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Mental imagery-based self-regulation: Effects on physical activity behavior and its cognitive and affective precursors over time

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Abstract

Objectives: (1) Test whether a mental imagery-based self-regulation intervention increases physical activity behavior over 90 days; (2) Examine cognitive and affective precursors of change in physical activity behavior.

Design: A randomized control trial with participants (n=500) randomized to one of six intervention conditions in a 3 (risk communication format: bulleted list, table, risk ladder) x 2 (mental imagery behavior: physical activity, active control [sleep hygiene]) factorial design

Methods: After receiving personalized risk estimates via a smartphone website, participants listened to an audiorecording that guided them through a mental imagery activity related to improving physical activity (intervention group) or sleep hygiene behavior (active control). Participants received text message reminders to complete the imagery for 3 weeks post-intervention, 4 weekly text surveys to assess behavior and its cognitive and affective precursors, and a mailed survey 90 days post-baseline.

Results: Physical activity increased over 90 days by 19.5 more minutes per week (95%CI: 2.0, 37.1) in the physical activity than the active control condition. This effect was driven by participants in the risk ladder condition, who exercised 54.8 more minutes (95%CI 15.6, 94.0) in the physical activity condition than participants in the active control sleep hygiene group. Goal planning positively predicted physical activity behavior (b=12.2 minutes per week, p=0.002), but self-efficacy, image clarity, and affective attitudes towards behaviors did not (p>0.05).

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Ethical Approval: This study was reviewed and approved by the Washington University in St. Louis Institutional Review Board. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Conclusions: Mental imagery-based self-regulation interventions can increase physical activity behavior, particularly when supported by personalized disease risk information presented in an easy-to-understand format.

Keywords

Self-regulation; Mental imagery; Intervention; Physical activity; mHealth

Introduction

Regulating one's emotions, thoughts, and behaviors (i.e., *self-regulation*) is critical to initiating and maintaining health promoting behaviors (Bandura, 1991). Interventions that foster self-regulation skills help people set goals, develop plans for meeting those goals, and increase confidence in achieving those goals (i.e., *self-efficacy*). Self-regulation interventions can bridge the gap between intending to increase physical activity and actually increasing physical activity (Gollwitzer & Sheeran, 2006; Michie et al., 2011; Schwarzer, 2001; Zhang et al., 2019). Such interventions may ask participants to identify specific activities to engage in, plan when and how to engage in the activities, and develop strategies to overcome barriers to engaging in physical activity or to resume activity after having stopped.

Researchers have attempted to increase the efficacy of self-regulation interventions by augmenting them with mental imagery activities (Chan and Cameron, 2012; Loft and Cameron, 2013). Mental imagery has been used to improve athletic skills and motivation and to help visualize physical activity-related goal achievements (Martin et al., 1999). Mental imagery interventions have been used in several health-related contexts, with the majority showing beneficial results (Giacobbi et al., 2017), including for physical activity (Conroy & Hagger, 2018). (Chan and Cameron, 2012) reported that self-regulation interventions that incorporated approach imagery (i.e., attaining goals or behavior) and process imagery (i.e., the steps one takes to achieve goals or behavior) increased physical activity and cognitions over 4 weeks compared to interventions that included only process or neutral imagery. Perceived vividness/image clarity was also linked to effects of mental imagery (Chan and Cameron, 2012;Loft and Cameron, 2013).

Despite these promising findings, mental imagery studies represent a small proportion of behavior change interventions (Conroy & Hagger, 2018; Giacobbi et al., 2017), and even fewer mental imagery-based health behavior change studies have also incorporated elements of self-regulation theory (Chan and Cameron, 2012;Loft and Cameron, 2013). In addition, existing interventions are time intensive and may represent a major barrier to eventual uptake of interventions in a clinical setting. However, delivering such interventions via web or mobile devices could overcome this and other logistical barriers (Giacobbi et al., 2017).

Conceptual Framework and Hypotheses

This intervention was based on a conceptual framework that incorporates risk communication and mental imagery activities into the Health Action Process Approach (HAPA) theory (Schwarzer, 2001). Whereas our earlier work investigated the motivation phase of HAPA by communicating personalized risk information for multiple diseases simultaneously (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020), this study focused on the action phase (Figure 1). In the action phase, moving from intention to behavioral engagement depends on several self-regulatory processes, including goal planning (e.g., which specific actions will be taken at which time) and action, coping, and recovery self-efficacy (i.e., having confidence in one's ability to begin a behavior, overcome barriers to the behavior, and resume a behavior after a lapse, respectively) (Schwarzer, 2001; Zhang et al., 2019). Although HAPA does not explicitly include affect as a motivator of behavior change, we included it in our conceptual framework because the mental imagery literature indicates that images that produce more positive affective attitudes toward the behavior may be more effective; see meta-analysis (Conroy & Hagger, 2018). We included image clarity for the same reason (Chan and Cameron, 2012;Loft and Cameron, 2013).

In this study, we examined the longitudinal effects of a mental imagery-based self-regulation intervention on physical activity behavior, and how behavior was shaped longitudinally by cognitive and affective precursors of behavior change (e.g., self-efficacy). We proposed two main hypotheses and one exploratory research question.

Hypothesis 1 (H1): Based on prior research (Chan and Cameron, 2012;Loft and Cameron, 2013)(Gollwitzer & Sheeran, 2006; Michie et al., 2011; Schwarzer, 2001; Zhang et al., 2019), we hypothesized that participants who engaged in mental imagery-based self-regulation activities related to physical activity would have a larger increase in weekly minutes of physical activity from baseline to 90-day follow-up than participants in the active control group. We chose sleep hygiene as the active control because it was improved with a mental imagery-based self-regulation intervention similar to the intervention we used for this study (Loft and Cameron, 2013).

Hypothesis 2 (H2): Based on predictions made by HAPA (Schwarzer, 2001), we hypothesized that cognitive and affective precursors of behavior at one time point would be positively correlated with the subsequent time point's behavior. For example, time 1 image clarity, goal planning, self-efficacy, and positive affect would be positively correlated with minutes of physical activity at time 2.

Exploratory Research Question (RQ): Self-regulation and mental imagery interventions for adults are seldom described as being intentionally designed to be meaningful to people from underrepresented socio-demographic groups (but see (Joseph et al., 2020)), despite evidence demonstrating that these groups have, on average, lower engagement in some health promoting behaviors (including physical activity) and worse health outcomes than individuals who are white (National Academies of Sciences & Medicine, 2017; Watson et al., 2016). Therefore, we aimed to design an intervention that was as effective among populations who are underrepresented in health behavior interventions as it was among those who are typically included. To ensure that we achieved this goal, we examined whether the effects of the intervention on behavior were moderated by race/ethnicity, sex, education, age, health literacy, or self-reported health status.

Methods

Design Overview

These data originated from a two-component physical activity intervention. The first component examined strategies for communicating categorical personalized risk information for multiple diseases (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020). The second component consisted of using a mental imagery-based self-regulation intervention (here after referred to as "mental imagery") to facilitate behavior change initiation and maintenance over 90 days.

Participants were randomly assigned to one of six intervention conditions according to a 3 (risk communication format: bulleted list, table, risk ladder) x 2 (mental imagery behavior: physical activity, active control [sleep hygiene]) between-subjects factorial design with a 1:1 allocation. Randomization occurred at the initial in-person visit (baseline), where participants first received their personalized risk results for up to five diseases (i.e., heart disease, diabetes, stroke, colon cancer, breast cancer [women only]). Personalized risk results were based on participants' self-reported standing on a variety of demographic, health history, and behavioral factors that are known to affect disease risk (e.g., age, family history, physical activity). Next, participants engaged in the mental imagery intervention activities. The final behavioral assessment occurred 90 days post-baseline. Study personnel were blinded to random assignment for the first component, but the structure of the second component precluded being able to blind them effectively. All study materials, including intervention materials, surveys, and de-identified datasets, can be viewed at (https://osf.io/b9ez6/). The study is registered on clinicaltrials.gov (NCT03255291).

Participants

Participant recruitment is described elsewhere (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020). Briefly, we recruited participants in (St. Louis, Missouri, USA), from July 2017-August 2018 through in-person outreach, flyers, advertisements (social media, online, print newspaper), University listservs, word of mouth, and research participant registry databases. Recruitment aimed to achieve a sample comprised of ≥50% individuals who had no more than vocational-technical training and ≥50% of people from underrepresented racial or ethnic groups (i.e., Black/African American, American Indian/Native American, Asian, Latino/a, multiracial). Participants were excluded if they were not age 30–64 (due to restrictions in the modeling required for the personalized risk assessment), did not speak English or meet US physical activity guidelines of at least 150 minutes of aerobic activity per week, or had three or more of the following comorbidities: diabetes, heart disease, stroke, or a history of non-melanoma cancer. Cancer qualified as two comorbidities for women because a "yes" response would preclude them from seeing breast and colon cancer risk information. The text messaging element of the intervention required that we also exclude people who either shared or did not own a cell phone or used text messaging <2 times in the last month.

We screened 1198 individuals (supplemental figure S1), of whom 554 (46%) were enrolled and randomized. Of those 554, 49 (9%) were excluded because they no longer met eligibility criteria at the time of data collection, leaving 505 (91%) who completed all baseline data collection activities. We excluded five additional participants for data collection problems, leaving a sample of 500 participants.

Study Procedures and Materials

Eligible participants were scheduled for an in-person 60-minute baseline session. For the first intervention component (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020), participants used a smartphone to answer demographic and health history questions. Based on that information, they were shown categorical personalized risk information (e.g., “low risk”) of developing up to 5 diseases (heart disease, diabetes, breast cancer (women only), stroke, and colon cancer) if they *did not* attain 3 hours of weekly physical activity and their risk if they *did* attain 3 hours of weekly physical activity, displayed as a bulleted list, table, or risk ladder. Participants did not see risk information for diseases for which they reported a personal history; information about the risk of developing a disease they already had would not be useful. Then, participants completed written Baseline Survey 1. For additional details on the first intervention component, see (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020).

The second intervention component began immediately following Baseline Survey 1. It included: an audio-recording guiding participants through the mental imagery activities, a card to write down goals, and Baseline Survey 2. We adapted all the study materials from previous studies (Chan and Cameron, 2012;Loft and Cameron, 2013) and pilot tested them for comprehensibility, acceptability, and feasibility with 20 members of the target population (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020). Participants used the smartphone to listen to an audio-recording that assisted them in setting a goal for improving either physical activity or sleep hygiene behaviors [active control] and to imagine themselves meeting the goal and solving problems to reach their goal (supplemental materials part 2). Participants wrote down specific physical activity or sleep hygiene [active control] goals and goal attainment strategies on a form that could be folded into the size of a credit card (i.e., goal card) (supplement part 2). Next, participants completed Baseline Survey 2 (described below), were instructed to practice the mental imagery two times a day for five minutes each time over the next three weeks and were compensated $20.

In the next part of the intervention, we used Twilio, a cloud communications platform, to send text messages to participants over the subsequent four weeks (Twilio Inc., 2017). At 7pm on the night of enrollment, participants received a welcome text message with the study’s contact information and instructions. At noon on Monday, Wednesday and Friday for three weeks, participants received messages reminding them to practice the mental imagery activity (e.g. Remember to practice mental imagery 2 times a day for 5 minutes each time.”), along with a link to the audio-recording. At the end of each week for four weeks, participants completed a text message survey (described below). The system texted a reminder if the participants failed to complete the survey within 24 hours. The survey expired if the participant did not complete it within 48 hours. Participants were sent text surveys regardless of whether they completed the previous survey. Twilio provided notifications to the researchers if participants failed to receive messages due to problems with transmission. Participants received a $10 gift card for each completed text message survey.

Approximately 90 days post-baseline, participants received a follow-up survey by mail (described below). Non-respondents received a mailed reminder after two weeks and up to three reminder phone calls. We discontinued attempting follow-up after the third phone call or 8 weeks after the initial invitation was mailed, whichever occurred first. We received the last follow-up survey in December 2018. Participants received a $20 gift card for completing the follow-up survey.

Participant Retention

Of 500 participants who completed all baseline activities, 453 (91%) completed text survey 1, 460 (93%) completed text survey 2, 456 (91%) completed text survey 3, 459 (92%) completed text survey 4, and 464 (93%) completed the 90-day follow-up survey (supplemental materials figure S1). Additionally, 472 (94%) completed at least two of the four text messaging surveys, and 416 (83%) completed all 4 text surveys.

Measures

We obtained all measures from published research and, when necessary, modified them to reduce literacy requirements and to ensure relevance for this study. To limit participant burden, Baseline Survey 2 and the text message surveys included only items related to the participant's assigned condition (i.e., either physical activity or sleep hygiene [active control]). See supplemental materials table S1 for full measure descriptions, item wording, and measures of internal consistency.

Consistent with the conceptual framework, *Baseline Survey 2* included measures adapted from the literature (Chan and Cameron, 2012;Loft and Cameron, 2013). These included: action planning, coping planning, clarity of the images, action self-efficacy, recovery self-efficacy, coping self-efficacy, affective attitudes towards physical activity or sleep behaviors, and intentions to complete the physical activity or sleep behaviors in the next 7 days. We combined action planning and coping planning into one *goal planning* composite variable. We also combined action self-efficacy, recovery self-efficacy, and coping self-efficacy into one *self-efficacy* composite variable.

The *text surveys* measured the same constructs as Baseline Survey 2, as well as engagement in physical activity (adapted from (National Cancer Institute, 2005)) or sleep hygiene behaviors (adapted from (Loft and Cameron, 2013)) over the prior 7 days. Intervention adherence was also assessed (i.e., how much they practiced the mental imagery). The *90-Day Follow-Up Survey* included the same measures of physical activity and sleep hygiene behaviors as in the text surveys. It also assessed acceptability of the intervention (e.g., "For you, was doing the mental imagery 2 times a day for 5 minutes each time [very hard to very easy]"). Age, race, ethnicity, sex, educational attainment (National Cancer Institute, 2005), health literacy (Morris et al., 2006), and self-reported health status (National Cancer Institute, 2005) were obtained from *Baseline Survey 1* data.

Statistical Analysis

Effect of Mental Imagery on Physical Activity Behavior Change from Baseline to 90-Day Follow-Up (H1, RQ1).—We excluded participants from the analytic sample for H1/RQ1 if they (1) did not complete the 90 day follow-up survey (n=36), (2) completed the follow-up survey over 8 weeks late (n=20), (3) failed an attention check item (n=16), (4) had text messaging errors (n=3), (5) were in >99th percentile in change in minutes of physical activity per week (n=4), or (6) had missing data (n=1). The final H1/RQ1 analytic sample included 420 (84%) participants. An *a priori* statistical power analysis determined 438 participants would be adequate to detect a Cohen's *d* of 0.35, assuming the correlation between baseline and follow-up physical activity is 0.80, with 80% power and alpha of 0.05.

The primary outcome was difference in minutes of physical activity per week from baseline to 90-day follow-up. The main predictor was mental imagery condition (physical activity or active control). *A priori* covariates included: sex (female *versus* male), race/ethnicity (member of underrepresented group *versus* non-Hispanic white), age (≥50 years *versus* <50 years), education (associate degree or more *versus* some college or less), health literacy (high *versus* low), time of year during 90 day follow-up (fall, winter, spring, or summer), self-reported health status (continuous), baseline minutes of physical activity per week (continuous), risk communication format (ladder, table or list), and technical issue with risk communication results (yes *versus* no). We included perceived intervention acceptability (continuous) as an exploratory covariate.

We used ANCOVA to test the main effects of mental imagery condition on the difference score representing change in physical activity behavior. We added 2-way interaction terms between mental imagery condition and each participant characteristic to the ANCOVA models to determine whether the effect of mental imagery on behavior change varied by socio-demographic backgrounds. We also added an interaction term between risk communication format and mental imagery to ensure that there were no unexpected interactive effects of the intervention components. We probed the interactions using *post hoc* contrasts with a Dunnett-Hsu adjustment for multiple comparisons.

Effect of Cognitive and Affective Precursors on Physical Activity Behavior over Time (H2).—We excluded participants from the analytic sample for H2 for the following reasons: (a) having text messaging error that prevented use of the data (n=3), (b) skipping the entirety of three or four of the four text surveys (n=27), (c) failing an attention check item (n=14), and (e) having missing data on baseline covariates (n=8). Because items in the text messaging surveys were specific to mental imagery condition (e.g., participants in the physical activity condition answered questions only related to physical activity, not sleep hygiene), we also excluded the 219 participants in the active control condition for whom this analysis was not relevant. This left 229 participants for the H2 analyses.

The primary outcome for this analysis was minutes of physical activity per week measured at each time point. The main predictors for each time point's physical activity behavior were the previous time point's purported antecedents of behavior change: image clarity, goal planning composite, self-efficacy composite, and affective attitudes towards exercising. For example, week 1 antecedents were used to predict week 2 behavior; week 2 antecedents were used to predict week 3 behavior; and so on. We treated all predictors as continuous (supplemental table S1). *A priori* covariates were the same as in the H1/RQ1 analysis, except we used season during baseline data collection (as opposed to season at 90-day follow up); season during baseline data collection was closer in time to the text survey time points. The adherence to the intervention covariate was calculated as an average over the 4 weekly text surveys and dichotomized with a value of 3 or higher considered adhering to the intervention.

Repeated measures data for H2 (baseline, text surveys, 90-day follow-up) were analyzed using a marginal multilevel model using PROC MIXED in SAS. Minutes of physical activity in the *subsequent* week was the outcome. We added 2-way interaction terms between the time variable and each predictor to determine whether this relationship changed over time. To test if intervention adherence moderated this relationship, we added an interaction between the predictors and intervention adherence to the model. We could not conduct a formal between-group mediation analysis with the text message survey data because, due to concerns about participant burden, we did not ask participants in the physical activity condition about their sleep hygiene beliefs and behavior, and vice versa.

Results

More members of underrepresented racial/ethnic groups, men, and people with lower education were excluded from both analytic datasets. In addition, more participants with lower (vs. higher) baseline minutes of physical activity were excluded from the H1/RQ2 dataset. Table 1 shows demographic characteristics of the H1/RQ1 analytic sample by mental imagery group. There was no differential attrition for the overwhelming majority of time points and factors (but see Week 2). Table S2 shows demographic characteristics of the H2 analytic sample and figure S1 shows survey completion rates across the study period. The correlation between physical activity and sleep hygiene behavior was 0.10 (p=0.05) at baseline and 0.15 (p=0.003) at 90-day follow-up.

Effect of Mental Imagery on Physical Activity Behavior Change from Baseline to 90-Day Follow-Up (H1, RQ1)

Demographic characteristics among the 420 participants in the H1/RQ1 analytic dataset were evenly distributed between mental imagery conditions (Table 1). However, intervention acceptability was lower for the physical activity condition than the active control condition (p=0.02).

Participants who engaged in physical activity-related mental imagery increased physical activity levels by 19.5 more minutes per week (95% CI: 2.0, 37.1) than participants in the active control condition (see Table 2; p=0.03, partial η^2=0.01). However, this effect varied by risk communication format (p=0.02, partial η^2=0.02). Post-hoc analyses revealed that, among participants who saw personalized disease risk information as a risk ladder, engaging in physical activity-related mental imagery increased physical activity by 54.8 more minutes per week (95% CI 15.6, 94.0) than the active control condition (Figure 2). Engaging in physical activity-related imagery did not benefit participants who saw risk information as a table or bulleted list (Table 2). The effects of mental imagery on physical activity behavior did not vary among people from different socio-demographic backgrounds (*p*'s>0.05 for all interaction terms).

Effect of Cognitive and Affective Precursors on Physical Activity Behavior over Time (H2)

In the dataset used for the H2 analysis (N=229), demographic characteristics were evenly distributed between mental imagery conditions (supplemental table S2). However, participants in the physical activity condition reported lower adherence to the intervention than participants in the active control condition (p=0.02).

Among participants in the physical activity condition, physical activity minutes per week increased significantly between baseline and week 1 (from 48.1 to 95.0 minutes, p<.001) and between week 1 and week 2 (from 95.0 to 109.6 minutes, p=0.04), and then remained relatively steady between week 2 and week 4 (*p*'s>.05) (Figure 3). Although physical activity decreased slightly from week 4 to 90 day follow up (115.1 to 110.8 minutes), it remained higher than baseline (p<.001). See supplemental materials table S3 for adjusted means of variables over the time points.

Consistent with our conceptual framework, we examined variables related to self-regulatory processes (i.e., goal planning and self-efficacy) and mental imagery processes (i.e., image clarity and affect). For the self-regulatory processes, goal planning (Table 3) at one time point was positively associated with physical activity behavior at the next time point (b=12.2 minutes, p=0.002), but self-efficacy was not (p>0.05). For the mental imagery processes, image clarity and affective attitudes towards behaviors were not associated with physical activity at the next time point (p>0.05). The extent to which imagery and self-regulatory variables affected physical activity behavior maintained steady over time (p>.05 for interaction terms with time). The effects of imagery and self-regulatory variables on physical activity behavior were also not moderated by intervention adherence (*p*'s>0.05 for interaction terms with intervention adherence).[1]

Discussion

We tested how a mental imagery-based self-regulation intervention affected physical activity engagement. We also examined patterns of this behavior change over time, along with potential cognitive and affective precursors of physical activity behavior. Our study had high retention, and participants viewed it as highly acceptable, suggesting that it may perform well in practice and have high uptake. Our study was one of only a few of this type whose sample included a large proportion of individuals who identified as Black/African American.

We report three main findings. First, mental imagery-based self-regulation interventions increased physical activity behavior over time. This is consistent with other interventions that used self-regulation activities, mental imagery activities, or both to help participants

[1]Though this study was not designed to improve sleep hygiene behavior, we discovered in supplemental analyses that engaging in sleep hygiene-related mental imagery did not increase sleep hygiene behavior compared to physical activity mental imagery. However, sleep hygiene behavior, assessed as the number of days one took the steps needed to get a good night's sleep, increased by 0.5 days from Time 1 to 90-day follow-up. For additional information about these findings, including about the relationships between sleep-related cognitive and affective precursors and sleep hygiene behavior, see supplemental materials part 3.

increase their physical activity (Chan and Cameron, 2012)(Conroy & Hagger, 2018; Giacobbi et al., 2017). It is also consistent with studies reporting that physical activity can be increased by engaging in mental contrasting (i.e., defining a goal, identifying and fantasizing about the desired outcome of the goal, identifying obstacles to the goal, and imagining a way to avoid obstacles) (Cross & Sheffield, 2019). Our effect size is smaller than that reported in (Chan and Cameron, 2012), but our intervention required less time and effort from participants, had a larger sample size and differing sample characteristics (e.g., majority New Zealand/European and Asian ethnicity in (Chan and Cameron, 2012) versus majority US non-Hispanic Black and White in this study), and had a longer follow-up period. Nevertheless, the effects of our intervention extended three months from baseline, and two months past the last intervention-related contact (i.e., the last text survey). This demonstrates that a streamlined intervention that is purposefully designed to limit participant burden by using text messaging rather than less accessible cellular data or wifi can also be effective. Furthermore, we found no evidence that the intervention was less effective among historically marginalized and underrepresented socio-demographic populations. Therefore, this type of intervention may hold promise for future integration into clinical or applied public health settings without inadvertently exacerbating existing health disparities. Identifying strategies for scaling up this intervention may be particularly useful.

Second, we found that our intervention was only effective among people who received personalized disease risk information presented as a risk ladder, rather than as a table or bulleted list. This is consistent with other research that also suggested that behavior change interventions are more impactful when they address multiple elements of the behavior change process (e.g., knowledge and self-regulation skills) (Michie et al., 2011; Schwarzer, 2001). Although combining a mental imagery-based self-regulation intervention with a disease risk communication intervention has not been investigated previously, our finding is consistent with research highlighting how images can become more ingrained in memory and how fear arousal (as may have been activated by viewing personalized disease risks in a concrete format) may fuse this into long-term memory (Cameron and Chan, 2008). However, sensitivity analyses (supplemental materials 4) indicated that our findings were unlikely to be due to greater comprehension of the risk information when it was presented as a risk ladder. Future research should investigate how combining mental imagery-based self-regulation interventions and personalized disease risk communication affects engagement in many health-promoting behaviors.

The third major finding was that the precursors of behavior change need further investigation. That goal planning at one time point was positively associated with physical activity behavior the following week is consistent with the HAPA and other theories that assert that planning helps achieve behavior change (Gollwitzer, 1999; Michie et al., 2011; Schwarzer, 2001)(Zhang et al., 2019). However, that image clarity and affective attitudes about the behavior were not associated with physical activity conflicts with the mental imagery literature (Chan and Cameron, 2012;Loft and Cameron, 2013). These conflicting findings could be due to restricted item range or restricted scale variance between time points due to the four-point response options we used to limit participant burden and adhere to text messaging software requirements. It should be noted, however, that this same response scale was used to measure goal planning, which was related to physical activity behavior.

Self-efficacy was more complex; at one timepoint it was not important for subsequent physical activity, but sensitivity analyses (not shown) showed that self-efficacy *was* an important predictor of future physical activity when baseline physical activity was *not* controlled for. This seeming instability in the predictive value of prior self-efficacy for future behavior based on the presence of baseline behavior in the model is consistent with the idea that prospective correlations between a health cognition at one timepoint and a behavior at a subsequent timepoint may be less an indication of a causal relationship and more a reflection of the influence of *past* behavior on *future* cognitions, as well as the inertial effect of past behavior on future behavior (Weinstein, 2007). It is clear that more information is needed of the circumstances under which precursors are and are not important for behavior change.

Strengths, Limitations, and Future Directions

Our intervention showed high acceptability and retention rates. Other interventions were more intensive and had higher drop off rates (e.g., practice imagery 3 times a day for 4 weeks (Loft and Cameron, 2013). Our study adds to their findings by showing that the benefit of a 21-day intervention can be extended from 4 weeks to 12 weeks without increasing the intensity of the intervention itself and while maintaining high participation throughout. Second, sociodemographic characteristics were similar among those screened and those determined eligible and enrolled in the study, strengthening generalizability of our results. Third, using multilevel modeling for the H2 analyses limited the number of participants excluded due to missing data because it allowed us to include participants who missed 1 or 2 missing text message surveys.

Nevertheless, our results should be evaluated in light of several considerations. First, we used a self-reported measure of physical activity. Although self-reported measures reduce participant burden, future research should incorporate activity trackers to obtain more objective estimates. Second, in the text messaging surveys, we could not survey participants in the active control condition about physical activity due to concerns about over-burdening them. This limited statistical power for the H2 behavior change analyses and prevented a formal between-groups mediation analysis. Third, like many mHealth interventions, participants were required to know how to use text messaging and had to either have a smart device with cellular data or access to a computer to listen to the mental imagery audio. Furthermore, most participants had considerable education and adequate health literacy. This limits generalizability to participants without these advantages.

Fourth, although the effect of mental imagery condition on physical activity was almost 20 minutes per week, the standardized effect size was small (partial η^2=0.01). This was also true of our finding that the magnitude of this increase differed by risk communication format (overall interaction partial η^2=0.02). However, it is important to note that the effect size differed by risk display group (risk ladder: partial $\eta^2 = 0.03$; table: partial $\eta^2 = 0.00$; text: partial $\eta^2 = 0.00$); the overall effect size was being driven by those in the risk ladder condition, but diluted by those in the table and text conditions. Future research should consider strategies to increase the effectiveness of the intervention, such as allowing participants to set an alert that reminds them when it is time for them to engage in their chosen activities.

Conclusions

Our mental imagery-based self-regulation intervention, which included a large proportion of individuals who identified as Black or African American, increased physical activity over 90 days among people who saw personalized disease risk and risk reduction information as a risk ladder. It advances prior research by demonstrating that a low-touch, low-burden intervention can facilitate improvements in physical activity behavior that extend in duration beyond what has previously been reported, and to facilitate those changes to a similar extent among people from both advantaged and underrepresented backgrounds. Adapting this low-burden intervention for use in clinical and public health settings, or for widespread dissemination via mobile apps, may provide another tool for increasing physical activity behavior among people who do not meet current physical activity behavior guidelines.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability statement:

The data that support the findings of this study are openly available on Open Science Framework at https://osf.io/b9ez6/.

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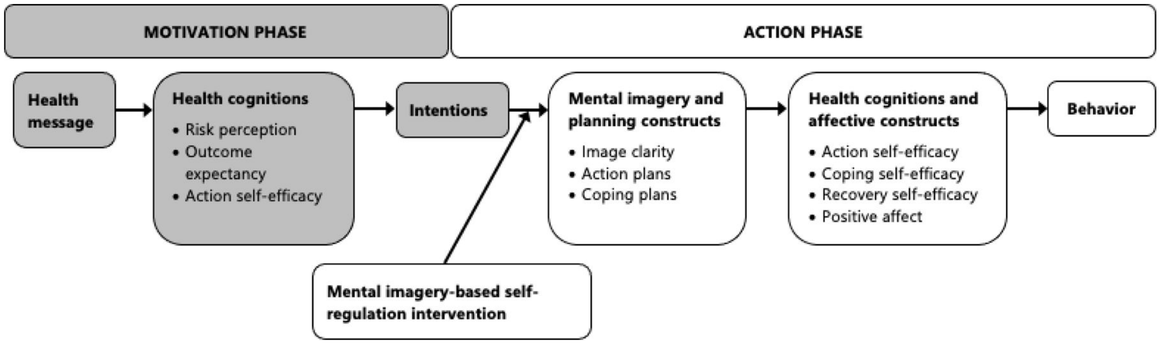

Figure 1. Conceptual model of the influence of a mental imagery-based self-regulation intervention on behavior (adapted from Schwarzer, 2001).

The present study addresses only the action phase of the Health Action Process Approach mode (white boxes with black text)l. Findings related to the motivation phase (grey boxes with black text) can be found in (Waters, Maki, Liu, Ackermann, Carter, and Dart, 2020). Action planning and coping planning were averaged to form the goal planning composite variable used in analysis. Action self-efficacy, coping self-efficacy, and planning self-efficacy were averaged to form the self-efficacy composite variable used in analysis.

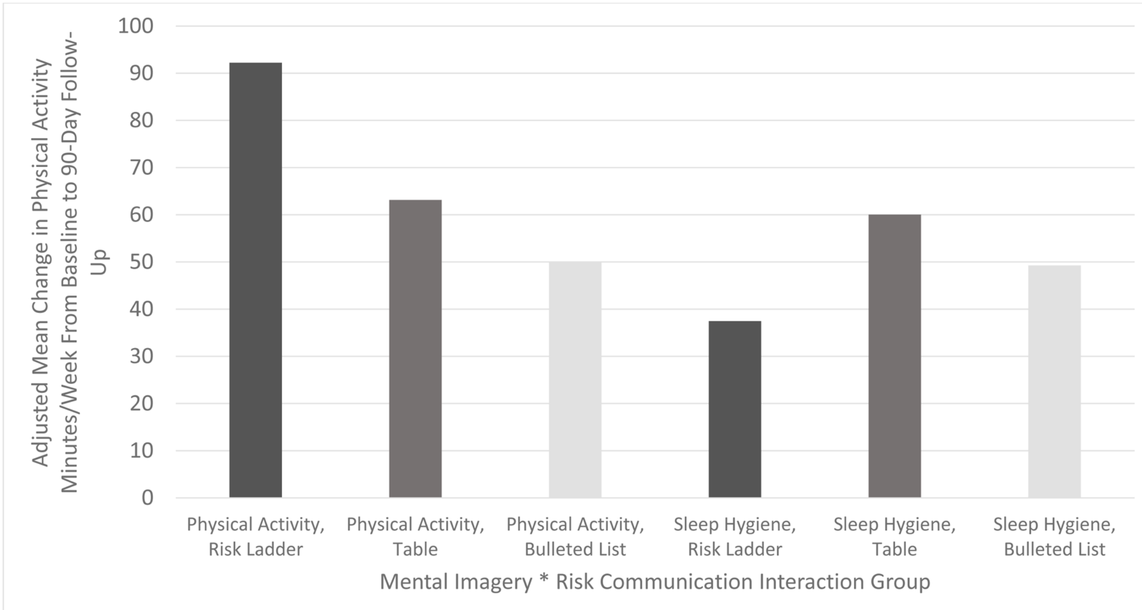

Figure 2.
Mental Imagery by Risk Display Condition: Change in Weekly Minutes of Physical Activity from Baseline to 90-day Follow Up

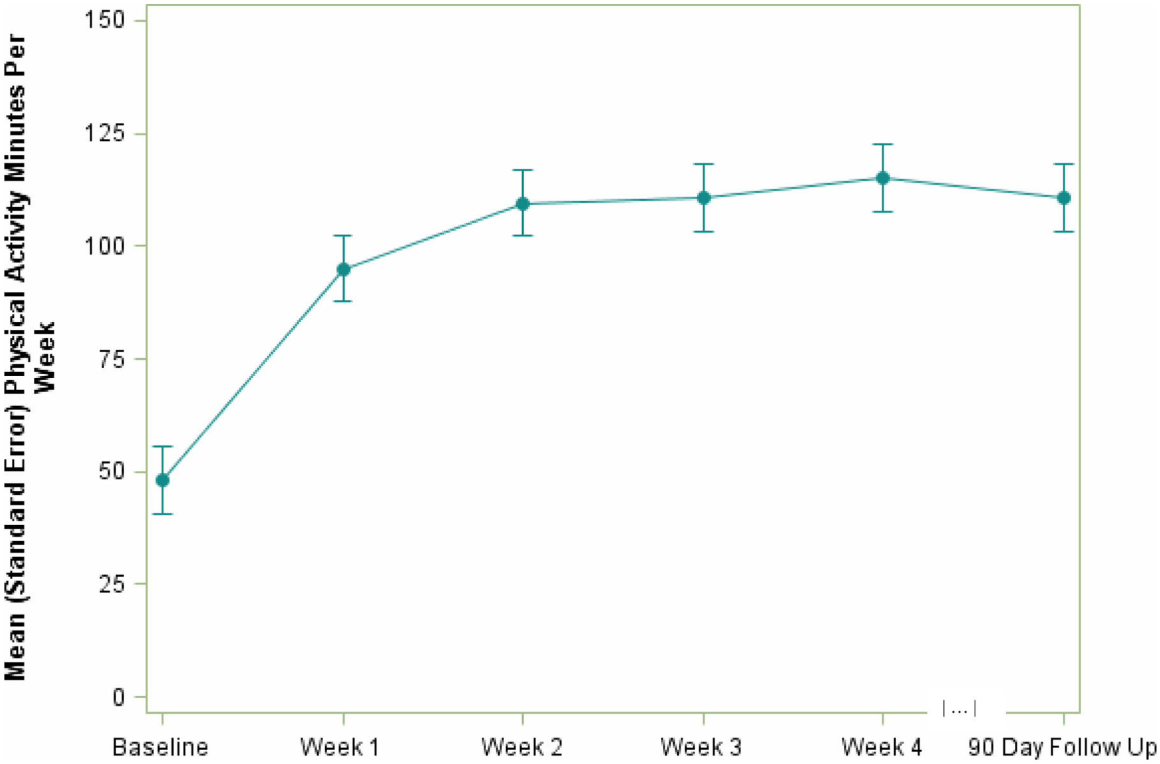

Figure 3.
Weekly Minutes of Physical Activity Over Time for those in the Physical Activity Condition (N=229)

Table 1.

Characteristics of Participants by Intervention Group (N=420)[†]

Variable	Category	Active Control [Sleep Hygiene] (N=205) – N (%)	Physical Activity (N=215) – N (%)
Sex			
	Female	177 (86.3%)	177 (82.3%)
Race			
	Members of underrepresented racial/ethnic populations	86 (42.0%)	89 (41.4%)
Education			
	Associates degree or more	138 (67.3%)	137 (63.7%)
Health Literacy			
	High	165 (80.5%)	173 (80.5%)
Age			
	50 years or older	97 (47.3%)	115 (53.5%)
Risk Communication Condition			
	Risk ladder	66 (32.2%)	70 (32.6%)
	Table	67 (32.7%)	72 (33.5%)
	Bulleted list	72 (35.1%)	73 (34.0%)
Risk Communication Technical Issue			
	Yes	25 (12.2%)	39 (18.1%)
Time of Year during 90-Day Follow Up			
	Spring	43 (21.0%)	47 (21.9%)
	Summer	54 (26.3%)	60 (27.9%)
	Fall	43 (21.0%)	50 (23.3%)
	Winter	65 (31.7%)	58 (27.0%)
Variable		Mean (SD)	Mean (SD)
Self-Reported Health Status		3.1 (0.9)	3.0 (1.0)
Baseline Physical Activity Mins/Week		57.0 (44.7)	52.3 (45.3)
Baseline Days Steps to Sleep/Week (n=407)		4.4 (2.4)	4.4 (2.4)

[†]Analytic sample size is 420 due to 80 participants being removed from full sample (n=500) for the following reasons: (1) did not complete the 90 day follow-up survey (n=36), (2) completed the survey over 8 weeks late (n=20), (3) failed an attention check item (n=16), (4) had text messaging errors (n=3), (5) were in >99th percentile in change in minutes of physical activity per week (i.e., an outlier) (n=4), or (6) had missing data (n=1)

Table 2.

Effects of Mental Imagery Condition on Change in Physical Activity Minutes/Week from Baseline to 90 Day Follow-Up (N=420)[†]

Effect	F	*df*	*p*	Partial η^2	Physical Activity Mean (95% CI)
Mental Imagery Condition	4.81	1, 419	0.03	0.01	
Physical Activity					68.5 (50.8, 86.1)
Sleep Hygiene					48.9 (30.2, 67.7)
Risk Communication Condition	1.10	2, 419	0.33	0.01	
Risk Ladder					64.9 (44.3, 85.4)
Table					61.6 (41.8, 81.4)
Bulleted List					49.7 (29.5, 69.8)
Mental Imagery*Risk Communication	3.88	2, 419	0.02	0.02	
Physical Activity, Ladder[‡]					92.2 (67.4, 117.1)
Physical Activity, Table					63.1 (38.7, 87.6)
Physical Activity, List					50.1 (25.5, 74.6)
Sleep, Ladder[‡]					37.5 (11.1, 63.8)
Sleep, Table					60 (34.6, 85.5)
Sleep, List					49.3 (23.7, 74.8)

[†]Adjusted for sex (men/women), race/ethnicity (member of underrepresented racial/ethnic population/non-Hispanic white), age (<50 / ≥50 years, education (college degree or more/some college or less), baseline physical activity (continuous), self-reported health status (continuous), health literacy (high/low), time of year during 90 day follow-up (fall/winter/spring/summer), technical issue with risk communication results (yes/no), acceptability of intervention (continuous); Analytic sample size is 420 due to 80 participants being removed from full sample (n=500) for the following reasons: (1) did not complete the 90 day follow-up survey (n=36), (2) completed the survey over 8 weeks late (n=20), (3) failed an attention check item (n=16), (4) had text messaging errors (n=3), (5) were in >99th percentile in change in minutes of physical activity per week (i.e., an outlier) (n=4), or (6) had missing data (n=1)

[‡]Statistically significant difference between groups (p=0.002)

Table 3.

Effects of Cognitive and Affective Precursors on Physical Activity Minutes/Week (N=229) †

Effect	Estimate‡	95% CI	F	*df*	*p*
Time point §			4.9	4, 811	<0.001
Text Week 1 (Reference)(Waters, 2020 #87)	0	--			
Text Week 2	19.2[b]	8.0, 30.3			
Text Week 3	21.0[b]	9.8, 32.2			
Text Week 4	21.0[b]	9.9, 32.1			
90 Day Follow Up	18.4[b]	7.1, 29.8			
Image Clarity	1.1	−6.3, 8.5	0.08	1, 811	0.77
Goal planning Composite ¶	12.2	4.5, 19.9	9.7	1, 811	0.002
Self-Efficacy Composite ¥	7.1	−0.4, 14.7	3.4	1, 811	0.06
Affective Attitudes: Enjoy Behavior	2.5	−4.5, 9.5	0.5	1, 811	0.48
Affective Attitudes: Behavior is Pleasant	4.2	−1.9, 10.3	1.9	1, 811	0.17
Risk Communication			4.4	2, 213	0.01
Risk Ladder	25.4 ^	7.8, 43.0			
Table	5.5	−12.1, 23.1			
Bulleted List (Reference)	0	--			

† Adjusted for sex (men/women), race/ethnicity (member of underrepresented racial/ethnic population/ non-Hispanic white), age (<50 / ≥50 years, education (college degree or more/some college or less), baseline physical activity (continuous), self-reported health status (continuous), health literacy (high/low), time of year during baseline visit (fall/winter/spring/summer), technical issue with risk communication results (yes/no), intervention adherence (yes/no)

‡ Estimates are unstandardized

§ Baseline physical activity was not included as a separate time point in this model and instead was included as a covariate due to the nature of modeling a previous week's cognitive and affective precursors with the next week's behavior; there was no prior measure cognitive and affective precursors before baseline behavior was collected

¶ Goal planning composite in an average of action planning and coping planning

¥ Self-efficacy composite is an average of action self-efficacy, coping self-efficacy, and planning self-efficacy

^ Statistically significant effect compared to reference group at p < .05.