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One Drop Improves Productivity for Workers With Type 2 Diabetes

One Drop for Workers With Type 2 Diabetes

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Objective: Diabetes research on work productivity has been largely cross-sectional and retrospective, with only one known randomized controlled trial (RCT) published, to our knowledge. Secondary analysis of the Fit-One RCT tested the effect of One Drop's digital health program on workplace productivity outcomes, absenteeism, and presenteeism, for employees and specifically for older workers with type 2 diabetes. **Methods:** Analysis of the 3-month Fit-One trial data from employees who have type 2 diabetes explored productivity using logistic analyses and generalized estimating equations. **Results:** Treatment and control group comparisons showed that workers ($N = 125$) using One Drop see direct benefits to workplace productivity, which leads to productivity savings for employers. **Conclusion:** This was the first RCT to demonstrate that a mobile health application for managing type 2 diabetes can positively affect productivity at work.

Keywords: productivity, mobile health, diabetes, health tech, employees, cost savings, occupational health, digital health

Of the estimated 21 million people diagnosed with type 2 diabetes in the United States, older individuals are disproportionately affected.[1] This has ramifications for the broader economy because the total estimated cost of diabetes in 2017 was $327 billion; $90 billion of this was attributed to lost productivity, including work days missed due to health conditions (absenteeism) and reduced productivity while working due to health conditions (presenteeism).[2] The constant upkeep and health maintenance required to manage diabetes places an additional financial and mental health burden on workers as well as time, attention, and energy constraints. The impact of diabetes on work remains an important area of exploration.

Work productivity loss due to type 2 diabetes has been defined as the indirect costs attributed to absenteeism and presenteeism[3] stemming from health complications associated with poor glycemic control[4] and psychological diabetes-related distress.[5,6] Workers with diabetes experiencing an associated neuropathic symptom are 18% more likely to lose 2 or more hours of work per week because of their health condition compared with workers without diabetes; workers diagnosed with diabetes and neuropathic symptoms are more likely to reduce their number of hours worked, change jobs, or report a significant negative impact on their job performance.[7] Furthermore, workers with diabetes are more than 3 times as likely to either retire early or change industries.[8] This premature exit of workers is a loss of experience and knowledge, both costly and difficult to replace for employers and industries alike.[9–11]

On an individual level, workers with diabetes stand to lose income of more than $160,000 over the course of their lifetime because of decreased physical functioning and possible limitations to career progress.[12] A recent systematic literature review revealed that a diagnosis of diabetes was associated with absence of employment, a higher rate of exiting the labor market completely when diabetes-related complications arise, early retirement, and permanent disability pension.[13] It is clear from research that individuals with diabetes experience impacts to productivity, raising concerns for older workers whose health may be more at risk.

The negative effect diabetes can have on work productivity, potentially exacerbating the occupational health issues of an aging adult workforce, warrants deeper examination. Given that both the median age of workers in the United States is 42 years and they are getting older[14] and that the prevalence of diabetes among working adults is expected to double by 2050,[15] changes will need to be made to accommodate older workers.[16] Adults with diabetes who are, on average, 45 years and older are especially vulnerable to productivity-related issues, with problems associated with physical functioning, social participation restrictions, and need for recovery.[17] Furthermore, research indicates that diabetes among older workers has a negative effect on productivity; a cross-sectional analysis of older workers showed that presenteeism was higher among people with diabetes and that active treatment of diabetes was associated with higher presenteeism.[18] In addition to productivity issues, workers 50 years and older with a diagnosis of diabetes had a 30% increased rate of leaving the workforce early.[19] A diabetes diagnosis increases the chance older workers will be afraid their health condition limits their ability to work, negatively affecting their work performance and limiting their desire to find work.[20] Prior research has shown that age amplifies diabetes-related health issues, which has serious consequences for the work productivity of older employees.

Mobile health (mHealth) apps can play a role in addressing diabetes-related health issues,[21–24] but have yet to be explored in addressing diabetes-related productivity declines at work. Mobile health interventions have demonstrated improvements in employee engagement and productivity[25]; however, this has not been explored for workers specifically dealing with diabetes. Although interventions to impact health-related productivity have addressed depression[5] and arthritis,[26] with both conditions being highly prevalent among older adults, the existing literature is limited on experimental studies examining the use of mHealth apps to improve work productivity specifically for those with diabetes. To our knowledge, to date, only one randomized controlled trial (RCT) on this topic has been conducted on the benefit of mHealth interventions on the work productivity of

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people with diabetes. That RCT examined the productivity (absenteeism and presenteeism) of individuals with type 2 diabetes using a personal digital assistant, chronic disease self-management program, or both, and found no evidence that these tools benefited productivity.[27] A majority of studies, to date, that have investigated mHealth interventions in the workplace have been interventions that promote physical activity and reduced sedentary behavior,[28] as well as mental health management.[25] The StopDia RCT is currently underway to explore the use of a digital health intervention to reduce the risk of developing type 2 diabetes with the effect on productivity as a secondary outcome[29]; however, no results from this trial have been published to date. Our review of the literature found limited research specifically examining the utility of mHealth interventions on work productivity among individuals with diabetes. To date, the present randomized experimental study design is the first to test whether an mHealth solution for managing chronic conditions can affect productivity among workers with type 2 diabetes.

The present study evaluates One Drop, a digital precision health solution that integrates a mobile app with one-on-one personalized coaching, educational content, data-driven feedback, blood glucose forecasting, and automated health information logging via connected devices. One Drop has been shown to significantly improve A_{1c} outcomes for people with diabetes.[21–24] The current study investigates workplace productivity outcomes for workers with type 2 diabetes who use the One Drop mHealth solution compared with a control group and focuses specifically on understanding these effects in workers older than 50 years. We perform secondary analysis of the Fit-One RCT data set to experimentally evaluate the effects of One Drop compared with a control group on health-related absenteeism, defined as missing work due to health issues, and health-related presenteeism, defined as showing up to work but lacking typical productivity due to health issues. In addition to testing the effects of One Drop on absenteeism and presenteeism for all workers, we specifically investigate workers older than 50 years to assess those who may be more susceptible to health-related productivity loss. In addition, we separately assess workers who experience presenteeism at baseline to better understand productivity decline among all workers, especially those older than 50 years. Lastly, we estimate cost savings associated with the productivity changes observed. Through this research, we provide data from a robust study design to address a clear gap in the literature and answer the call by the *Journal of Occupational/Environmental Medicine* for research on the connection between business practices and health outcomes.

METHODS

Participants and Procedure

Data for the current study were collected as part of a 3-month RCT, the Fit-One Trial, designed to test the effects of One Drop and a wearable activity tracker on hemoglobin A_{1c} (HbA_{1c}) outcomes for people with type 1 and type 2 diabetes (see Osborn et al[21] for further details including study flow diagram). The Fit-One RCT used a private institutional review board for approval of study procedures before recruitment. In the original data collection, study forms and self-report surveys were administered on-line, whereas A_{1c} blood samples were self-collected and mailed to a laboratory for processing. Surveys and an A_{1c} blood sample were completed at baseline and 3 months after baseline. Participants in the treatment condition with the One Drop program were given access to the digital solution including the mobile app, in-app direct messaging with a health coach, a Bluetooth-connected blood glucose meter, and a 3-month supply of test strips. Participants in the waitlist control group did not have access to all that is included in the One Drop program until after the study was complete. All participants were compensated for their time with free continued access to One Drop's solution and continued use of the Bluetooth-enabled devices after the study ended.

Participants had never used One Drop before randomization into either the treatment with One Drop or the waitlist control groups. The present study is a secondary analysis of trial data filtered to include study participants who were employed with type 2 diabetes (HbA_{1c} >7%) and completed the Work Productivity and Activity Impairment scale.[30]

Measures

Demographics

The baseline survey collected self-reported age, sex, race, and insurance status.

Diabetes Information

The baseline survey collected self-reported date of diagnosis with type 2 diabetes. Diabetes duration was calculated as the number of years elapsed between self-reported date of diagnosis and the date the baseline survey was completed.

Absenteeism

The six-item Work Productivity and Activity Impairment scale[30] was administered at baseline and in follow-up surveys. The item specifically used to measure absenteeism prompted participants to reflect on the past week and asked, "During the past seven days, how many hours did you miss from work because of your health problems?" The absenteeism variable used a ratio of missed work to total scheduled work hours that week, to develop a percentage of missed work due to illness. Thus, higher scores reflect greater absence from work.

Presenteeism

Presenteeism was measured using a different item from the six-item Work Productivity and Activity Impairment scale,[30] both at baseline and follow-up. Participants were prompted to reflect on the past week and asked, "During the past seven days, how much did your health affect your productivity while you were working?" Participants responded on a 10-point scale from 0 ("Health problems had no effect on my work") to 10 ("Health problems completely prevented me from working"). The presenteeism variable is expressed as a percentage of impairment at work, with a higher percentage indicating greater impairment and thus less productivity.

Estimated Cost Savings

Estimated cost savings due to presenteeism were calculated according to the methodology described by Goetzel et al.[31] The change in percentage of impairment at work attributable to the One Drop treatment was calculated by subtracting the difference in presenteeism from baseline to follow-up between the treatment and control groups. This difference was multiplied by 240 eligible working days in a year to obtain an estimated total number of productive days gained in a year due to One Drop. The US Bureau of Labor Statistics reports that the average hourly cost for employee compensation is \$40.35, or \$322.80 per day.[32] This daily cost was multiplied by the estimated productive days saved in a year to estimate yearly employer cost savings.

Analyses

To ensure that randomization successfully distributed baseline characteristics between the treatment and control groups, between-group differences were assessed for sex, age, race, insurance status, diabetes duration, and baseline HbA_{1c}. Differences were tested with independent-samples t tests for continuous variables and chi-squared tests for categorical variables.

Given the RCT design of the study, intention-to-treat (ITT) and per-protocol (PP) analyses were used to assess productivity data. Intention-to-treat analyses explored all participants who took part in the study, regardless of whether they followed up 3 months later, thus including all those we intended to treat. The PP analyses explored only

TABLE 1. Sample Descriptives

	Full Sample			
Variable	**All**	**Treatment**	**Control**	***P***
Total *N*	125	63	62	—
Sex, *n* (%)				0.41
Male	53 (42)	29 (46)	24 (39)	—
Female	72 (58)	34 (54)	38 (61)	—
Age, mean (SD), yr	48.8 (8.0)	48.3 (9.1)	49.5 (6.8)	0.40
Race, *n* (%)				0.30
White	88 (70)	47 (75)	41 (66)	—
Not White	37 (30)	16 (25)	21 (34)	—
Insurance status, *n* (%)				0.64
Insured	120 (96)	61 (97)	59 (95)	—
Uninsured	5 (4)	2 (3)	3 (5)	—
Years diagnosed with T2D, mean (SD)	8.9 (6.1)	8.3 (5.9)	9.5 (6.2)	0.25
Baseline HbA_{1c}, mean (SD), %	8.6 (1.5)	8.7 (1.5)	8.6 (1.4)	0.80

HbA_{1c}, hemoglobin A_{1c}; SD, standard deviation; T2D, type 2 diabetes.

those who followed the study procedures as they were intended. Specifically, for PP analyses, participants in the treatment group were instructed to engage with the treatment, and participants in the control group were instructed not to use the treatment during the study period. As recommended for clinical trial research,[33] we report results from both ITT and PP analyses, as each have different strengths and weaknesses. Although ITT analyses avoid overestimation of group effects by maintaining all those recruited regardless of whether they followed protocol and thus reflecting real-world scenarios,[34] the PP analyses provide a true estimate of the effects of the intervention as it was intended.[33] Therefore, to balance those limitations, we report both, which benefits the scientific and practical/clinical interpretation of findings.[35]

Complete data sets for use in the ITT analyses were developed using multiple imputation to correct for missing data[36] on outcomes, specifically, follow-up absenteeism ($n = 4$). Variables used in the process of imputation included baseline absenteeism, baseline presenteeism, follow-up presenteeism, age, sex, race, health insurance, and date since diagnosis. Treatment and control group data were imputed separately with 20 imputations per group condition. Imputed data were constrained by the group or condition (treatment or control) follow-up absenteeism minimum and maximum values, to maintain the true sample means. After imputation, data were merged before conducting analyses.

Intention-to-treat analyses used the multiple imputation data, thus reflecting all participants we intended to treat. Parameter estimates obtained from each imputed data set were pooled. These pooled parameter estimates are presented in the Results section. For the PP analyses, the control group was filtered to exclude participants who used or accessed One Drop during the study period and for those who did not have outcome or follow-up data. The treatment group was filtered to exclude participants who lacked engagement with One Drop—the treatment—and for those who did not have outcome data. Engagement was defined as messaging with a health coach in the app, pairing the Bluetooth-enabled blood glucose meter with the app, and app pings (active use of the app). Any of these elements occurring during the 3-month study period were considered engagement with the One Drop treatment. If participants lacked engagement, they did not receive the intended treatment and were therefore excluded from analyses. After filtering data for both the treatment and control groups, data were merged to develop the PP data set.

Because the variables of interest reflect low base rate–occurring phenomena, data were zero inflated. Therefore, we used generalized estimating equation (GEE) models with negative binomial distributions specified. These advanced statistical models are appropriate for longitudinal data and can accommodate a variety of data distributions.[37] However, absenteeism data had such a high rate of missingness, and relatively low-frequency models would not converge. Therefore, a dichotomous variable (absenteeism either occurred or did not occur) in logistic regression models controlling for baseline was used for absenteeism throughout. All models specified the control group as the reference group. In addition, all models were run with interactions included. If not significant, the interaction was removed from the reported model. For all analyses, a *P* value of 0.05 or less was considered significant.

After exploring the impact of the intervention on our sample, we assessed whether the intervention was helpful for older workers, a particularly vulnerable population. Furthermore, we explored the impact of the intervention (use of One Drop) on presenteeism further with post hoc analyses focused on only participants who reported experiencing some presenteeism at baseline and similarly performed logistic regression analysis for absenteeism and GEE models with negative binomial distributions specified for presenteeism. Monetization of productivity loss, specifically calculating cost savings with presenteeism, used the method deployed in previous research[31] with updated compensation estimates based on the US Bureau of Labor Statistics 2022 reports.[32] Calculations for cost savings used the percent score of change in presenteeism; thus, productivity was saved for 3 months and was estimated based on workdays for a year to develop annual cost savings.

RESULTS

Demographics

Each of the samples was mostly female, White, middle aged, and with health insurance (Table 1; Supplemental Table 1, http://links.lww.com/JOM/B93).

No between-group differences for sex, age, race, insurance status, diabetes duration, or HbA_{1c} were found between groups within any of the samples ($P > 0.05$; Table 1; Supplementary Table 1, http://links.lww.com/JOM/B93).

Full Sample Analyses

Intention to Treat

Absenteeism logistic analyses found a nonsignificant effect of group when controlling for baseline (Table 2).

Presenteeism GEE analyses showed a significant group effect ($B = -0.431$, $P = 0.044$), such that those in the treatment group were less likely to experience presenteeism at follow-up, controlling for baseline (Table 3).

Per Protocol

Absenteeism logistic analyses were not significant, indicating that the odds of absenteeism at follow-up were not dependent on the intervention condition when controlling for baseline. It is worth noting that, although the logistic regression analyses showed nonsignificant effects of group for absenteeism, the odds ratios were in the direction of intervention having a benefit (Table 2).

TABLE 2. Logistic Regression Models for ITT and PP Analyses for Absenteeism

	B	**OR (95% CI)**	***P***
Full sample			
ITT: group effect on absenteeism	−0.212	0.81 (0.34–1.92)	0.629
PP: group effect on absenteeism	−0.376	0.69 (0.26–1.81)	0.446
50-yr-and-older sample			
ITT: group effect on absenteeism	−1.212	0.30 (0.07–1.27)	0.101
PP: group effect on absenteeism	−1.720	0.18 (0.03–1.03)	0.053

The control group was used as the reference group. Baseline absenteeism was controlled for in all models.

CI, confidence interval; OR, odds ratio; PP, per-protocol; ITT, intent-to-treat.

TABLE 3. Generalized Estimating Equations for ITT and PP Analyses of Presenteeism

Variables	$N_{control}$	$N_{intervention}$	Control, Mean (SD) Baseline	Control, Mean (SD) 3 mo	Intervention, Mean (SD) Baseline	Intervention, Mean (SD) 3 mo	Group Effect B	Group Effect P	Interaction Effect Group × Baseline B	Interaction Effect Group × Baseline P
Full sample										
ITT: presenteeism	62	63	20.00 (23.61)	25.32 (25.84)	25.08 (23.27)	20.32 (23.76)	−0.431	0.044*	—	—
PP: presenteeism	59	58	20.17 (23.60)	23.73 (24.91)	23.97 (22.08)	20.34 (23.39)	−0.258	0.232	—	—
Age 50 yr and older										
ITT: presenteeism	31	26	22.58 (24.35)	30.97 (27.61)	26.54 (25.60)	15.00 (24.04)	−2.007	<0.001*	0.029	0.006*
PP: presenteeism	30	24	23.33 (24.40)	29.00 (25.78)	26.25 (25.16)	15.00 (24.67)	−1.640	0.003*	0.021	0.039*
Experienced presenteeism at baseline										
ITT: presenteeism	35	46	35.43 (20.91)	36.86 (23.98)	34.35 (20.51)	25.87 (24.73)	−0.397	0.025*	—	—
PP: presenteeism	34	43	35.00 (21.07)	36.76 (24.34)	32.33 (19.62)	25.35 (24.33)	−0.395	0.032*	—	—
Age 50 yr and older and experienced presenteeism at baseline										
ITT: presenteeism	19	19	36.84 (20.83)	40.53 (24.60)	36.32 (23.14)	20.00 (26.46)	−1.911	0.007*	0.027	0.043*
PP: presenteeism	19	18	36.84 (20.83)	40.53 (24.60)	35.00 (23.07)	19.44 (27.11)	−1.919	0.006*	0.027	0.043*

Negative binomial distributions were used. The control group was used as the reference group. All models controlled for baseline presenteeism. Significant interactions between baseline presenteeism and group were held and interpreted; these are reported in the Interaction Effect column. Nonsignificant interactions were dropped from the final reported models.

PP, per-protocol; SD, standard deviation; ITT, intent-to-treat.

*Statistically significant effect at $P < 0.05$.

The effect of group in the GEE model of presenteeism was not significant when controlling for baseline (Table 3).

Older Worker Sample

Intention to Treat

Absenteeism logistic analyses detected a marginal group effect when controlling for baseline (odds ratio, 0.30; 95% confidence interval, 0.07 to 1.27; $P = 0.101$; Table 2).

Presenteeism GEE analyses showed a significant group effect ($B = -2.007$, $P < 0.001$), such that those in the treatment group were less likely to experience presenteeism at follow-up, controlling for baseline. Furthermore, analyses showed a significant interaction of baseline presenteeism with group ($B = 0.029$, $P = 0.006$), indicating One Drop use (treatment) had a stronger effect for people with lower presenteeism at baseline (Table 3).

Per Protocol

Logistic analyses found a marginally significant group effect when controlling for baseline (odds ratio, 0.18; 95% confidence interval, 0.03 to 1.03; $P = 0.053$), replicating the ITT results for absenteeism (Table 2).

The GEE results indicated a significant group effect ($B = -1.640$, $P = 0.003$), such that participants in the treatment group were less likely to experience presenteeism at follow-up, controlling for baseline. Further analyses showed a significant interaction effect of baseline presenteeism with group ($B = 0.021$, $P = 0.039$), indicating that treatment had a stronger effect for people with lower presenteeism, replicating the ITT presenteeism results (Table 3).

To explore this interaction, a median split was performed on baseline presenteeism to obtain subgroups of participants with low and high presenteeism; participants with values at the median were pruned. Estimated means of follow-up presenteeism segmented by group and baseline presenteeism are presented in Table 4. To visualize this interaction, the linear predictor is plotted against group assignment for low and high levels of the covariate (Fig. 1). The linear predictor is expressed as the log of model-fitted values of follow-up presenteeism.

Experienced Presenteeism at Baseline Sample

Intention to Treat

The GEE results showed a significant effect of group ($B = -0.397$, $P = 0.025$) on follow-up presenteeism when controlling for baseline (Table 3).

Per Protocol

For participants who reported presenteeism, the GEE analyses found a significant effect of group ($B = -0.395$, $P = 0.032$) on follow-up presenteeism while controlling for baseline (Table 3).

Older Workers Who Experienced Presenteeism at Baseline Sample

Intention to Treat

The GEE results showed a significant effect of group ($B = -1.911$, $P = 0.007$) and a significant interaction effect of baseline presenteeism with group ($B = 0.027$, $P = 0.043$), indicating that treatment had a stronger effect for people with lower presenteeism (Table 3).

Per Protocol

For participants 50 years or older who experienced presenteeism, GEE analyses found a significant effect of group ($B = -1.919$, $P = 0.006$) and a significant interaction effect of baseline presenteeism with group ($B = 0.027$, $P = 0.043$), indicating that treatment had a stronger effect for people with lower presenteeism, replicating the ITT presenteeism results (Table 3).

TABLE 4. Per-Protocol GEE Analyses: Estimated Means of Follow-up Presenteeism

Condition	Baseline Presenteeism	n	Mean, %
Age 50 yr and older			
Control	Low	15	16.0
	High	12	48.7
Treatment	Low	8	3.3
	High	10	41.3
Age 50 yr and older and experienced presenteeism at baseline			
Control	Low	7	34.7
	High	10	45.0
Treatment	Low	8	8.4
	High	6	44.8

Low and high baseline presenteeism determined, respectively, by values below and above sample medians. Total N across each sample is not equal to the total N analyzed in PP analyses because participants with baseline presenteeism equal to their sample medians were pruned. Median baseline presenteeism was 20% for the 50-year-and-older sample and 30% for the 50-year-and-older and experienced presenteeism at baseline sample.

GEE, generalized estimating equation.

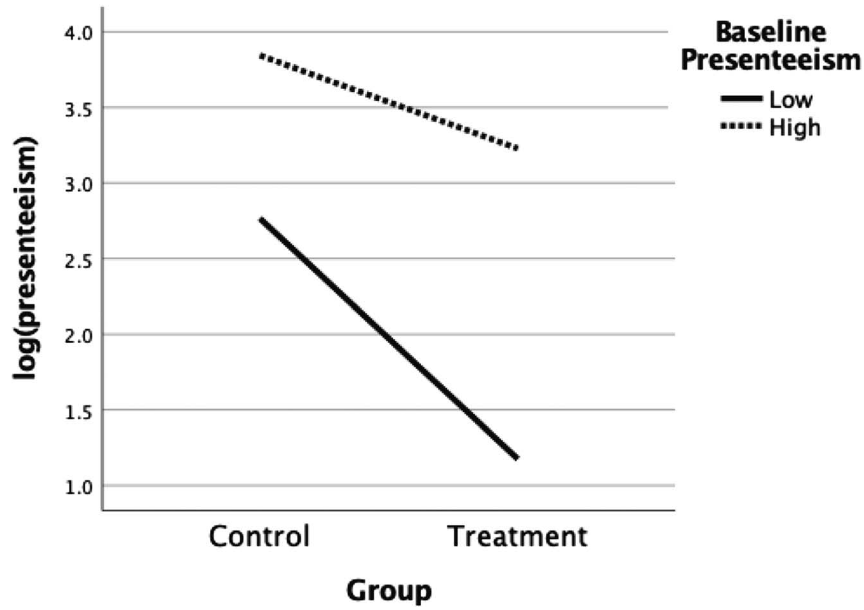

FIGURE 1. Per-protocol analysis: baseline presenteeism and group interaction in the 50-year-and-older sample.

This interaction is visualized in Figure 2 using the procedure described in the PP results for the older worker sample. Estimated means for follow-up presenteeism segmented by group and level of baseline presenteeism are displayed in Table 4.

DISCUSSION

Summary of Findings and Implications

This is the first RCT to examine the effect of the One Drop mHealth solution on workplace productivity among persons with type 2 diabetes. Intention-to-treat analyses showed that participants in the control group experienced increased presenteeism after 3 months (ie, increased on-the-job productivity loss), whereas those in the treatment group who used One Drop reported decreased presenteeism (ie, reduced productivity loss). Analyses for presenteeism looking at older workers showed that One Drop use had a stronger benefit for older workers with lower presenteeism. Those who experienced less presenteeism at baseline and used One Drop experienced a significant benefit to their productivity, as they were less likely to experience presenteeism at follow-up (ie, were less likely to experience on-the-job productivity loss). The interaction for those who experienced presenteeism at baseline and were older than 50 years indicates that using One Drop is especially beneficial for older workers who experience lower presenteeism.

The One Drop treatment tested has a beneficial impact on productivity for workers dealing with type 2 diabetes through presenteeism. One Drop's mHealth program offers many ways to engage and manage

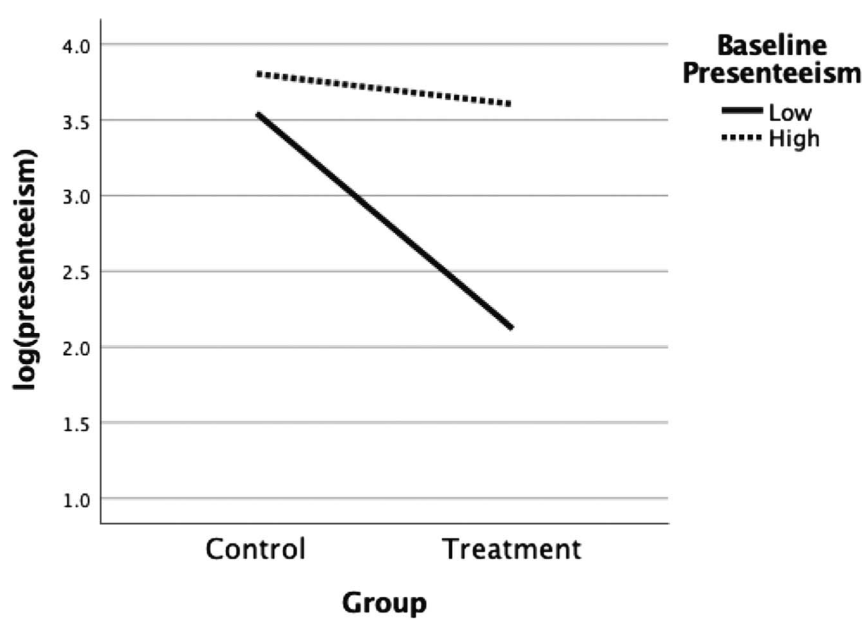

FIGURE 2. Per-protocol analysis: baseline presenteeism and group interaction in the 50-year-and-older and experienced baseline presenteeism sample.

health, allowing personalization to individual needs. This mHealth option for diabetes management has a broader impact to the individual beyond simply impacting direct health outcomes to impacting occupational health as well. Finally, although we will not interpret the marginal effects seen for absenteeism among those 50 years and older, we do note that absenteeism may be a more challenging productivity outcome to impact. This could be because individuals are more likely to struggle through their health issues, allowing it to impact work through presenteeism rather than missing work (absenteeism).

The results from this RCT showed that One Drop members who fully engage when using the service can improve their work productivity. In addition to One Drop program's immediate health benefits as previously shown,[21] the positive changes to productivity shown here have implications for improved job satisfaction, promotion potential, job security, and continued career development. Employers stand to gain directly from decreased spending on health insurance for their employees as well as reducing the indirect costs associated with productivity loss. For older workers, using One Drop saved 17% of on-the-job productivity over the 3-month trial, which equates to $13,106 saved annually per person. For all participants reporting presenteeism, using One Drop saved 9% of productivity over the 3-month study period, which equates to saving $6772 per person annually. Finally, for older workers who reported presenteeism, using One Drop saved 19% of on-the-job productivity over the 3-month trial, which equates to $14,913 saved annually per person. These results suggest that by using mHealth programs, such as One Drop, employees and employers will benefit from the improved workplace productivity as well as the previously established improvements to health outcomes.[21]

Limitations and Future Directions

Although this study employed an experimental design using validated instruments to measure productivity outcomes (Work Productivity and Activity Impairment scale[30]), as is the case with all studies, there are limitations to acknowledge. The information gathered from study participants was self-reported, which may reduce the validity because intentions of questions could not be clarified when needed and inconsistent responses were not probed for a more accurate representation of the participant's intention.[30,38] In addition, the self-reported nature of data collection opens the possibility of recall bias in the responses; however, the survey asked participants to reflect on the past week, which is a short-enough time frame to mitigate this bias. Furthermore, the survey did not collect information regarding the variety of job types and industries the participants work in. This prevents a more nuanced contextualization to our results and understanding of how these results might differ by industry.

This study was the first to use an RCT design to experimentally evaluate productivity changes in adults with diabetes from using a digital solution. Furthermore, this study design is the criterion standard for limiting bias and confounding. It is an important first step in studying an mHealth app's impact on variables outside of clinical health outcomes with respect to diabetes, specifically, studying implications for an individual's work productivity. Future research should explore and replicate these findings in a real-world setting to increase the generalizability of the mHealth-productivity effects and with larger study populations.

Health-related productivity declines at work, such as absenteeism and presenteeism, affect both the individual and the organization carrying the burden of lost productivity. Absenteeism and presenteeism are low base rate phenomena and must therefore be studied specifically among those who experience it. Furthermore, productivity research is needed to examine the effect of mHealth programs on productivity in relation to other illnesses beyond diabetes. The potential for mHealth programs to impact not only the health outcomes of the individual but also other aspects of their life also needs to be further elucidated; the COVID-19 pandemic, for example, has wide-ranging effects not fully understood. Recent research shows that the pandemic has impacted health-related productivity of workers across nearly every industry. Probst and colleagues[39] explored the impact of the workplace environment on employee attitudes and subsequent presenteeism. In conjunction with the present study, this highlights an avenue for future research to explore how mHealth apps could benefit workplace and health outcomes with consideration for chronic health conditions.

Conclusion

The present study is the only RCT to examine the productivity gains found by using an mHealth app for workers with diabetes, as the only previous RCT we are aware of found no benefit to productivity with the self-management program they assessed.[27] To date, previous research has demonstrated the health benefits of using One Drop's digital health solution.[21–24] The present study shows that using One Drop is also beneficial for employee productivity, especially for older workers, which may translate into improved job security, career advancement, and job satisfaction for individuals. The productivity gains demonstrated in this study can benefit employers too, as mitigating the deleterious effects of diabetes on workforce productivity translates to greater throughput for the resource investment as well as optimization and retention of employee skills and expertise, especially among older workers.

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