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Examining Mobile Health App Engagement in a North American Employee Population: A One-Year Longitudinal Observational Study

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Abstract

BACKGROUND: Mobile health (mHealth) apps may help promote physical activity and other health behaviours among office-based workers. Low app engagement, however, leading to little or no effect, is typical. **OBJECTIVE:** To examine engagement with a rewards-based mHealth app and identify factors influencing engagement. **METHODS:** A one-year observational study was conducted with Canadian and U.S. *Sprout at Work* app users (N = 2253; Female: 35.7%; Age: 39.3 years). Kaplan-Meier survival curves were used to examine engagement patterns from a 'multiple-lives' perspective (i.e., time to first disengagement, re-engagement, second disengagement). Regression models were used to identify factors influencing engagement. **RESULTS:** After one month of app use, 51.2% of participants disengaged. Nine out of ten did not re-engage. Risk of first disengagement was highest for 56-75 year-old participants (44%-106% higher), while rewards worth $10 per month lowered this risk (46% lower). **CONCLUSION:** Findings may help stakeholders address persistent low app engagement moving forward.

Keywords

mHealth, Digital Health Intervention, User Engagement, Usage Attrition, Behavioural Economics, Self-Determination Theory, Workplace Wellness, Office Workers

Summary for Lay Audience

Health promoting interventions delivered through mobile apps have increased in popularity as they are easily accessible and scalable. Although, in order to be effective, users must remain engaged with the intervention to achieve their desired health goals and adopt long-term behaviour change. This study examined engagement patterns over one year in 2253 users of the *Sprout at Work* app, a multicomponent app that encourages and rewards physical activity and other well-being behaviours. User activity with the app was examined to determine critical time points of user disengagement, re-engagement, and second disengagement. Furthermore, we explored if specific characteristics influenced users' engagement with the well-being platform. User disengagement was highest during the first few weeks of app usage with only a small proportion of users re-engaging. Risk of disengagement was greatest for older adults and for those who were offered rewards at an inconsistent rate. On the contrary, risk of disengagement was lowered for users who were offered a financial reward of $30 per quarter. The only factor which influenced the likelihood of a user re-engaging was the duration of their initial engagement period with the app. The results of our study may be informative to future intervention developers looking to retain users and enhance their mobile heath platform. More research is needed to determine the optimal combination of app features that elicits the greatest engagement response.

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Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1

1 Introduction

1.1 Physical Activity and Sedentary Behaviour

The World Health Organization (WHO) recommends that adults accumulate 150 minutes of moderate-to-vigorous intensity physical activity (PA) per week (World Health Organization, 2020a). Regular PA is an important determinant of health and among the wide range of benefits are reduced chronic disease risk and premature mortality (Lee et al., 2012; Warburton & Bredin, 2017). PA is also associated with lower levels of psychological distress (e.g., depression and stress; Rodriguez-Ayllon et al., 2019), greater psychological well-being (e.g., self-image and satisfaction with life; Rodriguez-Ayllon et al., 2019) and better overall quality of life (Cunningham et al., 2020; Rodriguez-Ayllon et al., 2019).

Physical inactivity is defined as “an insufficient physical activity level to meet present physical activity recommendations” (Tremblay et al., 2017, p. 9). Currently, 51% of Canadian (Statistics Canada, 2021a) and 55% of American adults meet this criterion (U.S. Department of Health and Human Services, 2018; Zenko et al., 2019). In addition to high physical inactivity levels, the prevalence of sedentary behaviour (SB), defined as “any waking behaviour characterized by an energy expenditure ≤ 1.5 metabolic equivalents (METs), while in a sitting, reclining, or lying posture” (Tremblay et al., 2017, p. 9), is also too high (Matthews et al., 2021; Patterson et al., 2018). The Canadian 24-Hour Movement Guidelines for Adults suggest “limiting sedentary time to 8 hours or less per day including no more than 3 hours of recreational screen time and breaking up long periods of sitting where possible” (Canadian Society for Exercise Physiology, 2021). Canadian and Americans adults, for example, spend on average 9.5 hours a day engaging in SB (Matthews et al., 2021; Prince et al., 2020). Notably, the risks associated with excessive SB are independent from physical inactivity. In a single day, a person can be highly sedentary but also physically active, therefore meeting WHO’s PA recommendations. For example, a recent systematic review and meta-analysis including 34 studies, found that SB, independent of PA levels, is linked to an increased incidence of type 2 diabetes and all-cause mortality among adults (Patterson et al., 2018). Accordingly, efforts to both reduce SB and increase PA have been identified as international public health priorities (World Health Organization, 2018).

1.2 Employee Physical Activity and Sedentary Behaviour

Over the years, as occupational tasks have become less laborious, most sedentary time today is accumulated in the workplace (Jung & Cho, 2022; Loyen et al., 2018; Segura-Jiménez et al., 2022). High rates of physical inactivity and SB are especially prevalent in the working population, placing employees at greater risk of not only developing, but also worsening, poorly managed chronic diseases (Prince et al., 2019; Shrestha et al., 2018; Thivel et al., 2018). A recent cross-sectional study by Rosenkranz et al. (2020) examined the relationship between workplace SB and workplace productivity among 2068 full-time office-based government employees in the State of Kansas. The researchers found that office workers were highly sedentary during the workday, sitting for 78% of their time spent at work (Rosenkranz et al., 2020). Another systematic review and meta-analysis by Prince et al. (2019) included 132 studies and used device measured movement (sedentary time, light intensity PA, moderate-to-vigorous PA, and steps) to compare levels of PA and SB among occupational groups. On average, working adults spent 60% (95% CI [54.2–65.7%], I^2 = 49%, p = 0.0399) of their time at work and 58.8% (95% CI [56.7– 59.8%], I^2 = 58%, p = 0.3240) of all wakeful hours of the day engaging in SB. Only four percent (95% CI [3.7–4.4%], I^2 = 83%, p = 0.0855) of the total day was spent performing moderate-to-vigorous PA (Prince et al., 2019).

Recently, rates of physical inactivity have been elevated following the declaration of the Covid-19 pandemic (Violant-Holz et al., 2020; World Health Organization, 2020b). In April and May 2020, public health restrictions in Canada were at their most stringent. During this time, Lesser and Nienhuis (2020) found that 22.4% of active and 40.5% of inactive Canadians were less active (Lesser & Nienhuis, 2020). The global pandemic has also caused many businesses in industrialized countries to shift their employees to remote and virtual working environments. In the United States, for example, over 30% of the US labour force transitioned to working-from-home between February and May of 2020 (Brynjolfsson et al., 2020). Similarly, in 2021, 32% of Canadians worked most of their hours from home compared to only 4% in 2016 (Statistics Canada, 2021c). A cross-sectional study involving 2303 American adults found that switching to working-from-home was associated with more time spent sedentary as compared to those whose employment remained unchanged (McDowell et al., 2020). These pandemic-driven changes have influenced daily employee activity (e.g., reduced active commuting time) and pose an added threat to occupational health (McDowell et al., 2020). Therefore, the contemporary workplace is an opportune setting to promote PA and reduce SB as it reaches a large proportion of the adult population and employees spend a significant amount of time at work (Jirathananuwat & Pongpirul, 2017). As a result, specific interventions promoting bodily movement in the workplace are needed.

1.3 Burden of Physically Inactive and Sedentary Employees

A growing evidence-base has linked diminishing employee health with increasing financial costs borne by employers (Goetzel & Ozminkowski, 2008; Grimani et al., 2019; Willis Towers Watson, 2020a). This economic burden is in part driven by lost productivity in the form of absenteeism (i.e., time away from work due to illness or disability; Grimani et al., 2019), presenteeism (i.e., reduced productivity while at work; Grimani et al., 2019) and direct healthcare costs (e.g., employer provided medical and pharmaceutical coverage; Willis Towers Watson, 2020a). In 2019, in addition to $950 billion USD spent on employee healthcare benefits in the United States, employers lost and estimated $575 billion USD due to illness-related lost productivity (Integrated Benefits Institute, 2020). According to Evans-Lacko and Knapp (2016), absenteeism and presenteeism due to mental health diagnoses alone account for $2700 and $5524 USD per person per year, respectively (Evans-Lacko & Knapp, 2016). Furthermore, Statistics Canada reports the total number of days lost in a year per worker due to illness or disability increased from 7.4 days in 2015 to 9.5 days in 2020 (Statistics Canada, 2021b). Both absenteeism and presenteeism are associated with insufficient PA and the poor management of existing chronic conditions, both of which are highly modifiable (Abdin et al., 2018; Grimani et al., 2019; Howarth et al., 2018). A Willis Towers Watson (2020) industry report suggests that employees who are thriving physically and emotionally, and who are financially secure achieve better business outcomes, including 22% higher earnings, and have $1000 USD lower annual healthcare costs (Willis Towers Watson, 2020b). Additionally, office workers engaging in lower levels of SB report higher job satisfaction and lower levels of fatigue (Rosenkranz et al., 2020). Companies, therefore, have a vested financial interest in employee PA and SB to enhance performance and productivity.

1.4 Workplace Wellness Programs

Workplace wellness programs can be broadly defined as employer-implemented strategies used to promote holistic employee well-being (Baid et al., 2021). These programs tend to target modifiable chronic disease risk factors (e.g., blood pressure, waist circumference) and promote healthy behaviours such as proper nutrition, mental well-being, and increased levels of PA (e.g., the number of steps taken each day; Baid et al., 2021). Moreover, a workplace wellness program provides businesses the opportunity to showcase their desire to foster an active, healthy work environment, retain employees (i.e., limiting turnover), all the while enhancing performance and reducing employee healthcare costs (Tarro et al., 2020). The incorporation of workplace wellness programs has become increasingly prevalent as more organizations recognize the importance of a healthy workforce (Song & Baicker, 2019; Willis Towers Watson, 2020a). In the United States in 2018, for example, a wellness program was offered to employees in 53% and 82% of small and large businesses, respectively (Song & Baicker, 2019). From an employee perspective, a company’s wellness culture is considered an important factor to 86% of Canadians when deciding whether to accept a job offer or to remain with an organization (Sanofi, 2020). Some traditional workplace wellness programs encourage healthy behaviours by making physical changes to the work environment (e.g., replacing conventional desks with height adjustable sit-stand desks). However, these changes may come with considerable cost to employers and may negatively affect performance and productivity (Shrestha et al., 2018). For example, workers using a treadmill or cycling desk may have their attention divided between work and safety, and working while simultaneously performing fine motor skill tasks, such as using a keyboard and mouse, can prove to be difficult (Shrestha et al., 2018). Other approaches to improving workplace well-being include providing employees with health-risk assessment surveys, delivering year-round education on the benefits of regular PA, and holding company-wide wellness events (e.g., charity walks/runs, group fitness classes; Willis Towers Watson, 2020a). More recently, digital health interventions have emerged as an attractive alternative to traditional workplace wellness programs given the advantages of easy implementation, wide accessibility, and scalability (Short et al., 2018; Stratton et al., 2021).

1.5 Digital and mHealth Interventions

A digital health intervention, as defined by WHO (2019), is "the use of information and communications technology in support of health and health-related fields" (p. ix). Mobile health (mHealth) is a subset of digital health and can be defined as "the use of mobile wireless technologies (e.g., smartphones) for public health" (World Health Organization, 2019, p. ix). In today's world, smartphones are pervasive, with over 35 million Canadian and 294 million American smartphone users (Statista, 2021a, 2021b). As a result, mHealth apps are increasing in popularity to support people's healthy behaviours. In 2020 alone, 71,000 new health and fitness apps were launched globally along with a 30% increase in health and fitness app downloads worldwide (Data.ai, 2021). In the workplace setting, digital interventions and mHealth apps have become a primary instrument to monitor and improve healthy behaviours as they can be easy to implement and have the potential to reach a significant proportion of employees, especially in the current remote-friendly office environment (Howarth et al., 2018). To justify implementing these programs in the workplace, studies have been conducted to determine if digital and mHealth interventions are efficacious in improving health-related behaviours and outcomes, as well as employee productivity. An overview of this literature is provided next.

A systematic review and meta-analysis by Jung and Cho (2022) aimed to demonstrate the effectiveness of mHealth interventions in promoting PA and weight loss among healthy working adults in a workplace setting. The study included eight randomized control trials (RCTs) in which participants interacting with the mHealth tools showed small to moderate improvements in PA levels (SMD = 0.22, 95% CI [0.03-0.41], $p < 0.001$) when compared to controls receiving no intervention. No significant weight loss differences were detected (SMD = 0.02, 95% CI [-0.07-0.10], $p = 0.48$; Jung & Cho, 2022). Similar results can be seen in the systematic review by Howarth et al. (2018) who assessed the impact of digital interventions in the workplace on a variety of health-related outcomes. A narrative summary of the 22 included RCTs reported that workplace digital health interventions significantly improved not only PA levels ($n = 3$), but also SB ($n = 3$), sleep, and mental health (Howarth et al., 2018). Carolan et al. (2017) conducted another systematic review and meta-analysis to identify if occupational digital mental health interventions were effective in promoting employee psychological well-being and work effectiveness (Carolan et al., 2017). The authors examined 21 RCTs collectively including 5260 participants. Most of the included studies (12/21) used interventions informed by cognitive behavioural theory. In addition, three interventions were based on coping with stress, two on mindfulness, and one each on social cognitive theory, problem solving training, positive psychology, and acceptance and commitment therapy. Overall, a small positive effect on psychological well-being ($g = 0.37$, 95% CI [0.23-0.50], k = 21) and work effectiveness ($g = 0.25$, 95% CI [0.09-0.41], k = 13) was observed (Carolan et al., 2017). The researchers also suggested that occupational digital health interventions have outcomes on par with other more traditional, nondigital occupational programs (Carolan et al., 2017).

This research alludes to the effectiveness of mHealth interventions in increasing levels of PA, decreasing SB, and improving psychological well-being and work effectiveness among employees. However, each review expressed concern regarding the strength of their findings due to the high heterogeneity found among the included RCTs, the small sample sizes, and the short-term intervention periods (Carolan et al., 2017; Howarth et al., 2018; Jung & Cho, 2022). Furthermore, Carolan et al. (2017) and Howarth et al. (2018) reported a wide range of user attrition (3% to 95% and 0% to 60%, respectively) which raises an important question regarding the impact of user engagement on results (Carolan et al., 2017; Howarth et al., 2018). mHealth app engagement is a relatively new dependent variable and is increasingly being recognized as a critical precursor to intervention success (e.g., improved health behaviours or outcomes). The literature to-date suggests that mHealth interventions may be effective *when users engage* sufficiently (McLaughlin et al., 2021; Spaulding et al., 2021). However, low app engagement leading to high user attrition unfortunately remains an industry hallmark (Carolan et al., 2017; Cole-Lewis et al., 2019; Guertler et al., 2015; Howarth et al., 2018; Rayward et al., 2021; Short et al., 2018). Research assessing user engagement patterns and predictors for the purpose of better addressing the low mHealth engagement issue is needed.

1.6 Defining mHealth Engagement

mHealth app *engagement* is a familiar term used in the field of digital health. However, its definition can be abstract, and in different settings, it can be difficult to measure engagement in a valid and reliable way. *Engagement*, defined by Alshurafa et al. (2018), is the "…specific interaction and use patterns with the mHealth tools such as smartphone applications for intervention…" (Alshurafa et al., 2018, p. 1). This term can be further described as the "extent of usage over time" (i.e., frequency [how often contact is made with the intervention] and depth [use of intervention components]; Perski et al., 2017). Intervention usage is an effective indicator of overall engagement and the use of digital platforms allows for automatic tracking of user interactions (Short et al., 2018). Common objective measures of engagement include number of logins, time spent online, and the amount and type of content used (Perski et al., 2017; Short et al., 2018). The level of user engagement is also largely influenced by intervention features such as content, mode of delivery, and individual characteristics (e.g., internet self-efficacy, level of digital literacy, etc.; Short et al., 2018). Notably, engagement is not synonymous with "adherence" which is defined as "…the extent to which the patient's behaviour matches the recommendations that have been agreed upon with the prescriber" (Kelders et al., 2012; Short et al., 2018). In other words, "adherence" refers to the proportion of participants who use an intervention as intended, and "engagement" refers to the overall intensity and extent of user involvement.

It is widely accepted that user engagement is vital to the success of digital health interventions (Edney et al., 2019; McLaughlin et al., 2021; M. Mitchell et al., 2020; Spaulding et al., 2021). If user engagement is not sustained, their interaction with in-app behaviour change components will be limited, thus minimizing the likelihood of improving targeted health behaviours or outcomes (Cole-Lewis et al., 2019). A meta-analysis consisting of 11 studies conducted by McLaughlin et al. (2021) demonstrated the importance of engagement with digital health interventions for improving PA. Using the definition of engagement by Perski et al. (2017), engagement was defined in this meta-analysis as the extent of usage with digital interventions and the objectively-measured number of logins, time spent online, and number of activities completed. The pooled estimate of the standardized regression coefficient indicated a significant positive relationship between engagement and PA (0.08, 95% CI [0.01-0.14], $p = 0.02$, SD 0.11, $I^2 = 77\%$) in 11 studies (McLaughlin et al., 2021). More recently, Mitchell et al. (2020) came to a similar conclusion in their 12-month quasi-experimental study examining daily step count data among 39,113 app study participants. The aim of their research was to evaluate whether *Carrot Rewards*, an mHealth app incorporating multiple behaviour change techniques (i.e., goal setting, team challenges, financial incentives), could increase step count in two Canadian provinces (i.e., British Columbia and Newfoundland and Labrador). Participants were classified as 'physically active' (i.e., baseline steps per day ≥ 5000) or 'physically inactive' (i.e., baseline steps per day < 5000). Participants were further categorized into four engagement groups (i.e., Limited [1-11 weeks], Occasional [12-23 weeks], Regular [24-51 weeks], and Committed [52 weeks]) based on number of weeks with four or more days of app opens. Baseline mean daily step count was compared with the average number of steps from the last two recorded weeks. When examining the entire sample in an engagement sub-group analysis, the authors observed a significant increase in step count for 'Regular' and 'Committed' users (448.8 steps and 884.6 steps, respectively), but a significant decrease in step count for 'Limited' and 'Occasional' users (-392.3 steps and -473.2 steps, respectively). Regardless of their level of engagement, a significant increase in step count was observed for all physically inactive participants, with the largest increase for those in the 'Regular' and 'Committed' engagement groups (i.e., 1215 steps and 1821 steps, respectively). Furthermore, significant small decreases in step count were observed for all participants except for those categorized as ‘Committed’ (M. Mitchell et al., 2020). Since participant engagement determines intervention exposure, increased engagement with mHealth apps may ultimately lead to greater intervention efficacy (Cole-Lewis et al., 2019; Edney et al., 2019; Schoeppe et al., 2016; Spaulding et al., 2021). Current digital workplace wellness programs generally do not incorporate behaviour change theory into program designs which may be a key limitation to user engagement (Adu et al., 2018; Klonoff, 2019).

1.7 Low Engagement Issue

Despite the availability of mHealth apps, low user engagement is a prevalent industry issue (Carolan et al., 2017; Cole-Lewis et al., 2019; Guertler et al., 2015; Howarth et al., 2018; Rayward et al., 2021; Short et al., 2018). A 2019 study by Baumel et al. (2019) collected user data from 93 mental health apps. Relative to users who opened the app on day zero, 69.4% of participants opened the app on day one, and only 3.9% on day 15 (Baumel et al., 2019). Recent industry data corroborates the findings from this study suggesting that 69% of health and fitness apps are deleted within 90 days (Apptentive, 2021) and only 7% of app companies have greater than 50,000 monthly active users (MAUs)—number of unique users with at least one app view per month (Research2Guidance, 2018).

Researchers have conducted a number of studies to better understand mHealth app attrition, although only a few have contributed to identifying factors influencing intervention engagement. A systematic review and meta-analysis by Meyerowitz-Katz et al. (2020) investigated user attrition in mHealth apps designed to assist in the management of chronic diseases. Of the 17 included studies (9 RCTs and 8 observational studies), 14 sought to improve a range of chronic conditions (e.g., lower back pain, kidney disease), and the remaining studies looked to improve general lifestyle behaviours (e.g., eating habits, PA). The studies ranged significantly in size (20 to 200,000 participants) and duration (two weeks to one year). The overall mean attrition rate was 43% (95% CI [29%-57%]) however, when excluding the RCTs and only considering the real-world observational studies, user attrition grew somewhat to 49% (95% CI [27%-

70%]; Meyerowitz-Katz et al., 2020). The researchers also identified factors associated with lower participant dropout rates. Younger individuals, those with higher levels of education and health literacy, and a desire to be more committed to their health, were associated with lower levels of attrition (Meyerowitz-Katz et al., 2020).

Jackob et al. (2022) had a similar objective with their systematic review which included 99 studies. For each study, the researchers derived an intervention "adherence score" by calculating a ratio of intended use to actual use. Mean adherence across all mHealth interventions was 56% (SD = 24.4%; range 2.6%-96.0%). However, due to the majority of studies having a short intervention period (average 60.8 days), the authors were doubtful whether this level of adherence would persist in more prolonged studies (Jakob et al., 2022). Corresponding with the findings from Meyerowitz-Katz et al. (2020), studies using real-world publicly available mHealth apps ($r = 0.324$, $p = 0.001$) and users lacking health literacy demonstrated lower levels of adherence. However, other participant-level factors such as age ($r = 0.105$, $p = 0.32$), gender ($r = -0.031$, $p = 0.77$), and pre-existing health conditions ($r = -0.049$, $p = 0.63$), had no significant effect on adherence levels (Jakob et al., 2022). Since mHealth apps have largely different intended uses, both reviews stated high heterogeneity as study limitations. The authors presented a notable gap in the present literature in which the current body of evidence lacks concise definitions and measures to evaluate user engagement with digital interventions (Jakob et al., 2022; Meyerowitz-Katz et al., 2020). Meyerowitz-Katz et al. (2020) also emphasized the paucity of studies investigating participant- and intervention-related variables influencing mHealth engagement and suggest future studies look into the reasons behind elevated levels of user attrition (Meyerowitz-Katz et al., 2020).

In the digital health literature to date, most research appears to consider users to have a 'single lifetime', suggesting that users do not return once disengaging with the intervention. However, user engagement may not follow this typical modelling, with some suggesting that a 'multiple-lives' perspective may be more informative (Bohm et al., 2020; Lim et al., 2019; Lin et al., 2018). While little is known about the 'multiple-lives' of mHealth app users, early evidence suggests that after long periods of inactivity users may indeed re-engage with mHealth apps (Bohm et al., 2020; Lim et al., 2019; Lin et al., 2018). The concept of 'multiple-lives' is illustrated in an observational study conducted by Lin et al. (2018). The researchers compiled data from a mobile activity tracking app, *Argus* by *Azumio*, and the final dataset included over one million users logging-in over the course of 31 months. The researchers discovered that after 30 days of inactivity, over 75% of participants became active again. Participants often returned more than once. Fifty-nine percent had at least three active periods where each time they were inactive for greater than 30 days. Even among participants who were absent for greater than 90 days, 58% returned for at least one active period (Lin et al., 2018). Building on the early work of others then, the current study embraces this 'multiple-lives' perspective, to further emphasize the need for research that considers user *re-engagement* when trying to promote healthy behaviours like PA or reducing SB.

1.8 Theoretical Considerations

The goal of mHealth interventions is to stimulate interest in well-being practices and promote long-term behaviour change. Psychologists have developed behavioural theories to help understand factors behind human motivation and decision making (Ryan & Deci, 2000; Thaler & Sunstein, 2008). Currently, many mHealth interventions are not optimally designed because they often are not theoretically informed by behaviour change theories (Adu et al., 2018; Klonoff, 2019; Schoeppe et al., 2016). In a 2016 systematic review evaluating the efficacy of mHealth apps to improve diet, PA, and SB, 15 of the 27 included studies reported incorporating behaviour change theory in intervention designs. Some of the more commonly cited theories of behaviour change include Self-Determination Theory (SDT), Transtheoretical Model (TTM), Social Cognitive Theory, and the Theory of Planned Behaviour (Schoeppe et al., 2016). A more recent review by Adu et al. (2018) examined the developmental considerations of mHealth apps in diabetes self-management trials. Of the 11 included studies, only one cited behaviour change theory. In particular, the app was informed by the motivation behaviour skill model and delivered automated personalized feedback to the user. In addition, five studies reported significant improvements in HbA_{1c} levels between intervention groups. Each of these studies provided an educational component to the participants, either through the app directly, or by text messaging or teleconsultation

(Adu et al., 2018). Researchers conducting mHealth app engagement studies should look to relevant behaviour change theories to inform design, as well as the evaluation of interventions. In particular, two behaviour change theories that provide valuable insight include behavioural economics (BE; Thaler & Sunstein, 2008) and SDT (Ryan & Deci, 2000). These are briefly introduced next.

BE is one theoretical model from which practical solutions to the mHealth app engagement-effectiveness problem can be developed. Specifically, BE has accelerated interest in using financial incentives to promote PA and other well-being behaviours (Thaler & Sunstein, 2008). Often referred to as "Nudge Theory", BE suggests that a "choice architecture" exists in which the design of the physical, social, and psychological environment may subtly influence one's decisions (Thaler & Sunstein, 2008). Although individuals make decisions while preserving their freedom of choice, systematic "decision biases" can also make it difficult for people to make self-beneficial choices (Thaler & Sunstein, 2008). For instance, "present bias" describes the human tendency to make disproportionate choices that favour immediate desires at the expense of one's future well-being (Camerer et al., 2004). By increasing the immediacy of rewards with incentives (e.g., financial incentives, recognition) for engaging in healthy behaviours, individuals may be more willing to partake in activities that benefit their long-term well-being. Other "decision biases" including "loss aversion" (i.e., tendency to prefer avoiding losses over acquiring equivalent gains), "probability weighing" (i.e., tendency to believe events have a higher chance of occurring than they actually do), and "default bias" (i.e., tendency to stick with the *status quo* or with previously made decisions) have been leveraged to boost behaviour change potential as well. Recent systematic reviews supporting the effectiveness of BE-informed healthy living interventions are presented next.

Landais et al. (2020) aimed to summarize studies-to-date that evaluated "choice architecture" interventions in the environment (e.g., motivational posters/signage, footprint stickers, email encouragements to walk, etc.) that encouraged PA (predominantly stair use) or discouraged SB in adults. The systematic review included 88 studies, the majority of which (n = 86) targeted PA. Additionally, two studies measured

SB and one targeted both PA and SB. The intervention techniques employed were prompting ($n = 53$), message framing ($n = 24$), social comparison ($n = 12$), feedback ($n = 8$), default change ($n = 1$), and anchoring ($n = 1$). Significant effects for both PA and SB were seen in 67.6% of the studies when in the presence of the intervention, and in 47.1% of studies after the intervention was removed (Landais et al., 2020). Another systematic review and meta-analysis conducted by Mitchell et al. (2020) aimed to demonstrate the impact financial incentives had on PA levels in adults. All 23 included studies leveraged the BE concept of "present-bias". Findings indicated that incentives as little as $1.40 USD/day increased PA for short (<6 months) and long (>6 months) duration interventions, and PA improvements persisted even after incentives were removed. Meta-analysis of data pooled from 12 studies determined that incentives were associated with an increased mean daily step count (607.1 steps/day, 95% CI [422.1 to 792.1]) during the intervention period, and nine studies saw post-intervention (i.e., after incentives were removed) mean daily step count increases (513.8 steps/day, 95% CI [312.7 to 714.9]) as well. However, with regards to sustained PA, 'vote counting' indicated that only four out of 18 studies reported post-intervention PA benefits, thus bringing into question the long-term effectiveness of financial incentives (M. S. Mitchell et al., 2020). While BE is well-suited to describe situations in which behaviours may be *stimulated*, a broader consideration of theories of human motivation may help explain situations where behaviours are likely to be *sustained*.

SDT is a global theory of human motivation consisting of four-mini theories, two of which are worth noting here (Ryan & Deci, 2000). First, cognitive evaluation theory pertains to conditions that may facilitate or hinder the development of intrinsic motivation (i.e., the extent to which a behaviour is performed "for its own sake"; Ryan & Deci, 2000). Cognitive evaluation theory posits that rewards may serve two functions: 1) an informational role by providing feedback on an individual's performance, or 2) a manipulative role if the objective of performing the behaviour is to attain the reward, rather than being intrinsically motivated. A so-called "over-justification" effect can occur, if rewarding individuals who participate in behaviours intrinsically reduces intrinsic motivation following reward removal (Ryan & Deci, 2000). Secondly, organismic integration theory describes the extent to which behaviours are motivated by extrinsic factors (e.g., financial incentives), and suggests there exists a continuum of "internalization" ranging from amotivation to intrinsic regulation (i.e., intrinsic motivation; Ryan & Deci, 2000). Movement along the continuum represents the degree to which behaviour is self-determined (i.e., internalized; Ryan & Deci, 2000). Individuals with intrinsic motivation have the highest degree of self-determination and perform healthy habits volitionally. Individuals with amotivation have low levels of self-determination and have no desire to engage in healthy behaviours. In order to progress along the continuum, interventions must fulfill three basic psychological needs: autonomy (i.e., the feeling one has choice and willingly endorses one's behaviours), competence (i.e., the feeling of being effective in one's activity), and relatedness (i.e., the need for belonginess and to feel connected with others; Ryan & Deci, 2000). The challenge remains to be able to have an incentive design that reinforces the three basic SDT needs whilst not depressing intrinsic motivation.

A meta-analysis conducted by Ntoumanis et al. (2021) appropriately demonstrates the utility of SDT in practice. The aim of the study was to evaluate the effect size differences SDT-informed interventions had on health behaviours, physical- and psychological-health outcomes, as well as on various SDT constructs (e.g., perceived need for support, psychological need satisfaction, autonomous motivation, controlled motivation, and amotivation; Ntoumanis et al., 2021). In total, 73 studies were included collectively recruiting 30,088 participants. Average duration of the intervention was 133.4 days and the follow-up period ranged from one week to 30 months. The authors measured effect size changes using Hedges' *g* and an increasingly positive *g* value represented a greater change in the experimental group over the comparison group (Ntoumanis et al., 2021). At the end of the intervention period, significant positive changes were observed in the following SDT constructs: need support ($g = 0.64$); competence ($g = 0.31$), autonomy ($g = 0.37$), combined need satisfaction ($g = 0.37$); and autonomous motivation ($g = 0.30$). At follow-up, significant effects were once again seen in outcomes of competence ($g = 0.33$) and combined need satisfaction ($g = 0.28$). Furthermore, participants' psychological health ($g = 0.29$) and health behaviours ($g = 0.45$) were significantly improved with a medium effect size. No immediate effects were seen on physical health outcomes, however, a small significant effect was observed at follow-up (g = 0.28; Ntoumanis et al., 2021). In summary, SDT-based interventions have demonstrated modest effects in improving health behaviours and other health indicators, which in part can be attributable to increases in participants' self-determined motivation (Ntoumanis et al., 2021). Therefore, app developers may want to consider SDT when aiming to promote behaviour change maintenance. More research is needed, though, to evaluate *long-term* mHealth app engagement through a theoretical lens, regardless of whether the intervention itself is explicitly grounded in theory.

1.9 Study Objectives

Despite rising interest in mHealth interventions in workplace settings, significant user attrition remains. Since mHealth app engagement is considered a necessary precursor to mHealth app effectiveness, the primary objective of this study was to examine mHealth app engagement with a rewards-based workplace wellness program that focuses on PA promotion in addition to other modifiable health behaviours. Secondary objectives were to explore participant- (e.g., socio-demographics, health characteristics) and company-level factors (e.g., company size, reward type and size) influencing engagement. Knowing more about mHealth app engagement patterns and predictors may help app publishers design better interventions in the future.

Chapter 2

2 Methods

2.1 Setting

Founded in 2012, *Sprout Wellness Solutions Inc.* (*Sprout*) is a Canadian health technology company with a vision of promoting employee well-being around the world. Their associated mHealth app *Sprout at Work* (Figure 1) has over 29,000 users across 65 companies, the majority of which are located in Canada and the United States. Companies remunerate *Sprout* for access to their digital platform which is then made available to their employees. App download is voluntary and free of charge. *Sprout at Work* is a multicomponent digital mHealth app that encourages users to engage in behaviours that promote physical and psychosocial well-being, most notably physical activity. The cornerstone app feature is goal setting and tracking of PA, specifically the number of steps taken per day, as it is the only activity that is objectively recorded and rewarded. The app incorporates many behaviour change techniques, such as goal setting, self-monitoring, social support, feedback on behaviour, health education, and reward as incentives (see Appendix A for full list; Michie et al., 2013). To further describe the intervention, the App Behaviour Change Scale (ABACUS), a 21-item checklist that can be used to evaluate the behaviour change potential of an app (McKay et al., 2019), is provided in Appendix B as well. The *Sprout at Work* app met 20 out of 21 ABACUS criteria. In addition, the app integrates gamification components, defined as "…the use of game design elements in a nongame context" (Brigham, 2015), via personalized challenges, a points leaderboard, and badges for achievements. The accumulation of points unlock bronze, silver, and gold badges for the user. Upon partnering with *Sprout*, companies have the option to financially reward their employees for achieving each badge level. Theoretical (i.e., BE) and empirical evidence suggest that financial incentives can encourage participation (Chokshi et al., 2018; Mason et al., 2018; Mitchell et al., 2013; M. S. Mitchell et al., 2020). Depending on the company and its reward program of choice, attaining a badge rewards the user with *SproutBucks,* 1 *SproutBuck* being equivalent to 1 CAD or 1 USD (depending on local currency), up to $100 USD quarterly. Incentives may be offered 'on-platform', in the form of in-app product and gift cards redemptions (Starbucks, BestBuy, Apple, Visa pre-paid gift cards, etc.,), or ‘off-platform’, in the form of premium deductions, sweepstakes and challenge prizing provided directly by the employer.

(a) (b) (c)

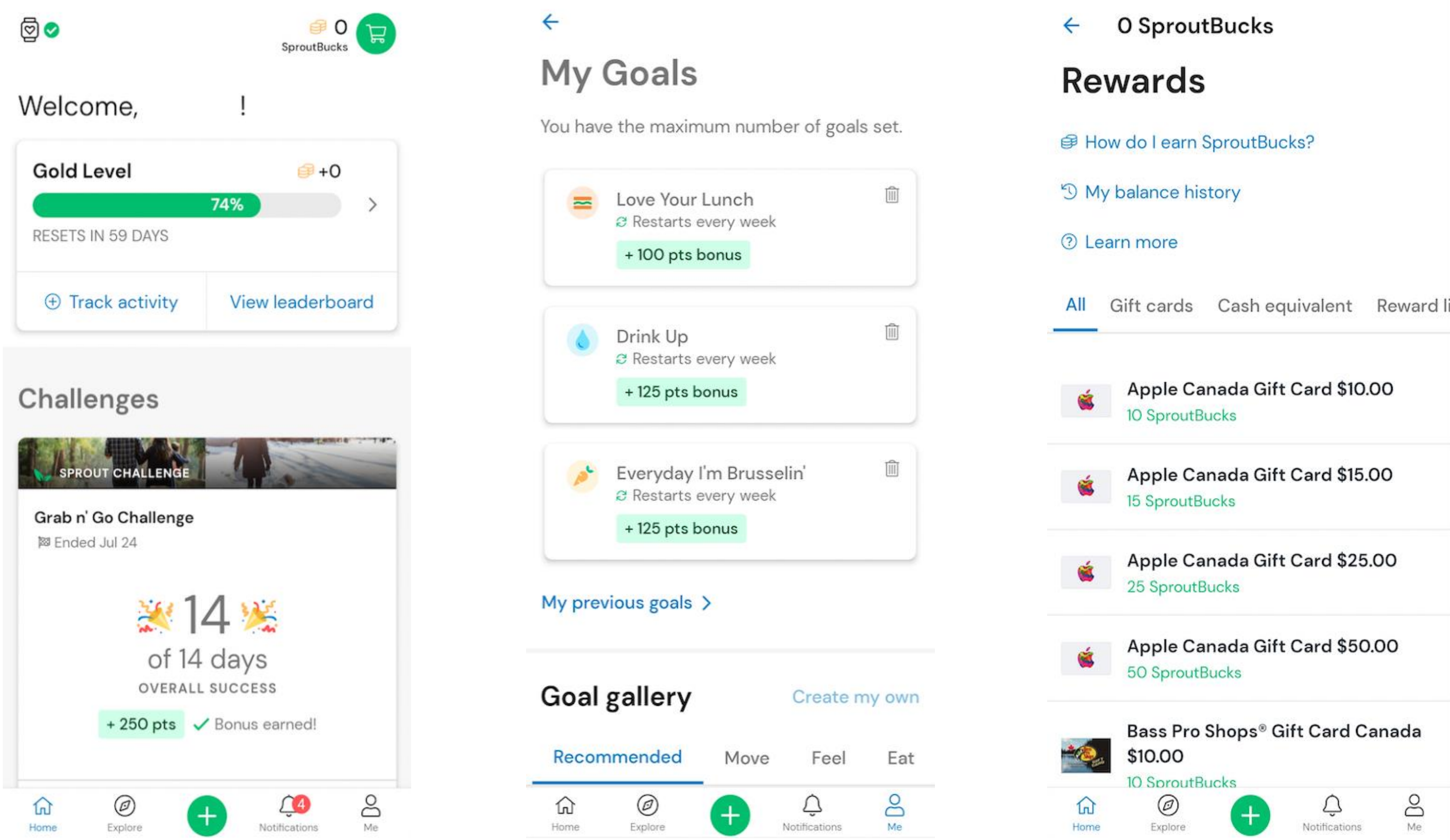

Figure 1. *Sprout at Work* (a) homepage, (b) goal gallery, and (c) 'on-platform' rewards redemption.

2.2 Study Design and Participants

We conducted a one-year single cohort observational study using data collected by the *Sprout at Work* app. Prior to gaining access to the app, all participants provided informed electronic consent allowing *Sprout* to share aggregated data (without identifiers) with third parties for internal analysis of products and services. Our sample was restricted to new app users who registered between January 1st and June 30th, 2020. As participants had varying registration dates, we collected only the first 52 weeks of each participants' interaction with the mHealth app. Only participants working for Canadian and U.S. companies were included. Ethical approval for this study was obtained from the Western University Human Research Ethics Board (#118323; see letter of approval, Appendix C) and follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for cohort studies (von Elm et al., 2007). The full STROBE checklist is presented in Appendix D.

2.3 Outcomes

The primary study outcome was weekly app opens (WAOs), defined as the "…number of times an individual app is launched per week" (Upland, 2020). It is a standard industry metric used to objectively measure user engagement and usage patterns (Short et al., 2018; Upland, 2020). Notably, participants were considered 'engaged' after their first app open. Alternatively, participants were considered 'disengaged' when experiencing their first occurrence of four consecutive weeks without an app open (Bohm et al., 2020; Edney et al., 2019; Meyerowitz-Katz et al., 2020). We operationally defined 'disengagement' in this way as an important performance indicator for companies in this industry is monthly active users (MAUs)—the number of unique users with at least one app view per month (Apsalar, 2016; Investopedia, 2022; Upland, 2020). Accordingly, a 'disengaged' participant was considered 're-engaged' after four consecutive weeks of app opens (Table 1).

Table 1. Operational definitions of mHealth app engagement.

Event	Definition
First disengagement	First occurrence of four consecutive weeks without an app open
Re-engagement	After being considered disengaged, four consecutive weeks with an app open
Second disengagement	After being considered re-engaged, another occurrence of four consecutive weeks without an app open

2.4 Co-variates

Participant co-variates were used to identify predictors of first disengagement and re-engagement. Upon registration, self-reported data were voluntarily provided by each participant, including: socio-demographics (e.g., age, gender, and country of residence), biometrics (e.g., height, weight, and body mass index [BMI]), health behaviour information (e.g., smoking status) and chronic disease diagnoses (i.e., type two diabetes, cardiovascular disease, high blood pressure, osteoarthritis, lung disease, and occurrence of lower back pain). During registration, completion of a well-being survey, considering personal health determinants, generates a baseline health risk assessment (HRA) score (scored from 0-100). HRA scores are calculated by comparing well-being survey responses provided by *Sprout at Work* users of the same age and gender. Additionally, company-level data including size (i.e., number of employees), the type of reward offered to employees (i.e., 'on-platform', 'off-platform', or no rewards), and the maximum reward value per quarter ($0-$100 CAD/USD, (depending on local currency)) was collected.

2.5 Statistical Analyses

2.5.1 Primary Analyses

Participant- and company-level co-variates are presented using means and standard deviations for continuous data, and using counts and percentages for categorical data. Three Kaplan-Meier (KM) survival curves were generated to examine app engagement (time to first disengagement, re-engagement and second disengagement). First, a KM curve was used to illustrate participant survival throughout the 52-week study period. Survival time was the number of weeks until the first disengagement occurred (i.e., the first occurrence of four consecutive weeks without an app open). To examine engagement from a ‘multiple-lives’ perspective, additional KM curves were created to show the fraction of participants that re-engaged, and for those that disengaged for a second time. To analyze changes in the number of app opens per week, a linear regression was conducted to describe the relationship between time and app open frequency (i.e., how often contact is made with the intervention). A histogram with the average number of WAOs summarizes the pattern of app open frequency over the 52-week study period as well. WAO averages do not include disengaged participants.

2.5.2 Secondary Analyses

Cox proportional hazards regression models were used to explore the impact of participant- and company-level co-variates on survival time until the first disengagement and survival time until re-engagement. The participant-level co-variates included in the model were gender, age, country of residence, BMI, baseline HRA score, smoking habit, chronic disease count, and occurrence of lower back pain. The company-level co-variates included were company size, reward type, and the maximum reward value per quarter. When modelling for re-engagement survival time, the sum of app opens, and the number of weeks until disengagement, were also included as continuous variables. Furthermore, based on likelihood of attrition, Poisson regressions were conducted at weeks one, four and eight, to analyze which co-variates predicted WAO frequency (Guertler et al., 2015; Rayward et al., 2021). Since participant co-variate data were self-reported, missing data were treated as a separate category (no response) to retain the full number of observations as recommended by Bohm et al. (2020). Statistical analyses were performed using IBM SPSS Statistics Version 25.

2.5.3 Sensitivity Analysis

Engagement is defined a myriad of ways and these varying definitions can influence mHealth app survival time outcomes. For this reason, a sensitivity analysis was conducted using another commonly used definition of disengagement, the first occurrence of a two-week lapse of mHealth app usage (Murray et al., 2019; Rayward et al., 2021). KM curves were recreated based on disengagement defined as the first occurrence of two consecutive weeks without an app open as others have done (Guertler et al., 2015; Kolt et al., 2017; Murray et al., 2019), and a disengaged participant was considered re-engaged after two consecutive weeks of app opens.

Chapter 3

3 Results

3.1 Sample Characteristics

The study sample included 2,253 participants (39.3±10.7 years; 35.7% female). Participant characteristics are summarized in Table 2. Twenty-one percent of our sample did not provide gender information. Most participants resided in Canada (57%). For participants providing height and weight information (2019/2252), the average BMI was 26.7±10.7 kg/m^2 (defined as 'overweight' by the WHO). Average baseline HRA score was 60.2±10.6 (operationally defined by *Sprout* as "Fair"). More than 15% of employees self-reported having at least one chronic disease diagnosis. Mean WAO frequency was 1.86±0.31. The sample was employed by 38 unique companies. Average company size was 2055±4464.45 employees. Company characteristics including reward style and value are summarized in Table 3. Included as an app feature, 82.2% of the participants set a goal, and 65.5% interacted on the social platform (i.e., shared a post, comment or 'like'). Among participants offered monetary rewards (1779/2253), 29.1% redeemed a reward.

Table 2. Participant characteristics ($N = 2253$).

Co-variates	Total participants
Country, *n* (%)	
Canada	1285 (57)
United States	968 (43)
No response	0 (0)
Gender, *n* (%)	
Female	804 (35.7)
Male	966 (42.9)
No response	483 (21.4)
Age, mean (*SD*)	39.3 (10.7)
18-25 years, *n* (%)	173 (7.7)
26-35 years, *n* (%)	663 (29.4)
36-45 years, *n* (%)	610 (27.1)
46-55 years, *n* (%)	396 (17.6)
56-65 years, *n* (%)	177 (7.9)
66-75 years, *n* (%)	10 (0.4)
No response, *n* (%)	224 (9.9)
BMI[a] (kg/m^2), mean (*SD*)	26.7 (10.7)
Underweight, *n* (%)	22 (1.0)
Normal weight, *n* (%)	592 (26.3)
Overweight, *n* (%)	628 (27.9)
Obese I, *n* (%)	334 (14.8)
Obese II, *n* (%)	145 (6.4)
Obese III, *n* (%)	56 (2.5)
Outside BMI parameters[b], *n* (%)	242 (10.7)
No response, *n* (%)	234 (10.4)
Baseline HRA score[c], mean (*SD*)	60.2 (10.6)
Poor (<50), *n* (%)	311 (13.8)
Fair (50-61.9), *n* (%)	681 (30.2)
Good (62-73.9), *n* (%)	743 (33.0)
Very good & Excellent (74-100), *n* (%)	160 (7.1)
No response, *n* (%)	358 (15.9)
Smoking habit, *n* (%)	
Never	1467 (65.1)
Former smoker	240 (10.7)
Current smoker	179 (7.9)
No response	367 (16.3)

Table 2 (continued).

Chronic disease count, *n* (%)	
Zero diagnoses	1508 (66.9)
One diagnosis	303 (13.4)
Two or more diagnoses	75 (3.3)
No response	367 (16.3)
Occurrence of lower back pain, *n* (%)	
Yes	599 (26.6)
No	1287 (57.1)
No response	367 (16.3)

Note: *SD*=Standard deviation, HRA=Health risk assessment.
[a]BMI group definition according to the World Health Organization, underweight=BMI<18.5, normal weight=25>BMI≥18.5, overweight=30>BMI≥25, obese I=35>BMI≥30, obese II=40>BMI≥35, obese III=BMI≥40.
[b]BMI parameters, 45≥BMI≥17.
[c]HRA group definitions according to Sprout Wellness Solutions Inc., poor=HRA<50, fair=50≤HRA≤61.9, good=62≤HRA≤73.9, very good & excellent=74≤HRA≤100.

Table 3. Company characteristics (*N* = 38).

Co-variates	Total participants
Company size[a], mean (*SD*)	2055 (4464.45)
Small (<500 employees), *n* (%)	399 (17.7)
Medium (500-1000 employees), *n* (%)	197 (8.7)
Large (>1000 employees), *n* (%)	1657 (73.5)
Reward style	
No rewards, *n* (%)	274 (12.2)
On platform[b], *n* (%)	1418 (62.9)
Off platform[c], *n* (%)	561 (24.9)
Maximum reward value per quarter[d]	
$0, *n* (%)	274 (12.2)
$20, *n* (%)	226 (10.0)
$25, *n* (%)	349 (15.5)
$30, *n* (%)	532 (23.6)
$35, *n* (%)	7 (0.3)
$50, *n* (%)	466 (20.7)
$75, *n* (%)	166 (7.4)
$85, *n* (%)	5 (0.2)
$90, *n* (%)	3 (0.1)
$100, *n* (%)	25 (1.1)
Challenge prizing, *n* (%)	68 (3.0)
Premium deductions, *n* (%)	37 (1.6)
Sweepstakes, *n* (%)	25 (1.1)
Unknown, *n* (%)	70 (3.1)

Note: *SD*=Standard deviation.
[a]Company size categories according to Sprout Wellness Solutions Inc.
[b]Benefits in the form of in-app product and gift cards redemptions.
[c]Employer-specific rewards (e.g., premium deductions, sweepstakes, etc.,).
[d]Rewards are in CAD/USD (depending on local currency).

3.2 Primary Analyses

Mean survival time until first disengagement was 11.9 weeks (*SE* = 0.346, 95% CI [11.194, 12.552], $p < 0.05$). Participants' first disengagement is illustrated with a KM curve in Figure 1 (a). The greatest attrition was observed within the first month of app usage. After the first week, 34.6% (779/2253) of the participants disengaged. Following four weeks, 52.1% (1174/2253) of the study sample met our disengagement criteria. Participants continued to disengage until the end of the study period albeit at a reduced rate. At the end of the observation period, 260 participants (11.5%) were engaged. The KM curve for participant re-engagement is shown in Figure 1 (b). Among those who disengaged, 89.2% (1777/1993) did not re-engage. Average time for participants to return to app usage was 47.1 weeks (*SE* = 0.259, 95% CI [46.587, 47.602], $p < 0.05$). Among re-engaged participants, 35.6% (77/216) disengaged for a second time (Figure 1 (c)). Mean survival time until the second disengagement was 28.0 weeks (*SE* = 1.36, 95% CI [25.351, 30.682], $p < 0.05$).

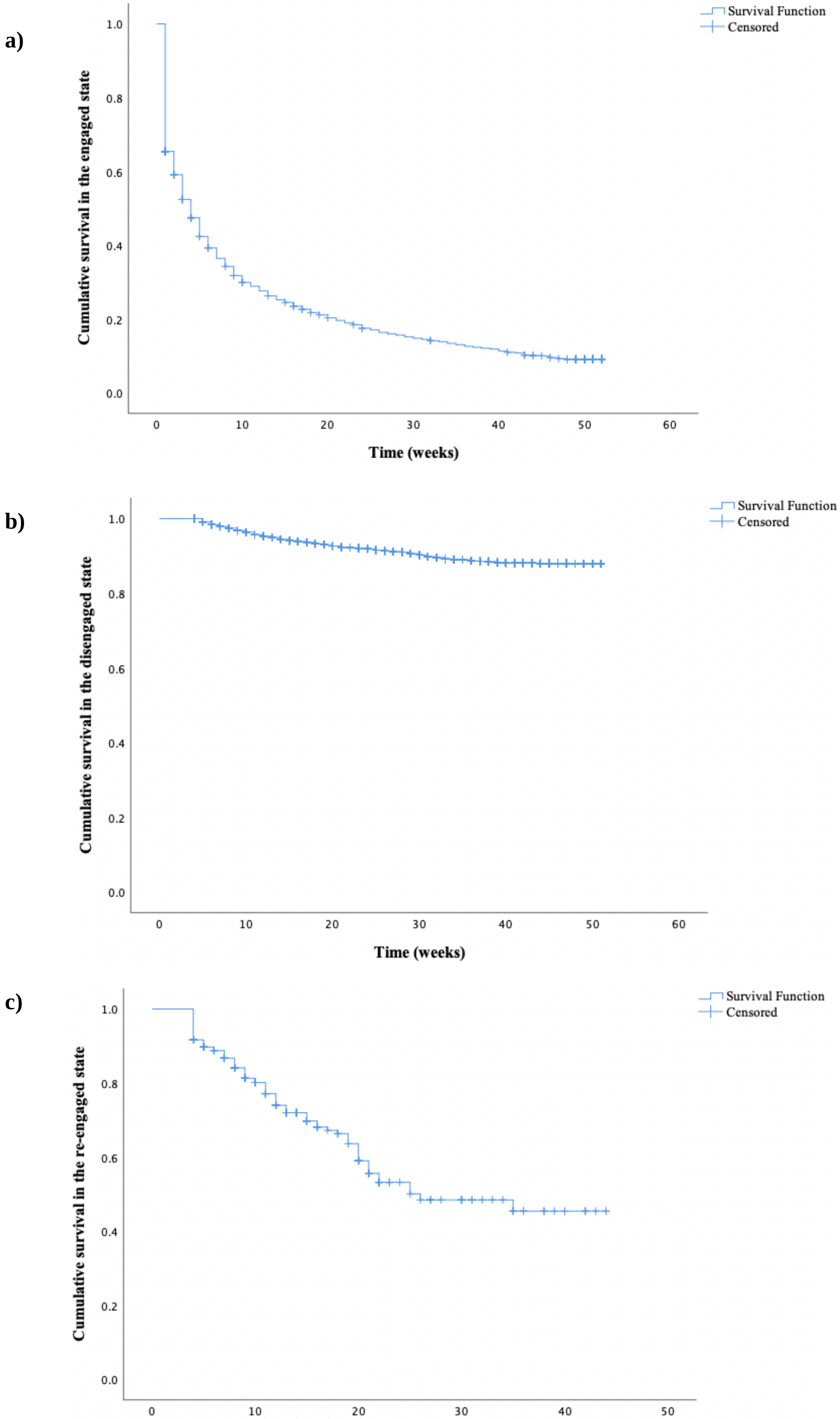

Figure 2. Kaplan-Meier curve illustrating participant (a) first disengagement, (b) re-engagement, and (c) second disengagement.

Note. Censored indicates weeks with participant time to outcome event not available.

In addition, a histogram with the average number of WAOs illustrates the pattern of participant activity over the 52-week study period (Figure 2). Including only participants remaining engaged at the respective weeks, mean WAO open frequency was 1.86±0.31. Simple linear regression was carried out to investigate the relationship between time (in weeks) and WAO frequency. The model explained that time was a significant predictor of WAO frequency ($F(1,50)=33.852$, $p<0.000$), as well as accounted for 40.4% of the variance in WAO frequency.

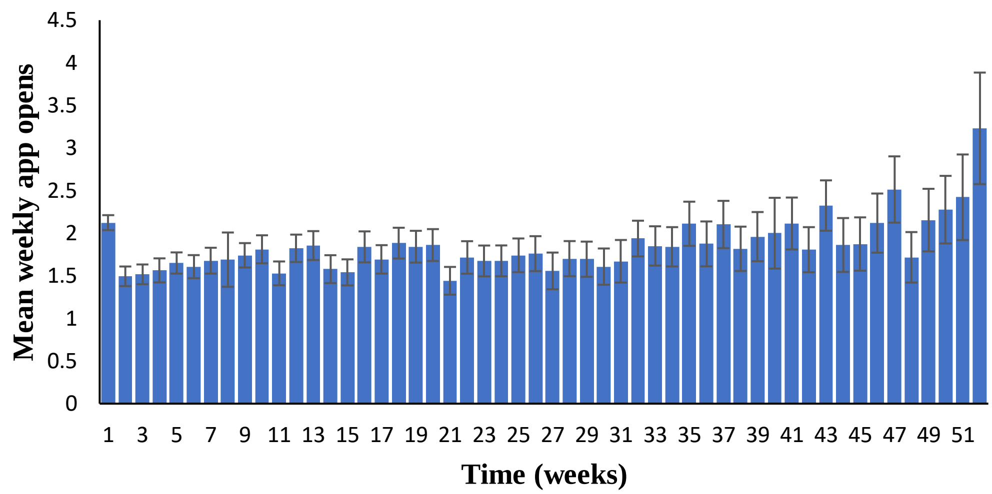

Figure 3. Mean weekly app opens (WAOs) among active participants with 95% confidence interval.

3.3 Secondary Analyses

For our secondary analyses, we aimed to explore the impact of participant- and company-level co-variates on survival time until the first disengagement, as well as re-engagement. Results of the multivariate Cox regression analyses are summarized in Appendix E. Regarding participant-level co-variates, we determined that the risk of disengagement was highest for 56- to 75-year-old participants (44%-106% higher) and for former smokers (19% higher). Notably, no significant difference was found between male and female, or Canadian and U.S., participants. Company characteristics predicted risk of disengagement as well. Participants offered 'off-platform' rewards had higher risk of disengagement (35.8% higher). As well, risk of disengagement increased with company size (i.e., 2.6% for every 1000 employees). A maximum quarterly reward value of $30 and $75 CAD/USD (depending on local currency) lowered disengagement risk by 46% and 36%, respectively. The only significant predictor of re-engagement was survival time until first disengagement. For every one-week increase in survival time, the likelihood of re-engaging increased by 5.6%. Poisson regression was conducted at pre-specified weeks to identify predictors of WAO frequency as well (Appendix F). During weeks four and eight, self-reporting as male, having a BMI above normal weight status, as well as having never smoked were identified as significant positive predictors of WAO frequency. Additionally, offering participants a maximum quarterly reward value of $75 CAD/USD (depending on local currency) was found to increase WAOs.

3.4 Sensitivity Analysis

To check the robustness of our primary analyses, KM curves were recreated to exhibit first disengagement, re-engagement, and second disengagement using two-week disengagement/re-engagement definitions (vs. four-week definitions; Appendix G). Mean survival time until first disengagement was 5.5 weeks (SE = 0.194, 95% CI [5.069, 5.832], $p < 0.05$). After the first week, 45.3% (1020/2253) of participants disengaged and following four weeks, first disengagement grew to 71.4% (1609/2253). At the end of the observation period, 63 participants (2.8%) remained engaged. Although a larger percentage, results support our primary analyses in which the greatest attrition was observed within the first week and month of app usage (Appendix G). On average, participant re-engagement took 32 weeks (SE = 0.459, 95% CI [31.069, 32.867], $p < 0.05$) and mean survival time until the second disengagement was 7.8 weeks (SE = 0.317, 95% CI [7.219, 8.463], $p < 0.05$). Compared to the results of the primary analyses, a greater proportion of participants re-engaged (46.3%) and disengaged for a second time (90.2%).

We also performed a *post-hoc* Cox regression to determine if the predictor variables differed when 2-week intervals (as opposed to four) were used to define disengagement and re-engagement. Consistent with our main findings, 56- to 75-year-old participants had a greater risk of disengaging and participants with a maximum reward value per quarter of $75 CAD/USD (depending on local currency) had a 32% lower risk of disengaging. In support of our secondary analyses, survival time until disengagement was a significant predictor of participant re-engagement. For every one-week increase in survival time, the likelihood of re-engaging increased by 6.4%. Other co-variates associated with a decreased likelihood to re-engage included, self-reporting as female (49%), not reporting age (52%) or smoking status (53%), and increasing company size (2.2%).

Chapter 4

4 Discussion

4.1 Main Findings

Since mHealth app engagement is considered a necessary precursor to mHealth app effectiveness (McLaughlin et al., 2021; M. Mitchell et al., 2020; Short et al., 2018; Spaulding et al., 2021), the aims of this study were to analyze mHealth app engagement with a rewards-based workplace wellness program and to identify participant- and company-level factors influencing engagement. Overall, we found first disengagement to be greatest during the first month of app usage. After four weeks, more than half (51.2%) of participants experienced first disengagement. The majority of these (66.4%) disengaged in the first week. The risk of first disengagement was highest for 56- to 75-year-old participants (44%-106% higher), as well as for participants who were part of larger businesses and whose companies offered “off-platform” rewards (2.6% and 35.8% higher, respectively). On the contrary, a maximum reward value per quarter of $30 and $75 CAD/USD were shown to lower first disengagement risk. Only a small proportion (11.5%) of our study sample was engaged at the end of the one-year study period. Nine out of ten participants did not re-engage with the app after ceasing usage. The only significant predictor of re-engagement was participants’ survival time until first disengagement. It appears that the longer it takes for a participant to disengage, the greater the likelihood of re-engagement. Sensitivity analyses confirm most of these findings. One notable difference was the higher re-engagement observed in our sensitivity analysis (46.3% using 2-week vs. 10.8% using 4-week re-engagement thresholds), presumably because with a more lenient re-engagement requirement, more participants were able to meet the threshold. Ultimately, this serves to illustrate that the way in which *engagement* is defined largely influences results.

This is one of the first studies to our knowledge to examine longitudinal mHealth app engagement patterns and predictors from a ‘multiple-lives’ perspective. User engagement is still a relatively novel area of research and only a few peer-reviewed studies have investigated it in this way (Lin et al., 2018; Meyerowitz-Katz et al., 2020).

The Covid-19 pandemic has accelerated interest in digital health promotion and knowing more about mHealth app engagement patterns and predictors may help digital health stakeholders address the persistent low app engagement issue moving forward. Taken together, our results suggest *Sprout at Work* and other similar mHealth apps consider intervening with older participants and those not offered monetary rewards at all in the first weeks of app exposure especially with targeted offers (e.g., time-limited rewards), feature enhancements (e.g., team goals), or special communications (e.g., tailored education) to maximize early engagement, as others have suggested (Biduski et al., 2020; Jakob et al., 2022). It is important to note that the Covid-19 pandemic was declared during our sample registration period which may limit the generalizability of our findings. As seen in the literature, pandemic-induced changes such as working-from-home, physical distancing, and social isolation, made it difficult for individuals to engage in PA outside of home and may have contributed to increased levels of employee SB and physical inactivity (McDowell et al., 2020; Violant-Holz et al., 2020). As a result, this may have decreased our sample's propensity to engage with well-being interventions such as the *Sprout at Work* app. Alternatively, observed engagement levels may have been heightened due to individuals' dependance on technology to connect socially and remain physically motivated (Jacob et al., 2022).

4.2 Compared to Similar Literature

Our findings are consistent with previous studies, reporting that mHealth app attrition is high (Edney et al., 2019; Murray et al., 2019; Rayward et al., 2021). A 2019 study by Edney et al. (2019) for example, examined user engagement with the gamified app, *Active Team*, which encouraged users to take 10,000 steps per day for 100 days. Participants were randomized to either have access to the gamified or basic versions of the app. Similar to how we operationalized 'disengagement', the researchers defined attrition participants ceasing app usage for 30 or more consecutive days (about four weeks). Additionally, a sensitivity analysis was performed by Edney et al. (2019) using a 14-day nonuse threshold. During the 100-day intervention period, attrition occurred for 31.9% and 39.4% of participants in the gamified and basic app groups, respectively. Sensitivity analysis, applying the 14-day nonuse threshold, found 48.9% and 58.7% of participants ceased usage in the gamified and basic app groups, respectively (Edney et al., 2019). In comparison, our sample demonstrated larger disengagement rates. At week 14 (approximately 100 days), 73.5% (1655/2253) and 89.8% (2025/2253) of participants had disengaged when both the four- and two-week definitions of ‘disengagement’ were operationalized, respectively. We believe a few factors may have contributed to Edney et al. (2019) lower disengagement rates. For example, the sample size (n = 301) was relatively small, possibly impacting engagement, and each study participant received a pedometer (Zencro, TW64S) to wear for the duration of the study. This may have encouraged user engagement since wearable devices and activity monitors have been recognized as a tool to increase PA participation (Brickwood et al., 2019).

Rayward et al. (2021) conducted an interesting observational study with data from the *10,000 Steps Physical Activity Program* as well, examining how different methods of step-logging (e.g., website only, app only, Fitbit only, website and app, and website, app, and Fitbit combination) affected participant engagement. Median survival time for app only users, as well as for all users combined, was 31 days (Rayward et al., 2021). Another study by Murray et al. (2019) investigated user engagement for a web-based, workplace PA intervention. During the six-month intervention period, overall attrition occurred for 88.9% of participants and median survival time was 26 days (Murray et al., 2019). Although Rayward et al. (2021) and Murray et al. (2019) defined non-usage as the first two-week lapse of recorded activity, our findings show similar results in which 52.1% of participants had their first disengagement by week four and 88.5% had disengaged by the end of the study period. However, when compared to the results of our sensitivity analysis, we observed slightly greater first disengagement rates at both week four (71.4%, 1609/2253) and by the end of the study period (97.2%, 2190/2253). This may be because our study was centered around mHealth app usage only. In the study by Rayward et al. (2021), regardless of the method of step-logging, all users had the potential to access a web-based platform as well (Rayward et al., 2021). On the other hand, the intervention used by Murray et al. (2019) offered all participants financial incentives worth £0.03 per minute of PA, for a maximum of 30 min per day. Compared to our study, the lower attrition rates seen in Rayward et al. (2021) and Murray et al. (2019) may be attributable to the impact of financial incentives and multicomponent interventions, both which have been seen to increase participant activity in previous studies (Bachireddy et al., 2019; M. S. Mitchell et al., 2020; Schoeppe et al., 2016).

Next, our findings should be compared to prior research that has examined user *re-engagement* with mHealth interventions. To explore the 'multiple-lives' perspective, Lin et al. (2018) conducted an observational study using 31 months of data collected from the *Argus by Azumio* app. In agreement with our study, passively logged activities from the smartphone's accelerometer were disregarded as user activity. The researchers found that most participant's lifetimes are episodes of active periods, with an average duration of 24 days, followed by long periods of inactivity (average duration 114 days). The total number of participants that experienced a period of inactivity was not reported. Over 75% of participants re-engaged with the *Argus by Azumio* app after 30 days of inactivity, and even after a more prolonged inactivity period of 90 days, 58% re-engaged. Furthermore, mHealth app usage after re-engagement resembled closely the start of the initial engagement period, rather than it being a continuation of the end of the initial engagement period (Lin et al., 2018). Comparatively, only 10.8% our sample re-engaged and average time to re-engagement was 47.1 weeks. A few considerations may help explain why we found much smaller re-engagement rates in the present study. Compared to our one-year long study, the longer observational period of 31 months in Lin et al. (2018) may have allowed more time for participant re-engagement. Furthermore, our operationalization of user re-engagement (i.e., four consecutive weeks with an app open) may be an overly conservative definition and may not have allowed many participants to meet that threshold.

There are very few studies that have examined predictors of user engagement. Regarding participant-level predictors, our findings suggest that neither gender, country of residence, nor a diagnosis of a chronic condition, are significant predictors of mHealth engagement. Primarily, our results suggest that risk of disengagement is greatest for older adults (≥ 56 years-old). This may be caused by older users having difficulties operating technology or being unfamiliar of the usage benefits (Jacob et al., 2022; University of Michigan Institute for Healthcare Policy and Innovation, 2022). These results, however, oppose the findings from Pontin et al. (2021) who utilized data from the *Bounts* app and determined that mHealth app usage was higher in females and was seen to increase with age (Pontin et al., 2021). All things considered, current evidence regarding participant-level predictors of user engagement is mixed. A systematic literature review conducted by Jacob et al. (2022) aimed to understand factors affecting user adoption of mHealth tools by considering sociotechnical factors (i.e., from a technical, social and personal, and health perspective). Specifically, the social and personal factors were divided into three subgroups: demographic factors, personal characteristics, and social and cultural aspects (Jacob et al., 2022). In some studies, older age was cited as a barrier for adoption and a negative relationship was suggested between age and willingness to use such tools. However, others have identified older age as a facilitator, especially in circumstances due to Covid-19 where a need for technology was developed. Concerning gender, many studies have suggested that females are more likely to adopt mHealth tools (Jacob et al., 2022; Pontin et al., 2021). However, an equal number of studies report that gender is not significantly associated with mHealth usage, and some have even suggested that adoption is more widespread among male users (Jacob et al., 2022). Ultimately, this review illustrates the discrepancy between current findings of personal-level predictors influencing mHealth engagement.

With regards to program-level predictors, although the monetary values may have been unknown, we found that ‘off-platform’ rewards (i.e., employer-specific rewards in the form of premium deductions, sweepstakes, and challenge prizing) increased the risk of disengagement. This finding is supported by Bachireddy et al. (2019) who conducted an RCT to determine if disbursing financial incentives at an increasing, decreasing, or constant rate would encourage PA among adults. Compared with the control group, those receiving constant incentives logged 306.7 more steps per day (95% CI [91.5-521.9], $p = 0.005$). Participants receiving decreasing incentives logged 96.9 more steps per day (95% CI [15.3-178.5], $p = 0.02$), and no significant change was found for those receiving increasing incentives (1.5 steps per day, 95% CI [−81.6 to 84.7], $p = 0.97$). Furthermore, one week after the intervention, only participants receiving constant incentives logged significantly more steps per day (329.5, 95% CI [20.6-638.4] $p = 0.04$] (Bachireddy et al., 2019). A possible explanation why financial incentives are more effective when offered at a constant rate is because fixed rewards are easier to remember, whereas other inconsistent rewards may seem confusing or unfair to the user (Bachireddy et al., 2019). It is important to note that the differences in findings may be caused by the variability of app features, the adopted definitions of usage, and by unmeasured confounding variables (e.g., household income, level of education, psychological aspects, etc.,).

4.3 Practical Implications

Our study presents another example of the challenges mHealth app developers face in sustaining user engagement, especially during the first few weeks of usage. We have identified critical disengagement and re-engagement time points, as well as participant- and company-level predictors of engagement, which should be considered by future intervention developers. Special focus should be placed on reducing early attrition since we found the first few weeks to have the largest first disengagement rates. Furthermore, we determined that a longer survival time until first disengagement translates to increased likelihood of the user re-engaging in the future.

One possible reason for the large early attrition rates is suboptimal service matching (Bohm et al., 2020). In other words, users may engage with the intervention, however, the mHealth app is not built to suit their exact needs. Secondly, to avoid widening existing health disparities, developers of mHealth tools may benefit from understanding how digital determinants of health can impact health equity. At the individual level, determinants of health include digital literacy, digital self-efficacy, and attitudes towards use (Richardson et al., 2022). Digital literacy refers to "… the skills and abilities necessary for digital access (i.e., an understanding of the language, hardware, and software) required to successfully navigate technology", whereas digital self-efficacy is "…the effective and effortless utilization of information technology and predicts proficiency" (Richardson et al., 2022, p. 2). Lastly, a user's attitude towards use may impact the mHealth tool's perceived usefulness and predicts technology adoption (Richardson et al., 2022). In the case of *Sprout at Work* app users, it is possible that users with a higher risk of disengagement (i.e., adults aged 56- to 75-years old) have low levels of digital literacy and lack awareness of the importance of using the mHealth app to achieve their well-being goals. We suggest that upon registration, along with collecting quantitative user data (e.g., biometric data), app developers may benefit from classifying users based on their behavioural intentions, health interests in general, and other factors (e.g., level of health and digital literacy, perceptions of app utility, and motivation to engage with the mHealth app; Meyerowitz-Katz et al., 2020; Simblett et al., 2018). This may allow for a higher degree of tailoring and intervention personalization. For example, a user with low levels of health literacy and diagnosed with cardiovascular disease could primarily be given educational content to learn about the severity of their ailment, and can then be guided to perform activities that can help manage their chronic condition. Users may also better understand the validity and practical use of the app if expert opinons from clinicians and health professionals were to be integrated (Adu et al., 2018; Richardson et al., 2022). Another user may not see the benefits of using the app and may express that they have a low motivation to engage with the intervention. Gamification features or increasing the amount of financial incentive in the short-term, strategies which have been seen to stimulate mHealth engagement (Maher et al., 2022; M. Mitchell et al., 2020), may increase their motivation to participate and overall app exposure, thereby limiting early app attrition.

Quarterly financial incentives of $30 and $75 CAD/USD (depending on local currency) were seen to decrease disengagement risk, possibly because participants were encouraged to continue reaping the monetary reward benefit. When considering what level of compensation is sufficient to achieve a relevant effect, app developers may consider $30 CAD/USD (depending on local currency) as a potential threshold at which disengagement risk begins to decrease. However, our results found that a maximum reward value per quarter of $35, $50, and greater than $75 CAD/USD (depending on local currency) had no effect on reducing disengagement. We believe this may be caused by the wide range of sample sizes shaping the maximum quarterly reward value subgroups (3 to 532 participants) and from unmeasured participant- (e.g., household income, level of education) and company-level co-variates (e.g., company industry, level of employer encouragement for app use, pre-existing workplace wellness programs). Additionally, participants exposed to “off-platform” rewards had a higher risk of disengagement. This suggests that rather than having an inconsistent reward structure, app developers offering rewards should maintain a constant dose of financial incentives

(Bachireddy et al., 2019). Alternatively, other strategies of disbursing financial incentives informed by BE, such as “loss-aversion” (i.e., tendency to prefer avoiding losses over acquiring equivalent gains), have demonstrated positive effects on user activity. For instance, in a RCT including 105 patients diagnosed with ischemic heart disease, participants in the intervention group were offered a “loss-framed” financial incentive, in which $14 USD was allocated to a virtual account each week (Chokshi et al., 2018). Every day the participant did not achieve their step goal, $2 USD was deducted. Compared to the control group who received no intervention, participants offered the “loss-framed” financial incentives had a significantly greater increase in mean daily steps over a six-month period, including eight weeks of follow-up without incentives (Chokshi et al., 2018). These findings demonstrate another avenue in which behavioural theories can be implemented to retain user engagement and promote PA along with other well-being behaviours.

4.4 Theoretical implications

To drive sustained health behaviour change (≥ 6 months is considered “maintenance” according to the TTM), it is important that users consistently engage with mHealth interventions (Prochaska & Velicer, 1997). To help app developers sustain usage early on, BE provides a practical framework from which solutions to the low engagement issue may emerge. With knowledge on the various BE “decision biases” (e.g., present bias, loss aversion, probability weighing), mHealth apps can be designed in a way that increase the propensity of individuals to engage in healthy behaviours (Thaler & Sunstein, 2008). Although behaviour change theory-informed features were not directly measured in this study, our findings corroborate previous research examining BE-informed financial incentive-based mHealth engagement. However, app developers must do so prudently as we found no significant difference in first disengagement between participants offered “on-platform” rewards and “no rewards” until the $30 CAD/USD (depending on local currency) threshold was met. In addition to employing app features informed by BE, SDT may also help understand the motivating factors behind an individuals’ sustained actions (Ryan & Deci, 2000). According to SDT, interventions should be designed to reinforce the three basic psychological needs (i.e., autonomy, competence, and relatedness). Satisfaction of these needs is theorized to help individuals progress along the SDT continuum (i.e., from amotivation to intrinsic regulation) and promote quality, long-term behaviour change (Ryan & Deci, 2000). In particular, SDT suggests that interventions offering financial incentives should be weary as to not promote extrinsic motivation. Long-term behaviour change is driven by intrinsic motivation which is an individual's desire to perform an action "for its own sake" at the absence of external pressures (Ryan & Deci, 2000). In the literature, Promberger and Marteau (2013) caution that financial incentives have the potential to "undermine" or "crowd out" intrinsic motivation. In this case, the goal of performing the behaviour then becomes the external driver (i.e., attaining the reward) and not the internal rewarding feeling (Promberger & Marteau, 2013).

Sprout at Work incorporates multiple gamification features (e.g., challenges, leaderboard, virtual rewards, etc.; Maher et al., 2022) and behaviour change techniques (e.g., goal setting, self-monitoring, social support, health education, reward as incentives, etc.; Michie et al., 2013). In addition, according to the ABACUS checklist, the mHealth app has a high degree of behaviour change potential (20/21 ABACUS criteria were met). However, despite all the included app features, our findings indicated relatively low levels of long-term user engagement. We speculate that users' feelings of autonomy seem to be preserved since maximum quarterly reward values are not outrageously large (controlling), and app use is voluntary and free from external pressures (i.e., employer obligation). On the other hand, we propose improvements can be made to reinforce feelings of relatedness and competence within the user. Personalization of the social platform and optimizing the social feed may prove to be useful, especially in circumstances within larger organizations where all users may not know one another on a personal, offline level. In addition, feelings of competence may be lessened if set goals and incentives are too difficult to achieve. Based on prior user activity, adaptive challenges and rewards may be helpful to make sure feelings of competence are being fulfilled to increase intrinsic app usage.

Another reason as to why *Sprout at Work* may be experiencing low levels of long-term user engagement may be in part due to 'sludge' (Soman et al., 2019). From a BE perspective that prioritizes decision making in intervention design, 'sludge' refers to any intervention component that "…makes it difficult for people to make decisions or to perform all of the actions needed to accomplish a task" (Soman et al., 2019, p. 13; The Behavioural Insights Team, 2014). Essentially, simplicity is key. Although the intention may be to enhance the mHealth intervention, apps that include too many features and behaviour change components may end up obscuring the intervention's true objective and impede users' progression towards their goal (Adu et al., 2018; Simblett et al., 2018; Soman et al., 2019; The Behavioural Insights Team, 2014). Therefore, pruning the app of excess or potentially unnecessary components, to remove 'sludge', may prove judicious. In a recent study using an in-app embedded questionnaire to assess long-term user experience, the most satisfying experiences took place during the first week of use and were associated with the usability of the app's features and feasibility of health care monitoring (Biduski et al., 2020). According to research by Simblett et al. (2018), technical issues and problems with usability are the most common reasons for a poor user experience and ultimately, lead to dropout (Biduski et al., 2020; Jacob et al., 2022; Simblett et al., 2018). Many individual differences (e.g., age, past experience with technology, disability status, etc.) can influence a user's attitude and the perceived usability of mHealth interventions as well. In particular, our findings suggested that older adults aged 56- to 75-years old had a 44% to 106% higher risk of first disengagement. This may be due to older users being unfamiliar with mHealth tools, having a lower level of digital literacy, and data privacy concerns as well (Adu et al., 2018; Bohm et al., 2020; Simblett et al., 2018).

To overcome these issues, first, it has been suggested that users need to understand why they should invest their time with the app (Adu et al., 2018; Bohm et al., 2020). Initial interaction with mHealth apps could begin with an educational component outlining the benefits of regularly engaging with the behaviour change platform (Adu et al., 2018; University of Michigan Institute for Healthcare Policy and Innovation, 2022). Secondly, by designing a user interface for increased usability for those with low levels of digital literacy (e.g., simple app design, larger fonts, features for specific disability groups, etc.), and by addressing individual concerns about data privacy (e.g., ensuring users personal data will be encrypted and will not be shared), may help reduce attrition rates for older adults (Adu et al., 2018; Bohm et al., 2020; Richardson et al., 2022; Simblett et al., 2018; The Behavioural Insights Team, 2014). Lastly, the developers of mHealth interventions may consider focussing on a single targeted health behaviour, rather than trying to improve multiple behaviours all at once (Bohm et al., 2020; Romeo et al., 2019; Schoeppe et al., 2016). In a 2019 review by Romeo et al. (2019) examining the effectiveness of smartphone apps for increasing objectively measured PA in adults, apps that targeted PA only were more effective than apps that targeted PA in combination with diet (Romeo et al., 2019). Bohm et al. (2020) found similar results in their longitudinal observational study examining user engagement with the *Cornerstones4Care* app for diabetes management. The mHealth app incorporated five modules (i.e., food intake, exercise, medication intake, blood glucose, and continuous glucose monitoring), however, 50% of participants used the app for a single purpose and only 21 out of 9051 total participants used all 5 app modules. This suggests that most users have different needs and may not require the full set of functionalities offered by the mHealth app. For this reason, designers of mHealth interventions could consider targeting a single chronic condition or health behaviour/outcome rather than trying to incite multiple behaviours simultaneously.

4.5 Strengths and Limitations

Key strengths of this single cohort observational study include the long evaluation period (i.e., one year) and relatively large sample size (*N* = 2253). Also, the sample was comprised of employees working for numerous companies (*N* = 38), varying in size (86 to 26,284, and offering a range of incentive structures, providing the heterogeneity needed to explore the impact of different incentive design components on mHealth app engagement in this observational setting. Third, in the current literature, engagement is more commonly measured subjectively rather than objectively (Molloy & Anderson, 2021). Since the majority of user activity data is now transmitted automatically, it creates ambiguity as to how engaged users really are (Bohm et al., 2020). We partly address this issue of automatically inputted data by only using WAOs as our outcome, therefore requiring the participant to intentionally click on the app. Last, we address the issue of observer bias, in part, by incorporating a sensitivity analysis. Not only did this allowed us to substantiate our findings, but it also demonstrated how different definitions of disengagement and re-engagement can affect results.

This study is not without limitations. First, the internal validity of our results may be limited since participant randomization to control and experimental groups was not possible within this observational study design. Second, we were not able to determine the effect of the Covid-19 pandemic on user engagement which may impact the generalizability of our findings. Additionally, selection bias may have influenced the external validity of our results since the *Sprout at Work* app is only available to employees of companies that have a partnership with *Sprout*. Therefore, our study sample may not be representative of the entire North American office-based employee population. Third, we could not minimize the effect of other possible confounding variables that may have influenced participant engagement (e.g., household income, level of education, and psychological aspects), nor did we know the monetary value of all the “off-platform” rewards. Fourth, missing data is a common issue when analyzing self-reported real-world data. Missing data ranged from 9.9% (224/2253) of participants who did not share information about their age, to 21.4% (483/2253) who did not share information about their gender. We addressed this issue by categorizing missing data in a no response group. Fifth, due to the nature of the data, some of the co-variate subgroups were small, thereby limiting the statistical power of the Cox and Poisson regressions in the secondary analyses. Finally, our definitions of disengagement and re-engagement (i.e., the first occurrence of four consecutive weeks without an app open and with an app open, respectively) may have contributed to the low levels of re-engagement and second disengagement. However, we believe by using four-week lapses, we reduced the occurrence of any observations that may not have been indicative of intentional actions.

4.6 Future Directions

mHealth app engagement is a complex and multifaceted term, primarily because the definition conforms somewhat to the intended goal of the intervention (Cole-Lewis et al., 2019; Perski et al., 2017). To ensure consistency among research findings, rather than creating a definition of engagement that can be applied for all mHealth interventions, researchers may want to consider constructing engagement thresholds based on the type of intervention and its intended outcome. Although intervention usage may be a useful indicator of engagement, on its own, it may not be a valid assessment for individual behaviour change progress (Short et al., 2018). Researchers aiming to measure engagement for the purpose of establishing behaviour change should consider different engagement measures such as qualitative measures, self-reported questionnaires, and ecological momentary assessments (Short et al., 2018). For example, a qualitative approach can include focus groups, think aloud activities, or interviews, which at the micro-level, allows for an in-depth understanding of a users' intervention experience, and at the macro-level, can be used to identify how the intervention has helped the user commit to the behaviour change process. Self-reported questionnaires may be beneficial to gain insight into a users' subjective experience and can be used to track their level of motivation-to-change (i.e., intrinsic motivation). Last, ecological momentary assessments are brief appraisals that may be self-reported on demand by the user or programmed to be sent randomly at varying times throughout the day. The objective is to capture a users' behaviour, perception, or experience in real-time in their naturalistic environment while mitigating recall bias (Short et al., 2018). Therefore, by incorporating a wide variety of measures, a more holistic understanding of user engagement can be established (Perski et al., 2017; Short et al., 2018).

Future work examining real-world data may increase the validity of results by utilizing large samples with similar sized subgroups to ensure analyses are sufficiently powered. Additionally, researchers may benefit from dividing participants into subgroups under circumstances where prominent events (e.g., the Covid-19 pandemic) occur during data collection. More research is needed to examine predictors of disengagement, and in particular, re-engagement, to identify factors that can help sustain health behaviour improvements in the long-term. We recommend approaching this task by consolidating mHealth interventions that have similar intended outcomes, because the factors influencing engagement may not be consistent among individuals who use different types of mHealth apps. Last, more long-term observational studies are required to examine engagement patterns in mHealth interventions that target different health behaviours/outcomes and that are used by people of different socio-demographic and cultural backgrounds as these factors may influence findings. Quasi-experimental and

RCT study designs can test various behaviour change theories to find optimal combinations of behaviour change techniques (e.g., prompts/cues, goal setting, social support, rewards, etc.; Michie et al., 2013) and gamification features (e.g., challenges, leaderboard, virtual rewards, etc.; Maher et al., 2022) to distinguish more effective from less effective intervention components. Specifically, researchers may want to identify the most appropriate set of intervention components given a particular set of user characteristics (Cole-Lewis et al., 2019; Michie et al., 2013). These studies can help demonstrate how purposefully designed behaviour change interventions can be effective in increasing user engagement and promoting long-term PA and well-being behaviours.

4.7 Conclusion

mHealth apps offer tremendous potential for the wide-scale adoption of PA and other well-being behaviours. User engagement is considered a necessary precursor to mHealth app effectiveness, therefore, evidence-informed strategies are required to optimize these interventions. Our study suggests *Sprout at work* app user disengagement is high following the first few weeks of app use, and only a small proportion of users re-engage. Our results also indicate older users and those offered rewards at an inconsistent rate have a higher risk of disengagement. Prudent use of financial incentives may decrease the risk of disengagement. These findings shed light on the predictive characteristics of users and may be applicable to future mHealth intervention developers. More studies are needed examining various in-app behaviour change components to determine the optimal combination of features that maximize user engagement given rising interest in digital health intervention more broadly.

4.8 Funding and Conflict of Interest

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Appendices

Appendix A: Behaviour Change Techniques Incorporated in the *Sprout at Work* App

Page	Grouping and BCTs
1	**1. Goals and planning**
✓	1.1. Goal setting (behavior)
✓	1.2. Problem solving
✓	1.3. Goal setting (outcome)
✓	1.4. Action planning
✓	1.5. Review behavior goal(s)
✓	1.6. Discrepancy between current behavior and goal
✓	1.7. Review outcome goal(s)
✓	1.8. Behavioral contract
	1.9. Commitment
3	**2. Feedback and monitoring**
✓	2.1. Monitoring of behavior by others without feedback
✓	2.2. Feedback on behaviour
✓	2.3. Self-monitoring of behaviour
✓	2.4. Self-monitoring of outcome(s) of behaviour
✓	2.5. Monitoring of outcome(s) of behavior without feedback
✓	2.6. Biofeedback
✓	2.7. Feedback on outcome(s) of behavior
5	**3. Social support**
✓	3.1. Social support (unspecified)
✓	3.2. Social support (practical)
✓	3.3. Social support (emotional)
6	**4. Shaping knowledge**
✓	4.1. Instruction on how to perform the behavior
	4.2. Information about Antecedents
✓	4.3. Re-attribution
	4.4. Behavioral experiments
7	**5. Natural consequences**
✓	5.1. Information about health consequences
✓	5.2. Salience of consequences
✓	5.3. Information about social and environmental consequences
	5.4. Monitoring of emotional consequences
	5.5. Anticipated regret
✓	5.6. Information about emotional consequences

Page	Grouping and BCTs
8	**6. Comparison of behaviour**
✓	6.1. Demonstration of the behavior
✓	6.2. Social comparison
	6.3. Information about others' approval
9	**7. Associations**
✓	7.1. Prompts/cues
✓	7.2. Cue signalling reward
✓	7.3. Reduce prompts/cues
	7.4. Remove access to the reward
	7.5. Remove aversive stimulus
✓	7.6. Satiation
	7.7. Exposure
	7.8. Associative learning
10	**8. Repetition and substitution**
✓	8.1. Behavioral practice/rehearsal
✓	8.2. Behavior substitution
✓	8.3. Habit formation
✓	8.4. Habit reversal
	8.5. Overcorrection
✓	8.6. Generalisation of target behavior
✓	8.7. Graded tasks
11	**9. Comparison of outcomes**
✓	9.1. Credible source
✓	9.2. Pros and cons
✓	9.3. Comparative imagining of future outcomes
12	**10. Reward and threat**
✓	10.1. Material incentive (behavior)
✓	10.2. Material reward (behavior)
✓	10.3. Non-specific reward
✓	10.4. Social reward
✓	10.5. Social incentive
✓	10.6. Non-specific incentive
	10.7. Self-incentive
	10.8. Incentive (outcome)
	10.9. Self-reward
	10.10. Reward (outcome)
	10.11. Future punishment
15	**11. Regulation**
	11.1. Pharmacological support
✓	11.2. Reduce negative emotions
	11.3. Conserving mental resources
	11.4. Paradoxical instructions

Page	Grouping and BCTs
16	**12. Antecedents**
✓	12.1. Restructuring the physical environment
✓	12.2. Restructuring the social environment
✓	12.3. Avoidance/reducing exposure to cues for the behavior
	12.4. Distraction
	12.5. Adding objects to the environment
✓	12.6. Body changes
17	**13. Identity**
✓	13.1. Identification of self as role model
✓	13.2. Framing/reframing
	13.3. Incompatible beliefs
	13.4. Valued self-identify
	13.5. Identity associated with changed behavior
18	**14. Scheduled consequences**
	14.1. Behavior cost
	14.2. Punishment
	14.3. Remove reward
	14.4. Reward approximation
✓	14.5. Rewarding completion
✓	14.6. Situation-specific reward
	14.7. Reward incompatible behavior
✓	14.8. Reward alternative behavior
	14.9. Reduce reward frequency
	14.10. Remove punishment
19	**15. Self-belief**
	15.1. Verbal persuasion about capability
	15.2. Mental rehearsal of successful performance
	15.3. Focus on past success
	15.4. Self-talk
19	**16. Covert learning**
	16.1. Imaginary punishment
	16.2. Imaginary reward
	16.3. Vicarious consequences

Appendix B: ABACUS Checklist for the *Sprout at Work* App

Table 3. Final app behavior change scale, including examples.

Scale: item number and question		Definition	Example or further information	Source of question (from Table 1)
1. Knowledge and information				
1.1	Does the app have the ability to customize and personalize some features? **Yes**	Elements of the app can be personalized through specific tools or functions that are specific to the individual using the app.	• To select a disease type from among several available and then to follow a specific path or set of tools or systems. • To select to receive emails or texts of a specific nature. • To choose "yes" or "no" to a specific capability of the app would be considered personalization. • To create a personalized exercise plan.	[44,54]
1.2	Was the app created with expertise and/or Does the app provide information that is consistent with national guidelines? **Yes**	This would be found in the about section or generally in the app.	• Does the app suggest 30 min of exercise each day? • Does it recommend 5 veg and 3 fruit? • Does it seek to build resilience and promote help seeking? • Is there any evidence that the app was created by an expert? (doctor/professional body/university)	[44,54]
1.3	Does the app ask for baseline information? **Yes**	This includes BMI[a], weight, smoking rate, exercise, or drinking behaviors	• This might be at the set-up phase or in a profile setting.	[28,85]
1.4	Does the app provide instruction on how to perform the behavior? **Yes**	The app is clear in telling the person how to perform a behavior or preparatory behaviors, either verbally, through video, or in written form. NB: the behavior that is seeking to be changed, not information on how to use the app	• This could include showing person how to use gym equipment, sharing sample plans for action, instruction on suitable clothing, recipes, and general tips.	[20,21,22,81]
1.5	Does the app provide information about the consequences of continuing and/or discontinuing behavior? **Yes**	The app gives the user information about the consequences of behavior in general, this includes information about the relationship between the behavior and its possible or likely consequences in the general case. This information can be general or personalized.	• Consequences may include health, feelings, or cost consequences.	[22,81]
2. Goals and planning				
2.1	Does the app ask for willingness for behavior change? **Yes**	Is there a feature during setup where you describe how ready you are for behavior change?	• This may be in the form of a scale of readiness or in a question that asks the user to describe how ready you are.	[17,85]
2.2	Does the app allow for the setting of goals? **Yes**	The person is encouraged to make a behavioral resolution. The person is encouraged to set a general goal that can be achieved by behavioral means. This includes subgoals or preparatory behaviors and/or specific contexts in which the behavior will be performed. The behavior in this technique will be directly related to or be a necessary condition for the target behavior.	• This is the explicit noting of a goal or choosing a goal from one provided within the app.	[20,21,40,44,54,55,81]

Scale: item number and question		Definition	Example or further information	Source of question (from Table 1)
2.3	Does the app have the ability to review goals, update, and change when necessary? **Yes**	Involves a review or analysis of the extent to which previously set behavioral goals (regardless of short or long) were achieved.	• This is where a goal can be changed. This allows people to act on previously set goals and then revise or adjust where needed.	[22,40,81]
3. Feedback and monitoring				
3.1	Does the app give the user the ability to quickly and easily understand the difference between current action and future goals? **Yes**	Allows user to see how they are tracking against a goal and to see the difference between what they want to do and what they are currently doing. This will give some feedback on where they are at and what they need to change to get to where they want to be.	• This could be in the form of a graph or some other visual describing how close the user is to meeting their goals.	[22,40,81]
3.2	Does the app have the ability to allow the user to easily self-monitor behavior? **Yes**	The app allows for a regular monitoring of the activity.	• Connects with watch that records daily steps that can be reviewed. • Allows for easy logging of exercise or meditation? • Allows for tracking of weight loss. • Allows logging of daily alcoholic drinks or cigarettes.	[20,21]
3.3	Does the app have the ability to share behaviors with others (including social media or forums) and/or allow for social comparison? **Yes**	The app allows the person to share his or her behaviors on social media or in forums. This could also include a *buddy* system or a leaderboard.	• Share with Facebook or other socials • Tell the user that they are doing x and at this time, other people like them are doing y	[4,20,21,22,85]
3.4	Does the app have the ability to give the user feedback—either from a person or automatically? **Yes**	The app is able to provide the person with feedback, comments, or data about their own recorded behavior. This might be automatic or could be personal.	• Does the app have a *coach* function?	[22,40,81]
3.5	Does the app have the ability to export data from app? **No**	The app allows for the export of information and progress to an external user.	• Export to a computer or to another user such as a doctor or fitness expert. • Sharing to Facebook does not count.	[65]
3.6	Does the app provide a material or social reward or incentive? **Yes**	App provides rewards for attempts at achieving a behavioral goal. This might include efforts made toward achieving the behavior or progress made in preparatory steps toward the behavior or in achieving a goal.	• Financial, either in returning money that was not spent on, for example, cigarettes or in paying someone to engage in a specific activity. • Social or public, for example, congratulating the person for each day that he or she meets his or her exercise target.	[22,40,81]
3.7	Does the app provide general encouragement? **Yes**	The app provides general encouragement and positive reinforcement on actions leading to the goal.	• This could include achievement badges or telling the user that they are a certain percentage closer to their goal.	[22,40,81]
4. Actions				

Scale: item number and question		Definition	Example or further information	Source of question (from Table 1)
4.1	Does the app have reminders and/or prompts or cues for activity? **Yes**	The app prompts the user to engage in the activity. The app has the ability to give notifications or reminders to cue the behavior.	• This could be like the apple watch reminding you to stand or a meditation app telling you to meditate now.	[20,21]
4.2	Does the app encourage positive habit formation? **Yes**	The app prompts explicit rehearsal and repetition of the behavior–not just tracking or logging.	• An example of this are the couch to 5 km apps that provide a training schedule.	[21,22,81]
4.3	Does the app allow or encourage for practice or rehearsal, in addition to daily activities? **Yes**	App does not have a lock on activities or a number that you cannot exceed daily.	• This would include allowing the user to undertake extra activities in a single day.	[20,21]
4.4	Does the app provide opportunity to plan for barriers? **Yes**	The app encourages the person to think about potential barriers and identify ways of overcoming them.	• Alcohol app might give strategies for a night out that would normally be a big night.	[55]
4.5	Does the app assist with or suggest restructuring the physical or social environment? **Yes**	The app prompts the person to alter the environment in ways so that it is more supportive of the target behavior.	• Might suggest locking up or throw away or their high-calorie snacks or take their running shoes to work.	[21,22,81]
4.6	Does the app assists with distraction or avoidance? **Yes**	The app gives suggestions and advice on how the person can avoid situations or distract themselves when trying to reach their goal.	• For example, a smoking cessation app may suggest that the user not drink coffee if this is typically combined with smoking behaviors that they are trying to cease.	[21,22,81]

Appendix C: Ethical Approval

Date: 4 August 2021

To: Professor Marc Mitchell

Project ID: 118323

Study Title: Applying Behavioural Economics in the Examination of Physical Activity App Engagement in 2,920 North American Employees

Study Sponsor: Social Sciences and Humanities Research Council

Application Type: HSREB Initial Application

Review Type: Delegated

Full Board Reporting Date: 24/Aug/2021

Date Approval Issued: 04/Aug/2021

REB Approval Expiry Date: 04/Aug/2022

Dear Professor Marc Mitchell

The Western University Health Science Research Ethics Board (HSREB) has reviewed and approved the above mentioned study as described in the WREM application form, as of the HSREB Initial Approval Date noted above. This research study is to be conducted by the investigator noted above. **All other required institutional approvals and mandated training must also be obtained prior to the conduct of the study**.

Documents Approved:

Document Name	Document Type	Document Date	Document Version
data collection spreadsheet	Other Data Collection Instruments		
BEE_Protocol	Protocol	30/Jul/2021	2

Documents Acknowledged:

Document Name	Document Type	Document Date	Document Version
Budget Justification (Sprout)	Study Budget	18/Mar/2021	1

No deviations from, or changes to, the protocol or WREM application should be initiated without prior written approval of an appropriate amendment from Western HSREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University HSREB operates incompliance with, and is constituted in accordance with, the requirements of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2); the International Conference on Harmonisation Good Clinical Practice Consolidated Guideline (ICH GCP); Part C, Division 5 of the Food and Drug Regulations; Part 4 of the Natural Health Products Regulations; Part 3 of the Medical Devices Regulations and the provisions of the Ontario Personal Health Information Protection Act (PHIPA 2004) and its applicable regulations. The HSREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000940.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Ms. Jhananiee Subendran, Ethics Coordinator on behalf of Dr. Philip Jones, HSREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Appendix D: STROBE Checklist for Cohort Studies

STROBE Statement—Checklist of items that should be included in reports of ***cohort studies***

	Item No	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract (pg. ii)
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found (pg. ii)
Introduction		
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported (pg. 1-14)
Objectives	3	State specific objectives, including any prespecified hypotheses (pg. 14-15)
Methods		
Study design	4	Present key elements of study design early in the paper (pg. 19)
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection (pg. 16-18)
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up (pg. 19)
		(*b*) For matched studies, give matching criteria and number of exposed and unexposed (N/A)
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable (pg. 19-20)
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group (pg. 16-22)
Bias	9	Describe any efforts to address potential sources of bias (pg. 22)
Study size	10	Explain how the study size was arrived at (pg. 19)
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why (pg. 19-20)
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding (pg. 20-22)
		(*b*) Describe any methods used to examine subgroups and interactions (pg. 21-22)
		(*c*) Explain how missing data were addressed (pg. 21)
		(*d*) If applicable, explain how loss to follow-up was addressed (N/A)
		(*e*) Describe any sensitivity analyses (pg. 22)
Results		
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed (pg. 23)
		(b) Give reasons for non-participation at each stage (N/A)
		(c) Consider use of a flow diagram (N/A)
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders (pg. 23-26)
		(b) Indicate number of participants with missing data for each variable of interest (pg. 23-26)
		(c) Summarize follow-up time (eg, average and total amount) (pg. 26-29)

Outcome data	15*	Report numbers of outcome events or summary measures (pg. 23-31)
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included (pg. 26-31).
		(*b*) Report category boundaries when continuous variables were categorized (pg. 24-26)
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period (N/A)
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses (pg. 30-31)
Discussion		
Key results	18	Summarise key results with reference to study objectives (pg. 32-33)
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias (pg. 41-42)
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence (pg. 32-41)
Generalisability	21	Discuss the generalisability (external validity) of the study results (pg. 36-41)
Other information		
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based (pg. 44)

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Appendix E: Cox Regression Results (Secondary Analyses)

Table 4. Cox regression results of survival time until first disengagement.

Co-variates	B	P value	HR	95% CI
Country				
Canada	-	-	1.00	-
United States	0.013	0.826	1.013	0.901-1.139
Gender				
Female	-	-	1.00	-
Male	-0.033	0.553	0.968	0.868-1.079
No response	-0.223	0.002	0.800	0.695-0.920
Age				
18-25 years	-0.13	0.896	0.987	0.813-1.198
26-35 years	0.078	0.212	1.081	0.957-1.222
36-45 years	-	-	1.00	-
46-55 years	0.093	0.188	1.097	0.956-1.259
56-65 years	0.366	0.000	1.443	1.202-1.731
66-75 years	0.720	0.028	2.055	1.079-3.915
No response	0.584	0.001	1.792	1.282-2.505
BMI[a] (kg/m^2)				
Underweight	-0.860	0.721	0.917	0.571-1.473
Normal weight	-	-	1.00	-
Overweight	-0.750	0.260	0.928	0.815-1.057
Obese I	-0.113	1.90	0.893	0.754-1.058
Obese II	-0.177	0.134	0.838	0.666-1.056
Obese III	-0.346	0.049	0.708	0.501-0.999
Outside BMI parameters[b]	0.036	0.689	1.036	0.870-1.236
No response	-0.247	0.140	0.781	0.563-1.084
Baseline HRA score[c]				
Poor (<50)	0.229	0.072	1.257	0.980-1.613
Fair (50-61.9)	0.171	0.100	1.186	0.968-1.454
Good (62-73.9)	0.093	0.335	1.098	0.908-1.327
Very good & Excellent (74-100)	-	-	1.00	-
No response	0.010	0.968	1.010	0.610-1.675

Table 4 (continued).

Smoking habit				
Never	-	-	1.00	-
Former smoker	0.172	0.022	1.188	1.025-1.376
Current smoker	0.127	0.144	1.136	0.957-1.348
No response	0.523	0.028	1.687	1.059-2.686
Chronic disease count				
Zero diagnoses	-	-	1.00	-
One diagnosis	0.099	0.155	1.104	0.963-1.266
Two or more diagnoses	0.010	0.940	1.010	0.777-1.313
No response[d]	-	-	-	-
Occurrence of lower back pain				
Yes	0.063	0.253	1.065	0.956-1.187
No	-	-	1.00	-
No response[d]	-	-	-	-
Company size	0.026	0.003	1.026	1.009-1.004
Reward style				
No rewards	-	-	1.00	-
On platform[e]	0.161	0.361	1.175	0.831-1.662
Off platform[f]	0.306	0.038	1.358	1.017-1.813
Maximum reward value per quarter[g]				
$0	-	-	1.00	-
$20	-0.119	0.504	0.888	0.626-1.259
$25	0.006	0.970	1.006	0.723-1.400
$30	-0.620	0.010	0.538	0.336-0.861
$35	0.300	0.471	1.351	0.597-3.055
$50	-0.268	0.071	0.765	0.572-1.023
$75	-0.452	0.012	0.636	0.447-0.906
$85	-0.530	0.311	0.589	0.211-1.640
$90	0.215	0.718	1.240	0.385-3.994
$100	0.127	0.599	1.136	0.707-1.825
Challenge prizing	-0.770	0.687	0.926	0.636-1.348
Premium deductions	0.007	0.976	1.007	0.651-1.557
Sweepstakes	-0.370	0.146	0.691	0.419-1.139
Unknown[d]	-	-	-	-

Note: B=Regression coefficient; HR=Hazard ratio; CI=Confidence interval.
[a]BMI group definition according to the World Health Organization, underweight=BMI<18.5, normal weight=25>BMI≥18.5, overweight=30>BMI≥25, obese I=35>BMI≥30, obese II=40>BMI≥35, obese III=BMI≥40.
[b]BMI parameters, 45≥BMI≥17.

Table 4 (continued).

[c]HRA group definitions according to Sprout Wellness Solutions Inc., poor=HRA<50, fair=50≤HRA≤61.9, good=62≤HRA≤73.9, very good & excellent=74≤HRA≤100.
[d]Degree of freedom reduced because of constant or linearly dependent covariates.
[e]Benefits in the form of in-app product and gift cards redemptions.
[f]Employer-specific rewards (i.e., premium deductions, sweepstakes, and challenge prizing).
[g]Rewards are in CAD/USD (depending on local currency).

Table 5. Cox regression results of survival time until re-engagement.

Co-variates	B	P value	HR	95% CI
Country				
Canada	-	-	1.00	-
United States	0.280	0.115	1.324	0.934-1.876
Gender				
Female	-	-	1.00	-
Male	0.001	0.997	1.001	0.723-1.385
No response	0.227	0.280	1.255	0.831-1.897
Age				
18-25 years	0.218	0.429	1.243	0.725-2.132
26-35 years	0.089	0.632	1.093	0.759-1.575
36-45 years	-	-	1.00	-
46-55 years	0.186	0.354	1.204	0.813-1.784
56-65 years	-0.090	0.747	0.914	0.529-1.580
66-75 years	0.962	0.127	2.616	0.760-9.003
No response	-1.239	0.199	0.290	0.044-1.920
BMI[a] (kg/m^2)				
Underweight	-10.679	0.935	0.00	-
Normal weight	-	-	1.00	-
Overweight	0.049	0.799	1.050	0.723-1.525
Obese I	0.229	0.334	1.258	0.790-2.001
Obese II	-0.313	0.404	0.731	0.350-1.526
Obese III	0.027	0.960	1.027	0.361-2.925
Outside BMI parameters[b]	-0.074	0.790	0.928	0.538-1.602
No response	-0.156	0.864	0.856	0.144-5.083
Baseline HRA score[c]				
Poor (<50)	-0.271	0.471	0.763	0.365-1.594
Fair (50-61.9)	-0.011	0.970	0.989	0.560-1.747
Good (62-73.9)	0.042	0.876	1.043	0.616-1.766
Very good & Excellent (74-100)	-	-	1.00	-
No response	-0.420	0.595	0.657	0.140-3.094
Smoking habit				
Never	-	-	1.00	-
Former smoker	-0.147	0.515	0.864	0.555-1.343
Current smoker	-0.051	0.843	0.950	0.571-1.581
No response	-0.239	0.737	0.788	0.196-3.170

Table 5. (continued).

Chronic disease count				
Zero diagnoses	-	-	1.00	-
One diagnosis	-0.014	0.945	0.968	0.654-1.484
Two or more diagnoses	0.498	0.136	1.646	0.854-3.171
No response[d]	-	-	-	-
Occurrence of lower back pain				
Yes	-0.159	0.330	0.853	0.620-1.174
No	-	-	1.00	-
No response[d]	-	-	-	-
Company size	0.010	0.755	1.010	0.948-1.076
Reward style				
No rewards	-	-	1.00	-
On platform[e]	0.049	0.938	1.050	0.312-3.533
Off platform[f]	-0.160	0.774	0.852	0.286-2.539
Maximum reward value per quarter[g]				
$0	-	-	1.00	-
$20	0.154	0.804	1.167	0.345-3.951
$25	0.200	0.732	1.222	0.388-3.847
$30	-0.468	0.615	0.626	0.101-3.874
$35	1.101	0.232	3.006	0.494-18.291
$50	0.191	0.727	1.210	0.415-3.527
$75	0.327	0.590	1.387	0.422-4.567
$85	-10.150	0.978	0.00	-
$90	-11.018	0.979	0.00	-
$100	0.867	0.270	2.379	0.511-11.082
Challenge prizing	0.425	0.505	1.530	0.438-5.342
Premium deductions	-0.236	0.763	0.790	0.171-3.647
Sweepstakes	-0.227	0.798	0.797	0.140-4.539
Unknown[d]	-	-	-	-
Sum of app opens until disengagement	0.005	0.118	1.005	0.999-1.012
Survival time until disengagement	0.055	0.00	1.056	1.037-1.075

Note: B=Regression coefficient; HR=Hazard ratio; CI=Confidence interval.

[a]BMI group definition according to the World Health Organization, underweight=BMI<18.5, normal weight=25>BMI≥18.5, overweight=30>BMI≥25, obese I=35>BMI≥30, obese II=40>BMI≥35, obese III=BMI≥40.

[b]BMI parameters, 45≥BMI≥17.

[c]HRA group definitions according to Sprout Wellness Solutions Inc., poor=HRA<50, fair=50≤HRA≤61.9, good=62≤HRA≤73.9, very good & excellent=74≤HRA≤100.

[d]Degree of freedom reduced because of constant or linearly dependent covariates.

[e]Benefits in the form of in-app product and gift cards redemptions.

Table 5 (continued).

[f]Employer-specific rewards (i.e., premium deductions, sweepstakes, and challenge prizing).
[g]Rewards are in CAD/USD (depending on local currency).

Appendix F: Poisson Regression Results (Secondary Analyses)

Table 6. Poisson regression results with week one weekly app open data.

Co-variates	B	P value	HR	95% CI
Country				
Canada	-	-	1.00	-
United States	-0.011	0.779	0.990	0.919-1.065
Gender				
Female	-	-	1.00	-
Male	-0.083	0.020	0.921	0.859-0.987
No response	-0.058	0.203	0.943	0.862-1.032
Age				
18-25 years	0.021	0.733	1.021	0.907-1.150
26-35 years	-0.029	0.460	0.971	0.898-1.050
36-45 years	-	-	1.00	-
46-55 years	-0.024	0.593	0.976	0.894-1.066
56-65 years	0.049	0.420	1.050	0.933-1.181
66-75 years	-0.521	0.065	0.594	0.342-1.033
No response	0.065	0.600	1.067	0.836-1.362
BMI[a] (kg/m^2)				
Underweight	-0.073	0.645	0.930	0.682-1.267
Normal weight	-	-	1.00	-
Overweight	0.044	0.296	1.045	0.962-1.136
Obese I	0.167	0.002	1.182	1.065-1.312
Obese II	-0.050	0.526	0.952	0.816-1.110
Obese III	0.023	0.839	1.023	0.823-1.271
Outside BMI parameters[b]	0.013	0.819	1.013	0.904-1.136
No response	0.162	0.200	1.175	0.918-1.505
Baseline HRA score[c]				
Poor (<50)	0.002	0.980	1.002	0.855-1.175
Fair (50-61.9)	-0.007	0.915	0.993	0.872-1.130
Good (62-73.9)	0.070	0.255	1.072	0.951-1.209
Very good & Excellent (74-100)	-	-	1.00	-
No response	-0.139	0.369	0.870	0.642-1.179

Table 6 (continued).

Smoking habit				
Never	-	-	1.00	-
Former smoker	-0.149	0.004	0.862	0.779-0.953
Current smoker	-0.050	0.383	0.952	0.851-1.064
No response	-0.015	0.915	0.985	0.750-1.294
Chronic disease count				
Zero diagnoses	-	-	1.00	-
One diagnosis	-0.025	0.581	0.975	0.891-1.067
Two or more diagnoses	-0.177	0.060	0.838	0.697-1.007
No response[d]	-	-	-	-
Occurrence of lower back pain				
Yes	-0.054	0.127	0.947	0.883-1.016
No	-	-	1.00	-
No response[d]	-	-	-	-
Company size	0.014	0.017	1.014	1.002-1.025
Reward style				
No rewards	-	-	1.00	-
On platform[e]	-0.068	0.273	0.934	0.827-1.055
Off platform[f]	0.047	0.586	1.048	0.886-1.240
Maximum reward value per quarter[g]				
$0	-	-	1.00	-
$20[d]	-	-	-	-
$25	0.071	0.244	1.074	0.953-1.210
$30	-0.333	0.020	0.717	0.542-0.948
$35	-0.363	0.261	0.696	0.369-1.311
$50	0.068	0.329	1.071	0.934-1.228
$75	-0.007	0.935	0.993	0.849-1.163
$85	-0.038	0.910	0.963	0.502-1.846
$90	-0.731	0.212	0.482	0.153-1.517
$100	-0.233	0.173	0.793	0.567-1.108
Challenge prizing	-0.296	0.023	0.744	0.577-0.959
Premium deductions	-0.019	0.891	0.981	0.745-1.292
Sweepstakes	0.068	0.654	1.070	0.795-1.442
Unknown	-0.174	0.126	0.840	0.672-1.050

Note: B=Regression coefficient; HR=Hazard ratio; CI=Confidence interval.
[a]BMI group definition according to the World Health Organization, underweight=BMI<18.5, normal weight=25>BMI≥18.5, overweight=30>BMI≥25, obese I=35>BMI≥30, obese II=40>BMI≥35, obese III=BMI≥40.
[b]BMI parameters, 45≥BMI≥17.
[c]HRA group definitions according to Sprout Wellness Solutions Inc., poor=HRA<50, fair=50≤HRA≤61.9, good=62≤HRA≤73.9, very good & excellent=74≤HRA≤100.
[d]Set to zero because this parameter is redundant.

Table 6 (continued).

[e]Benefits in the form of in-app product and gift cards redemptions.
[f]Employer-specific rewards (i.e., premium deductions, sweepstakes, and challenge prizing).
[g]Rewards are in CAD/USD (depending on local currency).

Table 7. Poisson regression results with week four weekly app open data.

Co-variates	B	P value	HR	95% CI
Country				
Canada	-	-	1.00	-
United States	-0.79	0.236	0.924	0.811-1.053
Gender				
Female	-	-	1.00	-
Male	0.129	0.026	1.138	1.015-1.276
No response	-0.090	0.239	0.914	0.786-1.062
Age				
18-25 years	-0.148	0.156	0.862	0.702-1.058
26-35 years	-0.124	0.045	0.884	0.783-0.997
36-45 years	-	-	1.00	-
46-55 years	-0.171	0.018	0.843	0.731-0.972
56-65 years	0.228	0.012	1.257	1.052-1.500
66-75 years	-1.482	0.140	0.227	0.032-1.628
No response	-0.344	0.183	0.709	0.427-1.176
BMI[a] (kg/m^2)				
Underweight	-0.322	0.256	0.725	0.416-1.263
Normal weight	-	-	1.00	-
Overweight	0.115	0.087	1.122	0.984-1.280
Obese I	0.208	0.018	1.231	1.036-1.462
Obese II	0.434	0.000	1.543	1.224-1.945
Obese III	0.340	0.057	1.405	0.990-1.995
Outside BMI parameters[b]	0.236	0.013	1.267	1.050-1.528
No response	0.077	0.758	1.087	0.660-1.770
Baseline HRA score[c]				
Poor (<50)	-0.506	0.00	0.603	0.471-0.772
Fair (50-61.9)	-0.448	0.00	0.639	0.528-0.773
Good (62-73.9)	-0.185	0.033	0.831	0.701-0.985
Very good & Excellent (74-100)	-	-	1.00	-
No response	-0.746	0.006	0.474	0.279-0.805
Smoking habit				
Never	-	-	1.00	-
Former smoker	-0.197	0.026	0.821	0.691-0.977
Current smoker	0.089	0.340	1.093	0.911-1.312
No response	0.570	0.024	1.769	1.076-2.907

Table 7 (continued).

Chronic disease count				
Zero diagnoses	-	-	1.00	-
One diagnosis	-0.013	0.865	0.987	0.855-1.141
Two or more diagnoses	-0.027	0.844	0.973	0.745-1.272
No response[d]	-	-	-	-
Occurrence of lower back pain				
Yes	0.156	0.005	1.169	1.048-1.305
No	-	-	1.00	-
No response[d]	-	-	-	-
Company size	-0.003	0.696	0.997	0.980-1.013
Reward style				
No rewards	-	-	1.00	-
On platform[e]	-0.089	0.395	0.915	0.746-1.123
Off platform[f]	-0.307	0.041	0.736	0.548-0.988
Maximum reward value per quarter[g]				
$0	-	-	1.00	-
$20[d]	-	-	-	-
$25	-0.138	0.193	0.871	0.707-1.072
$30	-0.108	0.619	0.897	0.586-1.374
$35	-0.891	0.215	0.410	0.100-1.677
$50	-0.210	0.081	0.811	0.640-1.026
$75	0.427	0.001	1.532	1.204-1.950
$85	0.127	0.901	1.136	0.153-8.421
$90	-28.012	-	-	-
$100	0.804	0.001	2.236	1.365-3.661
Challenge prizing	0.818	0.00	2.267	1.522-3.376
Premium deductions	0.202	0.457	1.223	0.719-2.080
Sweepstakes	0.712	0.001	2.038	1.353-3.070
Unknown	-0.221	0.377	0.802	0.491-1.309

Note: B=Regression coefficient; HR=Hazard ratio; CI=Confidence interval.
[a]BMI group definition according to the World Health Organization, underweight=BMI<18.5, normal weight=25>BMI≥18.5, overweight=30>BMI≥25, obese I=35>BMI≥30, obese II=40>BMI≥35, obese III=BMI≥40.
[b]BMI parameters, 45≥BMI≥17.
[c]HRA group definitions according to Sprout Wellness Solutions Inc., poor=HRA<50, fair=50≤HRA≤61.9, good=62≤HRA≤73.9, very good & excellent=74≤HRA≤100.
[d]Set to zero because this parameter is redundant.
[e]Benefits in the form of in-app product and gift cards redemptions.
[f]Employer-specific rewards (i.e., premium deductions, sweepstakes, and challenge prizing).
[g]Rewards are in CAD/USD (depending on local currency).

Table 8. Poisson regression results with week eight weekly app open data.

Co-variates	B	P value	HR	95% CI
Country				
Canada	-	-	1.00	-
United States	-0.172	0.036	0.842	0.795-1.300
Gender				
Female	-	-	1.00	-
Male	0.191	0.005	1.210	1.059-1.383
No response	0.095	0.249	1.100	0.936-1.293
Age				
18-25 years	-0.036	0.762	0.965	0.766-1.216
26-35 years	0.014	0.848	1.015	0.875-1.176
36-45 years	-	-	1.00	-
46-55 years	0.368	0.00	1.445	1.240-1.685
56-65 years	0.186	0.149	1.205	0.936-1.551
66-75 years	0.101	0.865	1.107	0.345-3.547
No response	0.382	0.173	1.466	0.846-2.541
BMI[a] (kg/m^2)				
Underweight	0.153	0.581	1.165	0.677-2.005
Normal weight	-	-	1.00	-
Overweight	0.047	0.570	1.048	0.891-1.233
Obese I	0.390	0.00	1.477	1.213-1.799
Obese II	0.300	0.032	1.351	1.026-1.778
Obese III	-0.053	0.831	0.948	0.580-1.550
Outside BMI parameters[b]	0.240	0.053	1.271	0.997-1.621
No response	0.040	0.890	1.041	0.593-1.826
Baseline HRA score[c]				
Poor (<50)	-0.236	0.154	0.790	0.572-1.092
Fair (50-61.9)	0.015	0.911	1.015	0.782-1.317
Good (62-73.9)	-0.044	0.721	0.957	0.750-1.220
Very good & Excellent (74-100)	-	-	1.00	-
No response	-23.521	0.00	$6.094^{\wedge-11}$	$4.083^{\wedge-11}$-$9.096^{\wedge-11}$
Smoking habit				
Never	-	-	1.00	-
Former smoker	-0.410	0.00	0.663	0.532-0.827
Current smoker	-0.043	0.695	0.957	0.770-1.190
No response	23.536	-	$1.666^{\wedge10}$	-

Table 8 (continued).

Chronic disease count				
Zero diagnoses	-	-	1.00	-
One diagnosis	0.070	0.412	1.072	0.907-1.267
Two or more diagnoses	-0.288	0.180	1.750	0.492-1.143
No response[d]	-	-	-	-
Occurrence of lower back pain				
Yes	0.456	0.00	1.578	1.396-1.784
No	-	-	1.00	-
No response[d]	-	-	-	-
Company size	0.019	0.042	1.019	1.001-1.038
Reward style				
No rewards	-	-	1.00	-
On platform[e]	-0.526	0.00	0.591	0.475-0.735
Off platform[f]	0.211	0.228	1.235	0.876-1.740
Maximum reward value per quarter[g]				
$0	-	-	1.00	-
$20[d]	-	-	-	-
$25	0.016	0.897	1.016	0.795-1.300
$30	-0.753	0.002	0.471	0.294-0.756
$35	-23.373	1.00	7.068^-11	0.00-0.00
$50	-0.820	0.00	0.440	0.323-0.601
$75	0.371	0.010	1.450	1.094-1.920
$85	-1.193	0.245	0.303	0.040-2.272
$90	-23.552	1.00	5.911^-11	0.00-0.00
$100	-0.839	0.032	0.432	0.200-0.932
Challenge prizing	0.191	0.430	1.211	0.754-1.945
Premium deductions	-0.647	0.047	0.524	0.277-0.991
Sweepstakes	-0.422	0.095	0.656	0.399-1.076
Unknown	-0.592	0.038	0.553	0.317-0.967

Note: B=Regression coefficient; HR=Hazard ratio; CI=Confidence interval.
[a]BMI group definition according to the World Health Organization, underweight=BMI<18.5, normal weight=25>BMI≥18.5, overweight=30>BMI≥25, obese I=35>BMI≥30, obese II=40>BMI≥35, obese III=BMI≥40.
[b]BMI parameters, 45≥BMI≥17.
[c]HRA group definitions according to Sprout Wellness Solutions Inc., poor=HRA<50, fair=50≤HRA≤61.9, good=62≤HRA≤73.9, very good & excellent=74≤HRA≤100.
[d]Set to zero because this parameter is redundant.
[e]Benefits in the form of in-app product and gift cards redemptions.
[f]Employer-specific rewards (i.e., premium deductions, sweepstakes, and challenge prizing).
[g]Rewards are in CAD/USD (depending on local currency).

Appendix G: Kaplan-Meier Curves Using Two-Week Disengagement/Re-engagement Definitions (Sensitivity Analysis)

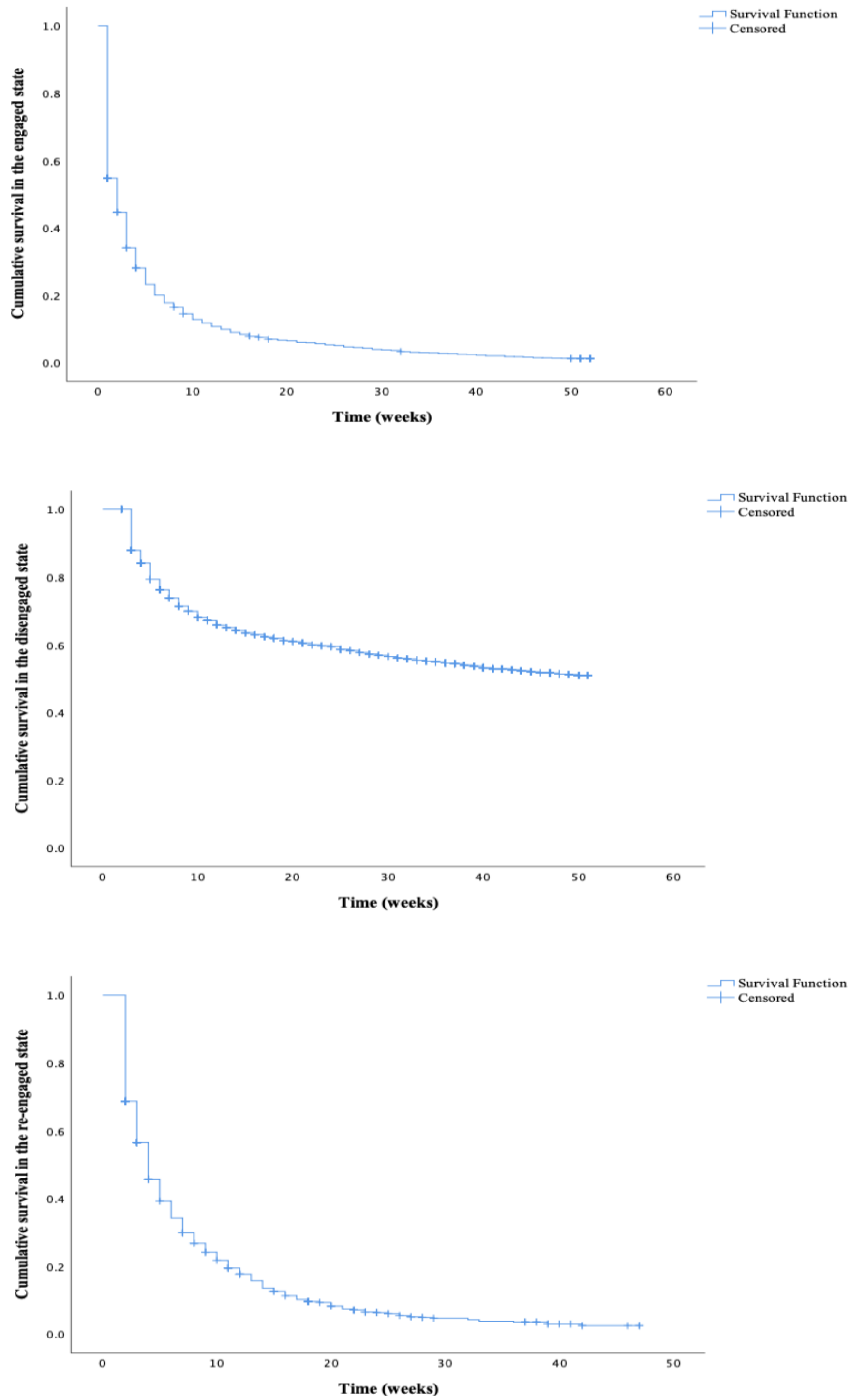

Figure 4. Kaplan-Meier curve illustrating participation a) first disengagement, b) re-engagement, and c) second disengagement, using two-week definitions of disengagement/re-engagement.

Note. Censored indicates weeks with participant time to outcome event not available.

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