scale offers an objective way for members to continually track their progress and provides immediate feedback that helps members relate changes in weight to other behaviors such as physical activity, diet, or sleep. Programs that automatically upload data have been shown to encourage sustained engagement of roughly four times that of manual entry.[51] An AI coach also serves to encourage self-tracking by providing "nudges," or reminders, to encourage members to engage. These reminders may be important for continued program engagement, as self-monitoring and self-reported exercise have been shown to increase in the days following a prompt-to-action compared with the days preceding the prompt.[52]

Study limitations

This study was retrospective, which prevented any determination of cause and effect. However, we acknowledge a strength of this study is that the participants were real-world members of a DPP where uptake and engagement in the program reflect personal motivation rather than the influence of a carefully controlled clinical trial. We did not compare to a control group that received no active intervention; however, other studies of digital DPPs have demonstrated that such a control group either lost a negligible amount of weight (~1%) or gained weight over the course of a year.[23,46] Our primary aim was focused on whether actively participating in the AI-powered DPP lessons would lead to clinically meaningful weight loss maintenance and, for this purpose, we were able to compare members who engaged with the DPP per CDC standards to members who did not. However, it is possible that there were unmeasured factors contributing to the observed results. For example, the CDC qualifiers may have represented the group of members with higher baseline motivation levels. For this reason, it will be important to compare to a well-balanced control group in the future.

We had limited access to demographic information (e.g. no education data) since members were not required to input these data. We also did not have access to medical information such as A1c results or diagnosis history. However, this study represents a real-world implementation of an AI-powered DPP and reflects the data that members were willing to share. Since members self-reported their inclusion criteria, we could not verify that the entire sample was clinically prediabetic; however, all members in this study had a high-risk score on the CDC prediabetes screener, and the average starting BMI was 36.2 kg/m^2, which is strongly associated with high risk for T2D.[4] We did not separately consider coaching exchanges per topic area (e.g. diet) in the regression analysis due to collinearity issues. However, certain types of coaching exchanges may be more important than others. We plan to explore the different factors related to AI coaching in future investigations.

Conclusions

DPPs powered by AI and backed by human coaches trained in the CDC curriculum have the potential to reach large numbers of individuals needing preventive care and offer real-time, 24/7 coaching and feedback. An AI-powered DPP was effective for weight loss, with members who engaged per CDC guidelines averaging 5.3% weight loss maintenance at 12 months and 40% achieving the ≥5% benchmark. In addition to the CDC educational lessons, interacting with a conversational AI coach and weigh-ins were independently associated with a higher likelihood of achieving ≥5% weight loss during the program. The need for accessible, preventive health care will continue to grow, as evidenced by events surrounding COVID-19 and the post-pandemic era.[53] The National DPP needs to scale and be more personalized and accessible to support the national goal of improving health and decreasing healthcare costs associated with T2D. This study supports adding AI-powered coaching to facilitate clinically meaningful reductions in body weight that can delay or prevent progression to T2D.

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