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Tailored eHealth and mHealth for Physical Activity Promotion

Ashlee Davis

ACCEPTANCE

This dissertation, TAILORED EHEALTH AND MHEALTH FOR PHYSICAL ACTIVITY PROMOTION, by ASHLEE S. DAVIS, was prepared under the direction of the candidate's Dissertation Advisory Committee. It is accepted by the committee members in partial fulfillment of the requirements for the degree, Doctor of Philosophy, in the College of Education & Human Development, Georgia State University.

The Dissertation Advisory Committee and the student's Department Chairperson, as representatives of the faculty, certify that this dissertation has met all standards of excellence and scholarship as determined by the faculty.

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- Ballard, A.M., **Davis, A.**, & Hoffner, C. (2020). The Impact of Health Narratives on Persuasion in African American Women: A Systematic Review and Meta-Analysis. *Health Communication.* doi: 10.1080/10410236.2020.1731936

- **Davis, A.** & Ellis, R. (2019). A quasi-experimental investigation of college-students ratings of two physical activity mobile apps with varied behavior change technique quantity. *Digital Health.* https://doi.org/10.1177/2055207619891347

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- **Davis, A.,** Appleton, S., Sweigart, R. & Ellis, R. (2020). Patterns of Individual Level Program Implementation in a Workplace Health and Well-Being Program. Poster to be presented at the annual meeting of the Society of Behavioral of Medicine, San Francisco, CA. *Canceled due to COVID19*

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- Ellis, R., Saringer, C., Biber, D., Ferrer, D., & **Davis, A.** (2019, March). Does the organization Desire2Move? Poster presented at the annual meeting of the Society of Behavioral of Medicine, Washington, DC.

- Ballard, A.M., **Davis, A.**, Warren, G., & Hoffner, C., The effect of health narratives on persuasion in African American women: A Meta-Analysis. (2018, September). Paper presented at the CDC National Conference on Health Communication, Marketing, and Media.

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Tailored eHealth and mHealth for Physical Activity Promotion

by

Ashlee S. Davis

Under the Direction of Rebecca Ellis, PhD

ABSTRACT

OBJECTIVES: The purpose of the literature review (Chapter 1) was to examine the literature on tailored mHealth interventions for physical activity (PA) in adults. The review demonstrated tailored mHealth programs were effective at promoting PA. Research was needed to test the impact of tailored materials over other types of materials. The purpose of the research study (Chapter 2) was to examine the impact of tailored versus targeted messages on participant non-compliance during Desire2Move (D2M; a health and well-being initiative promoting PA). METHODS: Eligible participants were D2M participants who were non-compliant (logged zero minutes during a program week) at least once. Departments were randomized into the "targeted message only" (TMO) or "targeted + tailored message" (TTM) group. Participants who did not provide a program goal were in the default control group (DC). After the first instance of non-compliance, participants received a targeted message. For subsequent instances of non-compliance, the TMO group continued to receive the same targeted message, up to three consecutive times. The TTM group received a message tailored to the participant's program goal. The DC group did not receive additional messages. RESULTS: A total of 149 D2M participants were included for analysis. Participants were mostly female (68.5%), staff (44.3%), with an average age of 43.66 (SD = 11.10). Age, employee status, and PA status were controlled for in each model. A nested ANCOVA revealed a significant difference in non-compliance between the TTM (M = 2.64, SD = 1.93) and TMO (M = 3.95, SD = 2.1) groups, $F(16,88) = 3.39$, $p < .001$, $\eta^2 = .38$; $d = .64$. The ANCOVA that compared the TTM (M = 2.64, SD = 1.93) and DC (M = 3.75, SD = 2.10) groups revealed a significant difference, $F(1,74) = 13.29$, $p < .001$, $\eta^2 = .152$; $d = .56$. There was not a significant difference between the TMO and DC groups, $F(1,80) = .10$, $p = .750$, $\eta^2 = .001$; $d = .02$. CONCLUSION: Tailored email messages appeared to improve program implementation and are encouraged for future programs. Additional research is needed to understand how message frequency influences non-compliance and how PA status influences message effectiveness.

INDEX WORDS: eHealth, mHealth, physical activity, tailored, personalized, wellness

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DEDICATION

To Kanaan, for keeping me company along the most challenging part of this journey, and to Julian, for encouraging me to keep going.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 A SYSTEMATIC REVIEW OF TAILORED MHEALTH INTERVENTIONS OF PHYSICAL ACTIVITY PROMOTION AMONG ADULTS (IN PRESS)

Low physical activity (PA) rates are consistently reported in the United States, with about 80% of adults not meeting recommended guidelines of 150 to 300 minutes of moderate-to-vigorous physical activity (MVPA) per week (U.S. Department of Health and Human Services, 2018). Although PA interventions are commonly used, previous interventions varied in quality and displayed modest effects (Conn, Hafdahl, & Mehr, 2011). As such, research should identify and utilize techniques that improve intervention outcomes and can reach large populations.

Mobile health (mHealth) emerged as an intervention delivery channel that can potentially address the public health need for PA promoting programs. The majority of Americans own a cellphone (96%), with 81% owning a smartphone specifically (Pew Research Center, 2019), and 52% owning a tablet computer (Pew Research Center, 2019). The wide reach of mHealth is encouraging because it may offer a way to reach populations traditionally underserved by PA interventions, such as racial minorities and individuals from low education/income households. About 26% of Americans living in low-income households are "smartphone dependent" internet users, meaning they lack broadband home service (Anderson & Kumar, 2019). Although African-Americans and Hispanics are less likely than Whites to own a desktop or laptop computer, they are equally as likely to own mobile devices (Perrin, 2017b). With the increasing ownership of mobile devices, mHealth is a feasible and relatively inexpensive delivery channel and a promising way to maximize the reach of PA interventions.

Several studies examined the use of mobile devices to promote health behaviors. Gal et al. conducted a systematic review and meta-analysis that examined the effectiveness of PA interventions using wearable devices and mobile apps (Gal, May, van Overmeeren, Simons, & Monninkhof, 2018). The authors identified 18 studies that either promoted PA through a mobile app (smartphone or tablet) supported by wearable devices or an accelerometer supported by an online dashboard (Gal et al., 2018). Overall, the authors found interventions using wearables and smartphone apps significantly improved PA. In the analysis, a moderate effect was identified for objectively measured change in MVPA and a moderate-to-large effect was identified for change in daily step count (Gal et al., 2018). The authors did not find a significant effect for subjectively measured change in MVPA (Gal et al., 2018). Similarly, Direito et al. performed a systematic review and meta-analysis to examine the effectiveness of mHealth on PA and sedentary behavior outcomes (Direito, Carraça, Rawstorn, Whittaker, & Maddison, 2017). The analysis included 21 randomized control trials (RCTs) and the results indicated a small-to-moderate positive effect for PA and walking outcomes (Direito et al., 2017); however, differences between intervention and control groups were not significant (Direito et al., 2017). Although the results from both studies provided support for the use of mobile devices to deliver PA interventions, they were limited by a low number of studies and high statistical heterogeneity. Therefore, additional research is needed to examine the effectiveness of mHealth interventions for physical activity behavior change.

Another way to increase the effectiveness of PA interventions is with tailoring. Kreuter and Skinner (Kreuter & Skinner, 2000) defined tailoring as “any combination of information or change strategies intended to reach one specific person, based on characteristics that are unique to that person, related to the outcome of interest, and have been derived from an individual assessment." Similarly, Beck et al. (Beck et al., 2010) suggested a tailored intervention is one that targets the characteristics of an individual, such as personality factors or goals, within a group. Tailoring is sometimes confused with targeted approaches, which are intended to reach a population based on a common characteristic (Kreuter & Wray, 2003). While targeted interventions deliver more personally relevant information than generic approaches, tailored interventions are theorized to be superior because they target individual characteristics (Kreuter & Wray, 2003). Tailored materials are thought to stimulate cognitive activity more than generic or standardized materials, thus encouraging more thoughtful appraisal of the information being delivered (Albada, Ausems, Bensing, & van Dulmen, 2009). Previous research demonstrated tailored materials were more effective at eliciting a behavior change than non-tailored materials (Kreuter, Oswald, Bull, & Clark, 2000).

Tailored interventions can vary drastically by the channel of delivery and dimension on which the tailoring occurs. Tailored materials delivered via print media, phone, and internet successfully promoted healthy behavior changes (Lustria, Cortese, Noar, & Glueckauf, 2009; Noar, Benac, & Harris, 2007). Interventions have also increasingly been delivered via mobile devices, such as cell phones (Enwald & Huotari, 2010). Regarding dimension, interventions were commonly tailored on theoretical frameworks and concepts (Lippke, Schwarzer, Ziegelmann, Scholz, & Schüz, 2010), personality (York, Brannon, & Miller, 2012), and behavior and demographics (Albada et al., 2009). Furthermore, there can be variability regarding the degree of individualization of the intervention and how many times the individual is assessed (static versus dynamic). Static tailoring refers to materials tailored based on a single assessment point, whereas dynamic tailoring refers to materials tailored based on iterative assessments (Krebs, Prochaska, & Rossi, 2010). Although there are a wide range of successful tailored study designs, the specific components required closer examination.

Two systematic reviews examined the impact of tailored interventions on PA (Neville, O'Hara, & Milat, 2009; Short, James, Plotnikoff, & Girgis, 2011). Neville et al. (Neville et al., 2009) found tailoring had a significant, positive impact on 14 out of 16 studies and Short et al. (Short et al., 2011) identified a significant, positive impact in 9 out of 14 studies. However, Neville et al. (Neville et al., 2009) also reported there were no significant between group (tailored treatment vs. control) differences for 7 out of 14 studies that demonstrated significant improvements. Additionally, four meta-analyses examined the effect of tailored interventions on health-related outcomes (Anderson, 2011; Krebs et al., 2010; Lustria et al., 2013; Noar et al., 2007). Three out of four meta-analyses (Anderson, 2011; Krebs et al., 2010; Noar et al., 2007) reported small, significant effects for tailored PA interventions ("improvement" $g = .20$, $p < 0.01$ and "CDC guidelines" $g = 0.32$, $p < .01$; $g = 0.16$, $p < .001$; $r = 0.028$) and one meta-analysis (Lustria et al., 2013) did not observe a significant effect for tailored PA interventions ($d = 0.059$, 95% CI -0.02, 0.138). Altogether, this evidence suggests tailoring may be an appropriate technique to promote PA, however it is not clear if this is true for all delivery channels. The focus of the aforementioned reviews and meta-analyses included tailored print interventions (Noar et al., 2007; Short et al., 2011) computer-tailored (tailored via a computer, but delivered through various channels) interventions (Anderson, 2011; Krebs et al., 2010; Neville et al., 2009), and web-delivered interventions (Lustria et al., 2013). With the increase in tailored mHealth interventions, a systematic review of the literature specifically examining tailored mobile interventions for PA is warranted.

Gaps in the literature make it necessary to gain a better understanding of how tailoring can be used with mobile technology to impact PA promotion. Ghanvatkar et al. conducted a scoping review to identify personalized, technology-based PA interventions (Ghanvatkar, Kankanhalli, & Rajan, 2019). They highlighted the various intervention components used in recent studies, however, this review was not limited to mobile devices, did not consider study quality, and included studies without results (e.g. published protocol); therefore, a more thorough investigation of the effectiveness of tailored mobile PA interventions is needed. The purpose of this review was to summarize and critically examine the current evidence, and to make recommendations for future research on tailored mHealth interventions for promoting PA in adult populations. This review sought to answer the following questions:

1. How do tailored mHealth interventions compare to non-tailored interventions?
2. How do tailored mHealth interventions compare to other forms of tailored interventions?
3. How do tailored mHealth design features differ on (a) mode of delivery, (b) tailoring dimension, (c) frequency of assessments, (d) PA outcome measure, and (e) objectivity of PA measurement?

Method

Literature search

In line with the PRISMA guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009), searches of the following databases were performed in June 2019: Cochrane Library Central Register of Controlled Trials, Medline, SportDiscus, PubMed, PsycINFO, and ProQuest. Databases were searched using the search terms *tailored or computer-tailored or personalized AND mobile device or smartphone or cellphone or tablet AND physical activity or exercise or physical exercise AND intervention or program or randomized control trial.* Two of the study authors

(AD & RS) independently examined article titles and abstracts for inclusion. Then, both authors reviewed the full text to determine eligibility. The reference lists of included articles were also manually searched. Two authors (AD & RS) also independently coded the included articles using the Risk of Bias 2 assessment (Sterne et al., 2019). The first author extracted study data and the second author reviewed the standardized spreadsheet for accuracy. The protocol was registered with PROSPERO (registration number CRD42019136592).

Eligibility criteria

Studies were eligible for this review if they consisted of either a randomized controlled trial or quasi-experimental study design. Studies could be published or quality unpublished studies. Only studies examining adult populations (18+ years) were eligible. Studies limited to athletic populations were not eligible because athletes likely possess a greater degree of motivation to be physically active, making it difficult to compare outcomes with non-athletic populations. Studies were eligible if they consisted of a tailored intervention that was delivered via a mobile device (i.e. cell phone, tablet). Studies that delivered a tailored mHealth PA intervention but were measuring an additional treatment element were excluded because we would not have been able to evaluate the effects of tailoring. Control groups could consist of no-treatment/wait list controls, minimal/generic information controls, or a non-mHealth tailored comparison group. Studies had to include a PA behavior as an outcome measure. PA could be assessed using self-report or objective measures. Studies only reporting fitness measures were excluded because these are not direct measures of behavior change. Lastly, studies not available in English were excluded.

Quality assessment: risk of bias

The study authors used the Cochrane Collaboration's Risk-of-Bias (RoB) 2 tool to assess study bias (Sterne et al., 2019). The tool was used to judge studies to be low or high risk-of-bias, or to raise some concerns for each of the following domains: bias arising from the randomization process, bias due to deviations from intended interventions, bias due to missing outcome data, bias in measurement of the outcome, and bias in selection of the reported results. Additionally, the authors reached an overall judgement of risk-of-bias for each study following the RoB 2 criteria (Higgins et al., 2016). If the study was judged to be low risk on all domains, the overall judgment was "low risk-of-bias". If the authors judged a study to raise some concerns on at least one domain, but not to be at high risk on any domains, the overall judgement was "some concerns". Lastly, if a study was judged to be high risk on one or more domain or to have some concerns on multiple domains, the overall judgement was "high risk-of-bias".

Data analyses

Data for this study were descriptively assessed by examining how tailored mHealth interventions for PA were delivered and how they impacted PA behavior. Specifically, we compared studies based on type of control group, how tailoring was implemented, mode of intervention delivery, PA outcome measures, frequency of contact by researchers, and intervention components. To make comparisons, the following data were extracted: study population, participant demographics, tailoring delivery channel, tailoring dimension, PA outcome measure and measurement tool, intervention components, type of control, frequency of participant assessments, and study outcomes.

Results

Study selection

The database searches yielded 1,260 results. An additional 8 studies were identified through reference list searches. With the removal of duplicates, a total of 1,227 abstracts and titles were screened, which led to the exclusion of 1,196 articles. The full text of the remaining articles were screened, and 13 were excluded because they did not meet the eligibility criteria. Two studies were represented by more than one article, so the articles reporting PA outcomes were used (Demeyer et al., 2017; Mistry, 2013). A total of 16 articles were included in the systematic review (see Figure 1.1).

Study characteristics

The 16 studies in this review included a total of 2,309 participants (*M* = 123.3; range = 17 - 343) from a variety of populations. Eight studies specifically targeted PA (Agboola et al., 2016; Demeyer et al., 2017; Martin et al., 2015; Mistry, 2013; Simons et al., 2018; Tucker et al., 2016; Yom-Tov et al., 2017; Zhou et al., 2018) and the remaining eight targeted weight loss or multiple health behaviors in which PA was an outcome (Hebden et al., 2014; O'Brien, 2014; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Rabbi, Pfammatter, Zhang, Spring, & Choudhury, 2015; Spring et al., 2017, 2018; Willcox et al., 2017). Twelve studies included healthy adults, with a focus on university students and/or staff (O'Brien, 2014; Rabbi et al., 2015; Zhou et al., 2018), sedentary adults (Martin et al., 2015; Mistry, 2013), overweight adults (Hebden et al., 2014; Spring et al., 2017, 2018), young adults (Partridge et al., 2015; Simons et al., 2018), clinic employees (Tucker et al., 2016), and pregnant women (Willcox et al., 2017). Four studies targeted patient populations with diabetes (Agboola et al., 2016; Yom-Tov et al., 2017), chronic obstructive pulmonary disease (Demeyer et al., 2017), and coronary heart disease (Pfaeffli Dale et al., 2015). All except four studies (Martin et al., 2015; Pfaeffli Dale et al., 2015; Rabbi et al., 2015; Yom-Tov et al., 2017) reported mostly female participants and the mean age range across all studies was 18.7 years to 59.5 years. In the nine studies that reported race, 61.4% of participants were White (Agboola et al., 2016; Martin et al., 2015; Mistry, 2013; O'Brien, 2014; Pfaeffli Dale et al., 2015; Spring et al., 2017, 2018; Tucker et al., 2016; Zhou et al., 2018). Eleven studies reported education and 68.3% of participants had at least some college education (Agboola et al., 2016; Mistry, 2013; O'Brien, 2014; Partridge et al., 2015; Rabbi et al., 2015; Simons et al., 2018; Spring et al., 2017, 2018; Tucker et al., 2016; Willcox et al., 2017; Zhou et al., 2018). Five studies reported on socioeconomic status (Hebden et al., 2014; Partridge et al., 2015) or income (Mistry, 2013; Pfaeffli Dale et al., 2015; Willcox et al., 2017). Seventy-three percent of participants were in the highest socioeconomic status quintile (81-100%) and 61.1% of participants reported household incomes over $50k.

Of the studies included, all but two were published in peer-reviewed journals. The unpublished studies were a master's thesis (Mistry, 2013) and a doctoral dissertation (O'Brien, 2014). A published article representing the Text2Plan study was identified in the search process, however PA outcomes were not reported, so the Mistry (Mistry, 2013) thesis was used. The mean study duration was 14.6 weeks and range was 3 weeks (Rabbi et al., 2015) to 26 weeks (Yom-Tov et al., 2017). The study targeting pregnant women lasted from the point of recruitment to 36 weeks gestation (Willcox et al., 2017). Eleven studies were RCTs (Agboola et al., 2016; Demeyer et al., 2017; Martin et al., 2015; O'Brien, 2014; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Rabbi et al., 2015; Spring et al., 2017, 2018; Yom-Tov et al., 2017; Zhou et al., 2018), two were cluster RCTs (Simons et al., 2018; Tucker et al., 2016), two were pilot RCTs (Hebden et al., 2014; Willcox et al., 2017), and one was quasi-experimental (Mistry, 2013). There were 38 intervention arms. Eleven studies had two arms (Agboola et al., 2016; Demeyer et al., 2017; Hebden et al., 2014; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Rabbi et al., 2015;

Simons et al., 2018; Tucker et al., 2016; Willcox et al., 2017; Yom-Tov et al., 2017; Zhou et al., 2018), four studies had three arms (Martin et al., 2015; Mistry, 2013; Spring et al., 2017, 2018), and one study had four arms (O'Brien, 2014). The study by Tucker et al. (Tucker et al., 2016) was a cross-over design, so for this review, the data reported at the 3 month point (before cross-over) was used to examine the impact of the treatment because a carry-over effect would be likely for this type of intervention. A summary of these studies is presented in Table 1.1.

Quality assessment

Figure 1.2 shows the review authors' judgements about the risk of bias items for the included studies. Inter-rater agreement ranged from 81.25 – 100% on the five domains (randomization process- 81.25%, deviations from intended intervention- 81.25%, missing outcome data- 100%, measurement of outcome data – 93.75%, selection of the reported results – 93.75%). For overall bias, seven studies were judged to have some concerns (Agboola et al., 2016; Hebden et al., 2014; Mistry, 2013; O'Brien, 2014; Simons et al., 2018; Spring et al., 2018; Yom-Tov et al., 2017), seven were judged to be low risk (Demeyer et al., 2017; Martin et al., 2015; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Rabbi et al., 2015; Willcox et al., 2017; Zhou et al., 2018), and two were judged to be high risk (Spring et al., 2017; Tucker et al., 2016). All but two studies described the use of random sequence generators for the randomization process. Mistry (Mistry, 2013) assigned participants based on date of birth. Tucker et al. (Tucker et al., 2016) did not describe in detail how the cluster randomization sequence was obtained. Only four studies reported participants were not aware of treatment conditions (Hebden et al., 2014; Mistry, 2013; Partridge et al., 2015; Rabbi et al., 2015), although participants were likely aware of the targeted behavior. One reported people delivering the intervention were not aware of treatment delivered (Yom-Tov et al., 2017). None of these studies explicitly stated how treatment conditions were concealed

(Hebden et al., 2014; Mistry, 2013; Partridge et al., 2015; Rabbi et al., 2015; Yom-Tov et al., 2017). The study by Tucker et al. (Tucker et al., 2016) was judged to be high risk on the "randomization process" domain because they did not indicate if the allocation sequence was concealed until participants were enrolled, and because there were significant baseline differences between groups. All studies were judged to be low risk on the "deviations from intended interventions" and "missing outcome data" domains. One study was judged to be high risk on the "measurement of the outcomes" domain because the measurement tools differed between groups (Spring et al., 2017). The outcome measure was percentage of days PA reported. It was measured by accelerometer in the technology intervention group and paper diary in the other two groups (self-guided and standard). The other studies were judged to be low risk on this domain. Six studies were judged to have some concerns on the "selection of the reported results" domain because the authors did not clearly indicate if the data were analyzed in accordance with a pre-specified analysis plan (Agboola et al., 2016; Hebden et al., 2014; Mistry, 2013; O'Brien, 2014; Simons et al., 2018; Tucker et al., 2016). The other studies were assessed as low risk on this domain.

Impact of tailored mHealth on PA

For overall impact of tailored mHealth interventions on PA, ten studies (62.5%) reported significant improvements in PA or greater PA levels for the intervention groups compared to the controls (Demeyer et al., 2017; Martin et al., 2015; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Rabbi et al., 2015; Spring et al., 2017, 2018; Willcox et al., 2017; Yom-Tov et al., 2017; Zhou et al., 2018). The other six found no between group differences (Agboola et al., 2016; Hebden et al., 2014; Mistry, 2013; O'Brien, 2014; Simons et al., 2018; Tucker et al., 2016). Of the studies that found no between group differences, two reported decreases in PA outcomes from baseline to follow-up (Agboola et al., 2016; Simons et al., 2018), three reported positive changes for both the intervention and control groups (Hebden et al., 2014; Mistry, 2013; Tucker et al., 2016), and one reported no within group differences (O'Brien, 2014).

How do tailored mHealth interventions compare to non-tailored interventions?

Control groups. Various control groups were used, and some study controls were provided more than one component. Five studies used generic information delivered by print materials (Demeyer et al., 2017; Hebden et al., 2014; Simons et al., 2018) or SMS and/or website (Mistry, 2013; Partridge et al., 2015). Four studies used non-tailored technology such as SMS (Mistry, 2013; Partridge et al., 2015), pedometers (Agboola et al., 2016), or accelerometers (Martin et al., 2015). Other control groups included usual care/standardized program (Pfaeffli Dale et al., 2015; Spring et al., 2017; Willcox et al., 2017), non-tailored recommendations/reminders (Rabbi et al., 2015; Yom-Tov et al., 2017; Zhou et al., 2018), in-person diet session (Hebden et al., 2014), sleep training contact control (Spring et al., 2018), and environmental intervention (Tucker et al., 2016). Only one study used a no-information control group (O'Brien, 2014). No differences in study outcomes based on control groups were observed. Three studies reported significant improvements in the control group. Hebden et al. (Hebden et al., 2014) used an in-person session with a dietitian and a 10-page printed booklet with generic PA and diet recommendations. Mistry (Mistry, 2013) used generic physical activity text messages. Tucker et al. (Tucker et al., 2016) used an environmental intervention that included treadmill desks, Wii play stations, instructional PA videos, and walking/stair climbing meetings.

Treatment arms. Of the five studies that included more than one treatment arm, three reported significant improvements in PA for the tailored intervention arm compared to the non-tailored treatment arms (Martin et al., 2015; Spring et al., 2017, 2018). The other two reported no between group differences (Mistry, 2013; O'Brien, 2014). A greater percentage of (81.8%) studies with only one treatment arm reported significant improvements in PA or greater PA levels for the intervention groups compared to the controls than did studies with multiple treatment arms (60%).

How do tailored mHealth interventions compare to other forms of tailored interventions?

None of the studies compared mobile tailored interventions to another form of tailored intervention (e.g. tailored print materials), so this question could not be addressed.

How do tailored mHealth design features differ on (a) mode of delivery, (b) tailoring dimension, (c) frequency of assessments, (d) PA outcome measure, and (e) objectivity of PA measurement?

Mode of delivery. Regarding the delivery of tailored materials, eight studies used short message service (SMS) (Agboola et al., 2016; Martin et al., 2015; Mistry, 2013; O'Brien, 2014; Pfaeffli Dale et al., 2015; Tucker et al., 2016; Willcox et al., 2017; Yom-Tov et al., 2017), four used mobile apps (Demeyer et al., 2017; Rabbi et al., 2015; Simons et al., 2018; Zhou et al., 2018), and two used phone calls (cellphones were provided to participants in intervention group for both studies; (Spring et al., 2017, 2018)). The remaining two used more than one channel to deliver tailored content (Hebden et al., 2014; Partridge et al., 2015). Of the studies that reported significant between group differences, four used SMS (Martin et al., 2015, Pfaeffli Dale et al., Willcox et al., 2017, Yom-Tov et al., 2017), three used mobile app (Demeyer et al., 2017, Rabbi et al., 2015, Zhou et al., 2018), and one used multiple delivery channels (SMS and phone call; Partridge et al., 2015). Both studies using phone calls reported significant improvements in tailored group over the control (Spring et al., 2017, 2018). Two of the studies that did not report significant between group differences but did report significant treatment group improvements used SMS as the delivery channel (Mistry, 2013; Tucker et al., 2016) and one used multiple modes of delivery (SMS, mobile app, and email; Hebden et al., 2014).

Tailoring dimension. Across studies, tailoring occurred on a variety of dimensions. Half of the studies reported tailoring on two or more dimensions. Tailored content was most commonly delivered as feedback on PA behavior (Agboola et al., 2016; Demeyer et al., 2017; Martin et al., 2015; Rabbi et al., 2015; Spring et al., 2017, 2018; Tucker et al., 2016; Willcox et al., 2017). This was followed by tailoring on personal information/preferences, such as name or the time of day messages were sent (Martin et al., 2015; Mistry, 2013; O'Brien, 2014; Pfaeffli Dale et al., 2015; Simons et al., 2018; Willcox et al., 2017), and tailoring PA goals (Agboola et al., 2016; Demeyer et al., 2017; Martin et al., 2015; O'Brien, 2014; Simons et al., 2018; Zhou et al., 2018). Only three studies reported tailoring on theoretical constructs. Two studies (Hebden et al., 2014; Mistry, 2013) used Transtheoretical Model constructs (processes-of-change; attitudes and perceived behavioral control). Rabbi et al. (Rabbi et al., 2015) used automatically generated behavior suggestions based on the Social Cognitive Theory, the Learning Theory, and the Fogg Behavioral Model. One study tailored on the type of feedback message sent to participants (Yom-Tov et al., 2017). This study used an algorithm-based learning system to identify the type of message that best encouraged an increase in PA for individual participants. Overall, it was difficult to assess differences in intervention effect based on individual tailoring dimensions because of the various ways tailoring was performed. More of the studies that reported tailoring on one dimension observed significant differences in PA compared to the controls (Demeyer et al., 2017; Partridge et al., 2015; Spring et al., 2017, 2018; Yom-Tov et al., 2017; Zhou et al., 2018) than did studies that tailored on two or more dimensions (Martin et al., 2015; Pfaeffli Dale et al., 2015; Rabbi et al., 2015; Willcox et al., 2017).

Of the six studies that reported no between group differences on PA outcomes, most of them used SMS to deliver the tailored materials (Agboola et al., 2016; Mistry, 2013; O'Brien, 2014; Tucker et al., 2016), one study used an app (Simons et al., 2018), and one study used both (Hebden et al., 2014). Two of the four studies that used SMS saw improvements for both groups (Mistry, 2013; Tucker et al., 2016) and the other two found either no within group change (O'Brien, 2014) or a decrease in PA (Agboola et al., 2016). In the study that used an app, both groups had a decrease in PA (Simons et al., 2018). The study that used both SMS and an app reported a significant improvement in light PA for the intervention group (Hebden et al., 2014).

Frequency of assessments. Participants were contacted on at least a weekly basis in all studies. Twelve studies used tailored content based on participant information retrieved from multiple assessments (dynamic tailoring) throughout the intervention (Agboola et al., 2016; Demeyer et al., 2017; Hebden et al., 2014; Martin et al., 2015; Mistry, 2013; Rabbi et al., 2015; Simons et al., 2018; Spring et al., 2017, 2018; Tucker et al., 2016; Yom-Tov et al., 2017; Zhou et al., 2018). This was most commonly done by assessing participant behavior and providing tailored feedback or goals (Agboola et al., 2016; Demeyer et al., 2017; Martin et al., 2015; Rabbi et al., 2015; Simons et al., 2018; Spring et al., 2017, 2018; Tucker et al., 2016; Zhou et al., 2018). Four studies only described a single assessment (static tailoring) at baseline (O'Brien, 2014; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Willcox et al., 2017). Six of twelve studies that used dynamic tailoring and three of four studies that used static tailoring reported significant between group differences for PA.

PA outcome measures. Most studies (n = 14) used either moderate to vigorous PA (MVPA), step counts, or walking minutes to measure PA behavior (Agboola et al., 2016; Demeyer et al., 2017; Hebden et al., 2014; Martin et al., 2015; Mistry, 2013; O'Brien, 2014;

Pfaeffli Dale et al., 2015; Rabbi et al., 2015; Simons et al., 2018; Spring et al., 2017; Tucker et al., 2016; Willcox et al., 2017; Yom-Tov et al., 2017; Zhou et al., 2018) and several studies used more than one measure (n = 7). Other outcome measures were light PA, total daily activity, adherence to PA self-monitoring, MET-min/week, aerobic time, and days of PA (Hebden et al., 2014; Martin et al., 2015; O'Brien, 2014; Partridge et al., 2015; Spring et al., 2018; Willcox et al., 2017). A summary of PA measurement outcomes and tools was presented in Table 1.2. All but one study (Spring et al., 2018) reporting significant group differences for the tailored group over the control used MVPA, step counts, and/or walking minutes as PA measures. Sprint et al. (2018) used percentage of days participants reported PA. All three of the studies that did not report significant between group differences but did report significant treatment group improvements used MVPA as a measure of PA (Hebden et al., 2014; Mistry, 2013; Tucker et al., 2016).

Objectivity of PA measurement. Eight studies measured PA objectively with an wearable accelerometer or pedometer, a smartphone accelerometer, or an iPhone health chip (Agboola et al., 2016; Demeyer et al., 2017; Hebden et al., 2014; Martin et al., 2015; Rabbi et al., 2015; Tucker et al., 2016; Yom-Tov et al., 2017; Zhou et al., 2018). Six studies used subjective measures (Mistry, 2013; O'Brien, 2014; Partridge et al., 2015; Pfaeffli Dale et al., 2015; Spring et al., 2018; Willcox et al., 2017). Two studies reported using both an objective and subjective measure (Simons et al., 2018; Spring et al., 2017). The study by Spring et al. (Spring et al., 2017) used an accelerometer for the TECH intervention group, while the other two groups used self-reported paper diaries. Of the 10 studies that reported significant differences in PA for the intervention group over the controls, 5 used objective measures (Demeyer et al., 2017; Martin et al., 2015; Rabbi et al., 2015; Yom-Tov et al., 2017; Zhou et al., 2018), 4 used subjective measures (Partridge et al., 2015; Pfaeffli Dale et al., 2015; Spring et al., 2018; Willcox et al., 2017), and 1 used both (Simons et al., 2018). For the six studies that reported no group differences, three used objective measures (Agboola et al., 2016; Hebden et al., 2014; Tucker et al., 2016), two used subjective (Mistry, 2013; O'Brien, 2014), and one used both (Spring et al., 2017).

Discussion

The present study was a systematic review of 16 studies that examined the effectiveness of tailored mHealth interventions for promoting PA in adult populations. Overall, tailored mHealth interventions were effective at promoting PA. Most of the studies (81.2%) reported an improvement in PA or a smaller reduction of PA (i.e. intervention group was less likely to reduce light or moderate PA during pregnancy). Significant differences compared to control groups were reported in 10 of 13 studies.

These results are comparable to the findings from a similar review (Ryan, Dockray, & Linehan, 2019) that examined the evidence for tailored eHealth interventions for weight loss. Ryan et al. (2019) reported tailored interventions were more effective in supporting weight loss than controls in four of the six studies reviewed. The authors also identified variations in effects between tailored and non-tailored interventions and types of tailoring (Ryan et al., 2019). Our review differed in that it focused on tailored PA interventions delivered via mobile devices. However, the results from both studies suggest tailoring combined with technology can be used to support health promoting behaviors.

Studies included in this review used varying types of control groups. None of them used a no information or waitlist control group. Several used generic information groups, however, the information was still provided in an active way, such as through frequent SMS or a mobile app. This may be a study limitation, but considering most studies reported significant between group differences in PA outcomes, it also demonstrates that tailored interventions may be more effective than other types of interventions for promoting PA. However, it should be noted that most of the reviewed studies included multiple intervention components. As a result, it was difficult to identify if tailoring was the mechanism that promoted behavior change. Lustria et al. (Lustria et al., 2013) suggested interactive elements, such as mobile app self-monitoring, might enhance participant engagement and make tailoring more effective. Therefore, it is important to understand adherence information, as well as to investigate what program components participants identify as appealing because participants may disengage from an intervention if their needs are not being met (Lie, Karlsen, Oord, Graue, & Oftedal, 2017). Twelve studies reported measuring participant engagement or program adherence. This is useful information and should be continued by researchers, as the feedback can help increase the impact of tailored mHealth programs for PA.

A secondary aim of this review was to examine differences in how tailoring was conducted (channel, dimension, and frequency of assessments), the PA outcome measure and measurement tool used, and the objectivity of PA measurement. Quantitative analyses were not completed in this study, so differences were difficult to discern. However, a few observations were made. Regarding tailoring channel, most of the studies that did not report between group differences used SMS to deliver tailored content (Agboola et al., 2016; Mistry, 2013; O'Brien, 2014; Tucker et al., 2016). Furthermore, only one of those studies included other substantial intervention components (Tucker et al., 2016). Studies successfully used SMS to promote PA behavior, but it is possible that SMS is best used to support additional intervention components rather than serve as the primary delivery channel (Fanning, Mullen, & McAuley, 2012). For tailoring dimension, 75% of studies that tailored on one dimension reported significant findings compared to

50% of studies tailored on two or more dimensions. In addition, more of the studies that used static tailoring reported significant between group differences compared to the studies that used dynamic tailoring. Together, these findings are interesting because a more personalized intervention should lead to increased participant engagement and theoretically, greater improvements in PA. Another observation was there were no differences in study outcomes by type of measurement tool (objective or subjective). This is in line with a meta-analysis of mHealth technologies for PA and sedentary behavior (Direito et al., 2017) in which the authors did not find significant differences in PA outcomes on objective versus subjective measures.

Limitations should be considered when interpreting the findings of this review. One concern is differences in how tailoring was used and described. Some studies specifically described interventions as being tailored, while others used terms such as personalized or individualized, in some cases with little detail. Discrepancies in how studies described tailoring may have led to some studies being missed during the search process. Additionally, there were substantial differences in the level of tailoring. For example, Hebden et al. (Hebden et al., 2014) tailored motivational advice based on participants TTM processes of change, whereas Pfaelli et al. (Pfaeffli Dale et al., 2015) tailored text messages on the participant's name, preferred time of day to receive texts, and activity recommendations based on preferred activities. It was argued that the greater the level of personalization, the greater the perceived relevance of the materials to the participant (Kreuter & Wray, 2003). Additional research is needed to test a possible dose-response relationship for the level of tailoring in PA programs.

Another limitation is the inability to generalize these results to all populations that use mobile devices. Aside from the focus on adults, we did not set restrictions on the type of populations eligible for inclusion. Although a strength of this review is the inclusion of patient and healthy populations, most participants were female, White, well educated, and higher earning. As previously mentioned, there are not significant racial differences in terms of who uses mobile devices in the U.S. Furthermore, individuals with lower household incomes are more likely to be smartphone dependent, but they were not represented in the studies reviewed. It should be noted, though, that the study by Simon et al. (Simons et al., 2018) specifically targeted lower educated working adults. mHealth has the unique potential to improve program reach to populations most in need; therefore, researchers should make a concerted effort to include samples more representative of the populations who use this technology.

Lastly, we were limited in our ability to draw conclusions regarding the effect of tailored mHealth interventions or identify potential moderators. We described the quality and tailoring techniques of included studies and made comparisons on PA outcome measures. Additionally, the studies reviewed represented a wide variation in study designs. Previous meta-analyses that examined similar types of interventions found significant heterogeneity (Direito et al., 2017; Gal et al., 2018). Although not measured, that would likely be the case among studies included in this review. A quantitative analysis is warranted to better understand the relationship between various aspects of tailored mobile PA interventions.

Our results have implications for PA promotion programs. First, practitioners and public health professionals interested in delivering scalable programs should consider using tailored mHealth to deliver PA programs because they can offer wider access than face-to-face programs. This is also in line with the Healthy People 2020 recommendation to increase access of health communication technology ("Health Communication and Health Information Technology | Healthy People 2020," n.d.). Based on the results of this review, programs can target MVPA, steps, or walking minutes using objective or subjective measures. Programs can be delivered using SMS, mobile apps, or phone calls. If SMS is the only feasible option available, it may be best used as a supporting feature to an additional program component. Second, formal frameworks, such as the Behavioral Intervention Technology Model (Mohr, Schueller, Montague, Burns, & Rashidi, 2014), should be researched and used to standardize the design of tailored mHealth programs. This will help operationalize the terms and identify active components of tailored mHealth materials. Lastly, our findings point to the need for formal process evaluations that should include cost-effectiveness analyses. Process evaluations are important for understanding tailored mHealth components like static versus dynamic tailoring, delivery channels (to ensure content is being received), and the representativeness of program participants. Existing gaps in the literature limit our ability to fully examine efficacy. Further, tailoring uses considerably more time and resources, making it less practical from a cost-effectiveness standpoint. Before making program recommendations, researchers should test whether the use of tailored materials leads to improvements that justify the cost over other types of materials.

The findings from this review can help shape future tailored mHealth programs for PA. mHealth programs can potentially have a larger reach than traditional programs and thus, should be designed to engage diverse populations. Future studies should be completed to specifically test the utility of tailored materials delivered via mobile device, without the inclusion of multiple intervention components, so the mechanisms that may promote PA can be identified. It is also necessary to identify how participants engage with tailored mHealth programs. Increasing program engagement may contribute to more sustained PA behavior change.

Conclusion

In summary, tailored mHealth interventions appear to be promising for promoting PA among adults. Most interventions used multiple intervention components. Additional research is needed to identify best practices and to make programs scalable.

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Table 1.1

Study Characteristics

Study	Population	N/M_{age} (years)/sex (% female)	Duration/tailoring frequency/treatment arm(s)	Control	Main findings
Agboola (Agboola et al., 2016)	English or Spanish-speaking adult patients with type II diabetes	126/51.4/ 51.6	6 months/Dynamic/(1)Tailored and targeted text messages	Pedometer-no texts	Intervention group had greater monthly step count, but not significantly different than control. Both groups decreased from baseline to end of study.
*Demeyer (Demeyer et al., 2017)	Patients with COPD	343/66.5/63.9	12 weeks/Dynamic/ (1) Initial counseling interview, pedometer, mobile app (self-monitoring, automated telecoaching), group texts with PA suggestions, phone call if non-compliant with pedometer	Standard info (leaflet)	Intervention group had significant increase over controls on mean steps/day (M = 1469, p > .001), 95% CI [937, 1965] and moderate PA min/day (M = 10.4, p > .001), 95% CI [6.1,14.7].
Hebden (Hebden et al., 2014)	Overweight Young Adults	51/22.8/80	12 weeks/Dynamic/ (1) mHealth program using mobile app (self-monitoring, tailored advice, feedback on population health recommendations), tailored SMS and email messages, internet forums	Generic info and diet counselling session	Intervention group significantly increased light intensity PA min/day by (M = 34.2, SD = 35.1, p = .006) but between group differences were not significant.
*Martin (Martin et al., 2015)	Adult patients age 18-69 not meeting PA guidelines	48/58.8/ 46	5 weeks/Dynamic/ (1) Unblinded accelerometer, mobile app self-monitoring; (2) Unblinded accelerometer, mobile app self-monitoring, personalized SMS	Blinded accelerometer use	Text group increased daily steps over no text group (M = 2534; p < .001), 95% CI [1318, 3750], and blinded controls (M = 3376; p < .001), 95% CI [1951, 4801].

Study	Population	N/M_{age} (years)/sex (% female)	Duration/tailoring frequency/treatment arm(s)	Control	Main findings
Mistry (Mistry, 2013)	Inactive Canadian adults age 25-45 years	239/30.7/77	8 weeks/Dynamic/ (1) Generic texts, emails for PA planning; (2) Tailored text messages, emails for PA planning	Generic PA info texts, emails for PA planning	No significant difference between groups. All groups demonstrated an increase in PA.
O'Brian (O'Brien, 2014)	College students	151/8.7/73.5	30 days/Static/ (1) Health behavior feedback, (2) health behavior feedback, standardized text messages, (3) health behavior feedback, tailored text messages	Assessment only	No significant difference between tailored text message group and assessment only group or active control group on PA (increase in PA or meeting CDC recommendations).
*Partridge (Partridge et al., 2015)	Young adults	214/27.7/ 61.3	12 weeks/Static/ (1) Weekly motivational text messages, personalized coaching calls, access to mobile app (for self-monitoring and education), weekly emails, website with support resources, and handout	Generic info text messages, website and handout	Significant effect for intervention group on mean MET-minutes/week at 12 weeks (p = .05), 95% CI [-503.8, -1.2]. Total and walking PA days increased more in intervention group (p = .003), 95% CI [-2.2, -0.5], compared to control group (p = .0295), 95% CI [-1.1, -0.1].
*Pfaeffli (Pfaeffli Dale et al., 2015)	Adults with coronary heart disease	123/59.5/ 18.7	24 weeks/Static/ (1) mHealth intervention using tailored text messages and supporting website, usual care	Usual care (traditional cardiac rehab program)	Significant treatment effect on lifestyle behavior changes for intervention group at 3 months (AOR 2.55, 95% CI 1.12, 5.84; p = .03), but not at 6 months (AOR 1.93, 95% CI 0.83, 4.53; p = .13).

Study	Population	N/mean age (years)/sex (% female)	Duration/tailoring frequency/treatment arm(s)	Control	Main findings
*Rabbi (Rabbi et al., 2015)	University students and staff	17/28.3/47	3 weeks/Dynamic/ (1) Mobile app for self-monitoring and tailored suggestions on PA and food intake	Generic info	78% of experimental group had positive trends in walking, 75% of control group exhibited negative trends in walking. Ratio of positive changes between experimental and control groups was significant (*p* = .05).
Simons (Simons et al., 2018)	Adults	130/25/51.5	9 weeks/Dynamic/ (1) Mobile app (tailored info, tips, and facts), Fitbit	Generic print info	No significant between group differences for objective or subjective PA.
*Spring (Spring et al., 2018)	Adults with BMI between 30-40	212/40.8/ 76.4	12 weeks/Static/ (1) Simultaneous diet and MVPA training via Mobile app, tailored telecoaching; (2) Sequential diet and MVPA training via Mobile app, tailored telecoaching	Contact control (received sleep and relaxation training via mobile app)	Both treatment groups saw improvements in MVPA by 12.1 min/day, 95% CI [5.4, 18.9] over control group.
*Spring (Spring et al., 2017)	Overweight and obese adults	96/39.3/84.4	6 months/Dynamic/ (1) Group sessions, walking class, paper diary; (2) Group sessions, mobile app, personalized calls and messages	Self-guided diabetes prevention program + paper diary	Self-monitoring of PA was greater in tailored treatment group (M = 56.8, SE = 4.8) over non-tailored treatment group (M = 30.5, SE = 4.4) and control (M = 9.8, SE = 2.4; p < .001).

Study	Population	N/mean age (years)/sex (% female)	Duration/tailoring frequency/treatment arm(s)	Control	Main findings
Tucker (Tucker et al., 2016)	Clinic employees (nurses and medical assistants)	40/47.7/100	6 months/Dynamic/ (1) Environmental intervention (treadmill desk, stair and walking meetings, Wii video game system, 3 min PA videos), personalized SMS coaching	Environmental intervention only	Significant improvement in moderate PA (2.9%, *SD* = 4.5, $p < .01$) and steps (*M* = 99.9, *SD* = 311.8, $p = .05$) for early text group, not for delayed text group (control; *M* = 75.8, *SD* = 314.9, $p = .74$). No significant between group differences.
*Willcox (Willcox et al., 2017)	Pregnant women	91/32.5/100	Up to 36 weeks gestation/Static/ (1) Tailored text messages, link to website, video messages, Facebook chatroom	Usual care	Intervention group less likely to reduce mins of total daily PA compared to control group (β = 207, 95% CI 83,331; $p = .001$) Significant differences in adjusted light (β = 76, 95% CI 22,129; $p = .006$) and moderate (β = 92, 95% CI 22,156; $p = .005$) PA.
*Yom-Tov (Yom-Tov et al., 2017)	Adults with diabetes	27/57.8/33.4	26 weeks/Dynamic/ (1) Smartphone app to measure PA, SMS to send tailored feedback messages	Non-tailored exercise reminders	Control group reduced walking rate as experiment progressed. Personalized message group significantly increased ($p < .05$) walking rate.
*Zhou (Zhou et al., 2018)	University staff employees	64/41.1/83	10 weeks/Dynamic/ (1) Daily use of mobile app (automated personalized daily step goal, self-monitoring, push notification reminders)	Non-personalized step goal	Participants in intervention group performed 960 ($p = .03$) more steps than control 95% CI [90, 1830].

Table 1.2

Measurement of Physical Activity

Study	Physical activity outcome	Measurement instrument	Objective/subjective
Agboola et al.	Mean step count	Pedometer	Objective
Demeyer et al.	Steps/day, Moderate PA	Fitbug Air	Objective
Hebden et al.	Light PA, MVPA[a], MET[b]-min/week	Accelerometer, IPAQ[c]	Objective, Subjective
Martin et al.	Steps/day	Fitbug Orb	Objective
Mistry	MVPA	GLTEQ[d]	Subjective
O'Brian	MVPA	IPAQ	Subjective
Partridge et al.	Moderate, vigorous, total PA	IPAQ	Subjective
Pfaeffli et al.	MVPA	GLTPAQ[e]	Subjective
Rabbi et al.	% positive walking trends	Accelerometer app	Objective
Simons et al.	Light, moderate, vigorous PA	Actigraph GT3X+ accelerometer, IPAQ	Objective, Subjective
Spring et al. (2017)	MVPA	Shimmer accelerometer, mobile app	Objective, Subjective
Spring et al. (2018)	% days PA reported	Shimmer accelerometer, paper diary	Objective, Subjective
Tucker et al.	Moderate PA, steps	Accelerometer	Objective
Willcox et al.	Light, moderate, vigorous PA	Pregnancy Physical Activity Questionnaire	Subjective
Yom-Tov et al.	Walking min/day	Smartphone accelerometer	Objective
Zhou et al.	Steps/day	iPhone health chip	Objective

Note. [a]Moderate-to-vigorous physical activity, [b] Metabolic equivalents, [c] International Physical Activity Questionnaire, [d] Godin Leisure Time Exercise Questionnaire, [e] Godin Leisure Time Physical Activity Questionnaire.

Figure 1.1

PRISMA Flow Diagram of Study Selection

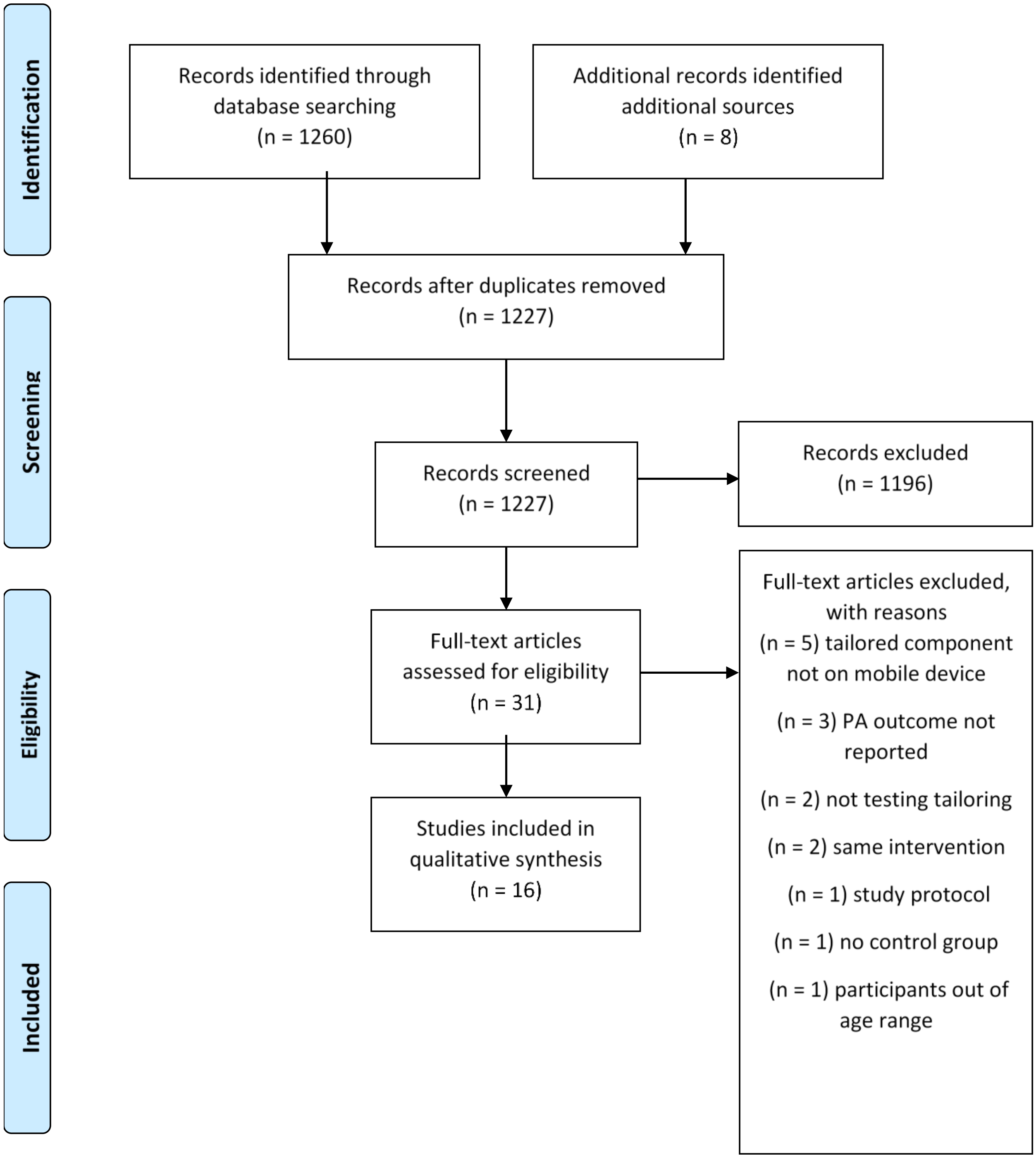

Figure 1.2

Risk of Bias Summary

Study	Randomization process	Deviations from intended interventions	Missing outcome data	Measurement of the outcome	Selection of the reported result	Overall Bias
Agboola et al. (2016)	+	+	+	+	?	?
Demeyer et al. (2017)	+	+	+	+	+	+
Hebden et al. (2014)	?	+	+	+	?	?
Martin et al. (2015)	+	+	+	+	+	+
Mistry (2013)	?	+	+	+	?	?
O'Brien (2015)	+	+	+	+	?	?
Partridge et al. (2015)	+	+	+	+	+	+
Pfaeffli et al. (2015)	+	+	+	+	+	+
Rabbi et al. (2015)	+	+	+	+	+	+
Simons et al. (2018)	?	+	+	+	?	?
Spring et al. (2018)	?	+	+	+	+	?
Spring et al. (2017)	+	+	+	–	+	–
Tucker et al. (2016)	–	+	+	+	?	–
Willcox et al.. (2017)	+	+	+	+	+	+
Yom-Tov et al. (2017)	?	+	+	+	+	?
Zhou et al. (2018)	+	+	+	+	+	+

+ Low risk

? Some concerns

– High risk

2 AN OBSERVATION OF THE IMPACT OF TAILORED MESSAGES ON PARTICIPANT NON-COMPLIANCE IN DESIRE2MOVE

Introduction

Despite the documented physical, cognitive, and emotional benefits of physical activity (PA), only 24.1% of adults meet federal aerobic and muscle strengthening recommendations (National Center for Health Statistics, 2018). Employed adults spend a third of waking hours at work, making the workplace an appealing setting to promote PA (Centers for Disease Control and Prevention, 2018). Organizations increasingly use health and well-being initiatives (HWBI) to influence employee health, but in 2017, only 28% of worksites offered HWBIs specifically for PA, fitness, or sedentary behavior (Centers for Disease Control and Prevention, 2017). Furthermore, most of the employers that offered HWBIs for PA promotion reported employee participation rates of less than 50% (Centers for Disease Control and Prevention, 2017). Researchers have designed and tested strategies within HWBIs to promote PA adoption and adherence with mixed results (Malik et al., 2014). Additional work is needed to identify strategies to improve employee participation, adherence, and program effectiveness.

Electronic health (eHealth), including mobile health (mHealth), has recently emerged as a program delivery channel to support HWBI. eHealth refers to the use of technology for health services (Borrelli & Ritterband, 2015). mHealth is a type of eHealth specifically related to mobile and wireless technologies used to deliver health information or programs (Borrelli & Ritterband, 2015). There are several benefits to eHealth, including its availability and accessibility. Most American adults own a cellphone (96%), a desktop/laptop (73%) or tablet computer (52%), and 81% report going online every day (Hitlin, 2018; Perrin & Kumar, 2019). The vast ownership of electronic devices makes eHealth programs feasible and relatively inexpensive, which is necessary for the scalability of PA interventions. Additionally, the wide reach of these technologies may offer a way to improve program participation by reducing common barriers to participation in face-to-face PA programs, such as lack of time or low self-efficacy (Ware et al., 2008).

Several authors examined the use of technology to promote health behaviors and found eHealth interventions significantly improved PA (Gal et al., 2018; Müller et al., 2016). However, authors reported conflicting outcomes on limitations such as non-usage or non-compliance attrition in studies designed to examine workplace eHealth PA programs (Reinwand et al., 2015; Ware et al., 2008). Non-usage or non-compliance attrition refers to participants who have not necessarily dropped out of an intervention but have stopped using the eHealth components (e.g. website, mobile app) or are no longer using them as instructed (Eysenbach, 2005). For this study, we will use the term “non-compliance” to represent non-compliance attrition. Further investigations are needed to improve adoption and implementation among participants in eHealth supported HWBIs targeting PA.

Another benefit of eHealth that is related to improving intervention non-compliance is the ability to deliver tailored message content. Tailoring refers to information or strategies intended to reach a specific person, based on characteristics derived from an individual assessment (Kreuter & Skinner, 2000). Targeted approaches, which are intended to reach a population based on a common characteristic, also deliver more personally relevant information than generic approaches, but tailored interventions are considered superior because they contain less redundant information, making them more engaging and better remembered (Kreuter & Wray, 2003). Although previous research examining the impact of tailored mHealth programs on PA demonstrated tailored interventions led to PA improvements (Davis, Sweigart, & Ellis, in press), the evidence directly comparing tailored and targeted materials was mixed. As such, additional research is needed to determine if tailored approaches are more effective than targeted materials for PA promotion in eHealth HWBIs.

Desire2Move (D2M) is an 8-week HWBI that encourages PA among university employees. The program is offered annually during the spring semester to employees of invited departments (pilot D2M offered Spring 2014). Participating departments are considered teams and compete with other teams for the greatest average minutes of PA. To participate, employees register on the D2M website, create a MapMyFitness account, and become "friends" with their team liaison (i.e. student research assistant) on the platform. During a program week (Monday – Sunday), participants record minutes of PA using the MapMyFitness app or website. The following Monday, the team liaisons view and record each participant's PA using a standardized spreadsheet. Each Tuesday, the program coordinator sends an email to team captains including the current team standings, program announcements, and a weekly motivational tip. Team captains are responsible for distributing this information to participants on their teams. At the end of the program, the team with the greatest average of PA minutes wins the traveling "Golden Shoe" trophy. Participants are also entered to win raffle prizes, such as sporting store gift cards and wearable fitness trackers.

Previous program evaluations of D2M used the RE-AIM framework to assess the "real world" impact of the program. RE-AIM is a multi-dimensional framework that includes: *reach* – the percentage and representativeness of people from the target population who participate in the program, *effectiveness* – the positive and negative consequences of program participation, *adoption* – the proportion and representativeness of target settings that adopt the program, *implementation* – the extent to which the program was followed as instructed by participants and program deliverer, and *maintenance* – the extent to which the program is sustained over time by the individual and organization (Glasgow et al., 1999). Positive results were reported for program effectiveness, adoption, implementation, and organizational maintenance (Biber & Ellis, 2016). Additionally, a separate evaluation of years 1, 3, and 5 revealed implementation at the organizational level influenced program satisfaction and PA outcomes (Ellis et al., 2020). However, a formal program evaluation at the individual level is still needed. Exploratory analyses of years 5 and 6 revealed most D2M participants were non-compliant during some point of the program (Davis et al., 2020). High levels of non-compliance may weaken program effectiveness because participants are not receiving the full potential benefits of the program. Therefore, research is needed to identify techniques to improve implementation (compliance) at the individual level.

The purpose of this study was to examine the impact of tailored versus targeted email messages on participant non-compliance during D2M. We hypothesized that non-compliant participants in the tailored message group would have fewer total weeks of non-compliance compared to participants in the targeted message group (H1). We also hypothesized that non-compliant participants in the tailored and targeted groups would have fewer total weeks of non-compliance compared to the default control group (H2). A secondary aim of this study was to identify reasons for non-compliance. Results of this investigation will inform future D2M program design and contribute to the research used to shape HWBI recommendations.

Method

Participants

Eligible D2M participants were any university employees (full-time, part-time, administration, faculty, staff, or graduate assistant) from the invited departments who volunteered to participate in year 7 of the program. Departments were selected for invitation based on colleague recommendations. The program coordinator contacted department heads of selected university departments by email to invite them to participate. Once the invitation was accepted, departments selected a team captain, who was responsible for recruiting employees to the department's D2M team.

Eligible and interested university employees were required to register on the D2M website to enroll in the program and this included the question about the program goal (employees were not required to provide an answer). Employees were included in this study if they were categorized as non-compliant (see measures) for one or more weeks of D2M. Year 6 of D2M had *N* = 286 participants who were mostly female (75.81%) with a mean age of 42.05 years (*SD* =11.93). The goal for year 7 of D2M was to have at least 350 participants. Based on previous year's compliance rates that were around 50% (had at least 1 week of non-compliance), we estimated 175 D2M participants would be non-compliant at least once.

Measures

Demographics. The D2M registration form included questions requesting the following information: gender identity, date of birth, employee status, department of employment, fitness app/device use, and PA status (whether participants were engaging in at least 150 minutes of moderate-to-vigorous physical activity [MVPA] before the start of D2M).

D2M goal. When registering for D2M, participants had the option to provide a participation goal (i.e., "what would you like to accomplish by participating in D2M?"). Program goals for year 6 of D2M were categorized and coded. Tailored email templates were created based on these themes.

Program non-compliance. Program non-compliance was categorized on a week by week basis. Team liaisons' collected PA minutes for their respective participants on Monday for PA logged the previous Monday to Sunday during the program. To record PA minutes, team liaisons accessed participant activity on MapMyFitness and entered it into a spreadsheet. Participants who failed to log any minutes during a program week (for any reason) were considered non-compliant for that week. If the participant logged PA minutes the following week, they were not categorized as a non-compliant for that week. Program non-compliance was measured by the number of times a participant is categorized as non-compliant during the 8-week program.

Reasons for non-compliance. Email responses from non-compliant participants were saved and compiled in a spreadsheet. The responses were categorized into higher order themes, then coded individually by the student PI and a second student assistant.

Procedures

Once participating teams were identified, teams were randomized into either a “targeted message only” (TMO) group or a “targeted + tailored message” (TTM) group. The allocation sequence was created before the start of D2M using a random number generator by a student research assistant. Participants who did not voluntarily provide a D2M goal were placed in the default control group, regardless of the treatment group of their respective team. The first time a participant, regardless of group, was categorized as non-compliant, they received a targeted email message directed toward participants who did not log minutes that week (see Appendix A). The targeted email template was updated after week 5 to include more sensitive language due to GSU campus closures to students and non-essential employees in response to the COVID19 pandemic (see Appendix B). The student PI sent targeted emails from the D2M email account.

TMO group. Participants in the TMO group who were considered non-compliant for a consecutive week were sent the same targeted email. This continued up to a maximum of three times. After a fourth consecutive week of non-compliance, the student PI notified the participant by email they were being removed from the team's spreadsheet, so not to pull down the team average. Removed participants were still allowed to access the resources provided to D2M participants (see Appendix C). When program non-compliance did not occur consecutively, participants were not removed from the team roster and they continued to receive targeted emails each time program non-compliance occurred.

TTM group. After a second instance on non-compliance, the student PI sent a tailored email messages using email templates based on program goal to participants randomized to the TTM group (see Appendix D – J). The tailored email templates were also updated after week 5 (see Appendix K). As with the TMO group, after a fourth consecutive week of non-compliance, the student PI notified the participant by email they were being removed from the team roster but would still be allowed to access the resources provided to D2M participants. When program non-compliance did not occur consecutively, participants were not removed from the team roster, and they continued to receive tailored emails each time program non-compliance occurred.

Default control. Participants who chose not to provide a program goal were in the default control group. Non-compliant participants in the default control group did not receive any additional targeted or tailored emails related to non-compliance after the first week of non-compliance. Participants in this group were also sent an email and removed from team rosters after a fourth consecutive week of non-compliance.

Analyses

Descriptive statistics (frequencies, proportions, means, and standard deviations) of study variables (age, employee status, fitness app or device use, gender identity, PA status) were calculated for the entire sample and for participants according to departments. Measures of skewness, kurtosis and the Shapiro-Wilks test were used to test normality before analyses. ANOVA and

Chi-square were used to assess group differences on baseline demographic variables. Any variables on which baseline differences were observed were included in the primary analyses as covariates. ANOVA and Chi-square were also used to examine differences on demographic variables between non-compliant participants and compliant participants, and between participants removed from team rosters after 4 weeks of non-compliance and remaining participants. Exploratory analyses were conducted to identify a potential relationship between PA status and non-compliance using point biserial correlation. In the case of a significant correlation, PA status was included in the model as a covariate. A nested one-way ANCOVA tested H1 with total non-compliance as the dependent variable, treatment group as a fixed factor, team as a random factor (nested within treatment group), and age, employee status, and PA status as covariates. Two one-way ANCOVAs tested H2. The first ANCOVA compared the difference in non-compliance between the TTM and DC groups while controlling for age, employee status, and PA status. The second ANCOVA compared the difference in non-compliance between the TMO and DC groups while controlling for PA status. Levene's test for homogeneity of variances was used to test the assumption of equal variances and eta squared and Cohen's d were calculated for effect size for all three models.

The year 6 program goal responses, as well as the email responses from non-compliant participants were recorded and summarized. Responses were categorized using a data-driven thematic analysis approach guided by the Grounded Theory (Braun & Clarke, 2006). Due to the exploratory nature of the qualitative analyses, themes were identified within the explicit meaning of the responses and were organized to identify patterns in responses. The categories were coded by the student PI and a second student assistant, then compared for consistency. For the email responses, two initially identified categories were collapsed into one (too busy and forgot to log) theme. When identifying email response themes, we separated responses related to COVID19 because this was an issue specific to year 7 of the program. Frequencies and proportions were calculated for email response themes.

Results

Participant Characteristics and Preliminary Analyses

A total of 289 GSU employees from 23 teams registered for D2M on the program website. Of those registered, 47 were removed from team rosters due to: (a) not completing additional program requirements (i.e. not accepting team liaison friend requests, not providing team liaison access to view PA activity; *n* = 15), (b) never logging any activity (i.e., four consecutive weeks of non-compliance; *n* = 22), (c) withdrew due to injury/medical concern preventing PA (*n* = 2), (d) too busy at work due to COVID19 (*n* = 1), (e) leaving the university (*n* = 1), and (f) entire team drop out because of loss of team captain (*n* = 6). Of the remaining 242 participants, 149 were categorized as non-compliant at least once and were included in analysis. Participants were mostly female (68.5%), staff (44.3%), with an average age of 43.66 (*SD* = 11.10). Most participants were meeting PA recommendations of 150 minutes of MVPA per week (55.0%) and most (56.4%) reported using a fitness related app or device. Participant characteristics are presented in Table 2.1. The groups included *n* = 54 in the TTM group, *n* = 62 in the TMO group, and *n* = 33 in the DC group.

Seven main themes were identified from program goals and used to tailor email templates: social support, competition, maintenance of PA behavior, PA adoption, fitness/performance goal, improve health-related outcome, and incentives. A total of 409 non-compliance emails were sent by the student PI throughout the program. The total emails sent each week by treatment group is presented in Table 2.2. Most participants were non-complaint ≥ 3 times (56.4%). Frequency of non-compliance by treatment group is presented in Figure 2.1.

Tests of normality for non-compliance revealed skewness of -.47 (SE = .20) and kurtosis of -1.00 (SE = .40), which fell within the acceptable ranges of -1, 1 for skewness and -2, 2 for kurtosis (George & Mallery, 2010). The Shapiro-Wilk test was significant, $W(149) = .89$, $p < .001$). Analyses proceeded as intended, as ANOVA is robust to non-normality of sample means (Blanca et al., 2017).

A significant correlation was observed ($r = -.171$, $p = .037$) between PA status and non-compliance, so PA status was included in the models as a covariate. There were no significant group differences at baseline on fitness app or device use, gender identity, or PA status. However, there were significant group differences at baseline on employee status, χ^2(df) = 24.01(6), $p = .001$, and participant age, $F(2, 147) = 4.27$, $p = .016$, such that non-compliance increased with age. These variables were also included as covariates in the primary analyses. There were no significant differences on any demographic variables between participants removed from team rosters after 4 weeks of non-compliance and remaining participants. There were significant differences between non-compliant participants and compliant participants on fitness app or device use, χ^2(df) = 12.64(1), $p < .001$, and PA status, χ^2(df) = 3.85(1), $p < .001$.

Comparison of TTM, TMO, and DC Groups

Six participants from four teams were removed from analysis because they did not contribute any or contributed very little variance to the model. Specifically, two teams only had one participant, so within group variance could not be calculated for those teams. Two other teams had two participants each but were removed to improve the power of the statistical tests. Levene's test for homogeneity of variance for the nested ANCOVA was not significant, F(16,91)

= 1.17, p = .309, so the assumption of equal variances was met. There was a significant group difference in non-compliance between the TTM and TMO groups, $F(16,88) = 3.39$, $p < .001$, $\eta^2 = .38$; $d = .64$, with the TTM group having lower non-compliance (M = 2.64, SD = 1.93) than the TMO group (M = 3.95, SD = 2.1). Age, $\beta = .04$, $p = .031$, $\eta^2 = .05$, and PA status, $\beta = -.82$, $p = .048$, $\eta^2 = .04$, were significant covariates with non-compliance. Employee status was not significantly related to non-compliance.

Levene's test for homogeneity of variances, $F(1,77) = .970$, $p = .328$, for the ANCOVA testing the TTM and DC groups showed the assumption of equal variances was met. The ANCOVA revealed a significant difference between group means, controlling for age, employee status, and PA status, $F(1,74) = 13.29$, $p < .001$, $\eta^2 = .152$; $d = .56$, with the TTM (M = 2.63, SD = 1.92) group having lower non-compliance than the DC group (M = 3.75, SD = 2.10). Age was the only significant covariate, $\beta = .06$, $p = .003$, $\eta^2 = .112$.

Levene's test for homogeneity of variances, $F(1,83) = .02$, $p = .889$, for the ANCOVA testing the TMO and DC groups also showed the assumption of equal variances was met. Between group differences were not significant for the TMO (M = 3.88, SD = 2.13) and DC (M = 3.84, SD = 2.08) group while controlling for age, employee status, and PA status, $F(1,80) = .10$, $p = .750$, $\eta^2 = .001$; $d = .02$. None of the covariates were significantly related to non-compliance.

Reasons for Non-Compliance

A total of $n = 60$ responses to non-compliance related emails were received from $n = 52$ different participants, with $n = 35$ responses received from the TTM group and $n = 25$ from the TMO group. No email responses were received from participants in the DC group. From the emails, eleven higher-order themes were identified: (1) participant was too busy or forgot to log, (2) participant was too busy or forgot to log due to COVID19, (3) technical issues, (4) medical reasons, (5) participant logged after weekly deadline, (6) participant thought program ended due to COVID19, (7) lack of motivation, (8) withdrew from program, (9), withdrew from program due to COVID19, (10) liaison reporting error, and (11) did not specify a reason. Overall, technical issues were the most cited reason for non-compliance (30%), followed by participant forgot to log (23.3%). When examined by group, the most cited reason for non-compliance in the TTM group was participant forgot to log (28.6%) and technical issues (44%) in the TMO group. A breakdown of email responses by group is presented in Table 2.3.

Discussion

The importance of regular PA has been consistently documented and previous studies demonstrated the workplace is an effective setting in which to deliver programs targeting PA (Burn et al., 2019; Centers for Disease Control and Prevention, 2018; Hipp et al., 2017). Although tailored approaches are increasingly used in PA interventions, the effectiveness of tailored emails on program implementation at the individual level has been understudied. This study examined the impact of tailored vs targeted email messages on participant non-compliance during an 8-week HWBI for PA. The results indicated participants who received tailored email messages (TTM group) had significantly fewer weeks of non-compliance than participants who received targeted email messages throughout the program (TMO group) and participants who only received one targeted email (DC group) during the program. These results support our first study hypothesis that they TTM group would have lower non-compliance than the TMO group. Unexpectedly, however, there was not a significant difference in non-compliance between the TMO and DC groups. This is in contrast with our second hypothesis, that both the TTM and TMO groups would have lower non-compliance than the DC group. Age and PA status were related to non-compliance in some models. Overall, after controlling for age and PA status, our findings demonstrate the effectiveness of tailored email messages for reducing non-compliance among university employees during a HWBI for PA promotion.

Previous studies examined the influence of tailored interventions on PA promotion and sitting time reduction and reported promising results (De Cocker et al., 2016; Neville et al., 2009; Short et al., 2011). Our results are similar to the findings from a study targeting workplace sitting by De Cocker et al., where employees either received a computer-tailored intervention, generic information (received information to reduce workplace sitting) or were in a waitlist control group (De Cocker et al., 2016). The authors reported a significant reduction in sitting for the computer-tailored group over the generic group and waitlist control, but the generic group did not have a greater reduction in sitting over the waitlist control group. Our study extends current research because it examines program implementation rather than a measure of PA or sedentary behavior (i.e., minutes of MVPA, sitting time, etc.). This is important because before a behavior change potentially occurs, the program or intervention needs to be properly delivered and enacted. Also, our study was not computer-tailored, so the results are useful for organizations unable to access technology needed to computer-tailor messages. Our results suggest tailored email messages have a substantial influence on non-compliance, even after controlling for age and PA status. There were moderate effect sizes (d = -.64) in both the model examining the TTM and TMO groups and the TTM and DC groups (d = -.56). These effects were slightly larger than those observed in a meta-analysis by Gal et al. (2018) that examined the effect of mHealth interventions on PA. The authors reported a small-to-moderate effect for PA in minutes per day (SMD = .43) and a moderate increase in daily step count (SMD = .51; Gal et al., 2018). However, this meta-analysis did not exclusively include tailored interventions and measured PA behavior. Our study provides evidence of the effectiveness of tailored eHealth programs in a real-world workplace, but additional research is needed to determine if tailored messages influenced non-compliance differently based on participant age and PA levels.

It is not clear why we did not observe a significant difference between the TMO and DC groups on non-compliance. Both groups received the same targeted message at least once, so the DC group did receive some degree of the same treatment as the TMO group. However, both groups were close in the percentage of participants who were only non-compliant one time (DC – 21%, TMO – 18.8%), so we would expect to see lower non-compliance for other participants (those who were non-compliant more than once) who continued to receive targeted messages. It is possible the targeted message content and/or frequency of delivery may not have been sufficient to encourage non-compliant participants in the TMO group to re-engage with the program. Previous researchers suggested messages that are gain-framed and inform participants why and how they should perform a behavior help motivate participants to engage in PA or other health behaviors (Latimer et al., 2010; Salovey & Williams-Piehota, 2004). In a systematic review of message approaches for constructing PA messages, Latimer et al. also advised that more frequent doses of information improve tailored message effects, which may also hold true for targeted messages. Redesigning the targeted messages and sending them more than once per week may make them more impactful.

Another possible contributing factor was the DC group consisted of participants who did not voluntarily provide a program goal during registration. There may be characteristics (i.e. lower need for social support) of this group that led participants to perform similarly to the TMO group. These characteristics may also explain why fewer of the DC group (60.5%) had 3 or more weeks of non-compliance than the TMO group (71%), and why none of the DC group participants responded to the non-compliance email. Also, although not significantly different, a greater percentage of participants in the DC group were engaging in at least 150 min/week of MVPA before the start of D2M than the TMO group. These differences suggests the DC group participants may have been less engaged in the program, but at least equally as motivated to perform PA. This is an important consideration, as several researchers suggested individual characteristics or personality traits influenced how participants interact with various behavioral intervention components (Bryan et al., 2017; Ferguson, 2013; Wilson, 2019; Wilson & Estabrooks, 2020). Personality informed HWBIs may offer a way to improve non-compliance in PA programs.

A secondary aim of this study was to identify reasons for non-compliance during D2M. About 35% of non-compliant participants responded to the email messages and the top two reasons for non-compliance reported by participants were technology issues and forgot/too busy to perform or log PA. Our findings are similar to results from another study on workplace HWBIs examining why employees did or did not participate in an eHealth workplace PA intervention (Bardus et al., 2014). The researchers reported “easy to use” and “receiving reminders” as the most common reasons for participation and “living a busy life” and “issues with technology” as the most common reasons for not participating in the intervention (Bardus et al., 2014). This parallels the reasons for non-compliance reported in our study. It is important to consider the difference in reported reasons for non-compliance between the TTM and TMO groups when interpreting the results. Almost half (44%) of participants in the TMO group reported technical issues as their reason for non-compliance. The targeted email messages may have simply served as a prompt for participants to troubleshoot an issue that some participants did not know they were experiencing (i.e. participants believed they were recording PA but were not for reasons such as syncing problems). We may not have observed a significant group difference in favor of the TTM group had we used a different program platform that was easier to use. Conversely, the most cited reason for non-compliance in the TTM group was forgot/too busy (28.6%) to log or do PA. For participants who simply forgot to log PA completed that week, the email may have served as a reminder to back log their activity for the previous week. A tailored message may not have been needed to prompt the participant to comply.

A strength of this study was that it was delivered in a real-world setting, which enhances the public health significance. This study was the first attempt to understand why non-compliance was so high during previous program cycles. As a result, in our effort to manipulate treatment groups, many of variables that were important to understand (such as reasons for non-compliance) were difficult to control for in the study design. There were several additional limitations to consider, some of which were due to the applied nature of this study. Our study population was relatively young, mostly female, and mostly meeting PA recommendations before D2M, so the results can only be generalized to these demographics in a workplace setting. Some of the more pressing limitations involved the eHealth components of the program. One concern stemmed from the platform (MapMyFitness) participants used to record PA. About 30% of participants who responded to non-compliance emails had issues related to difficulty saving workouts or syncing with other fitness tracking devices. It is possible that more participants who did not respond to emails also experienced technology related issues. Another concern was our inability to determine if emails were read by participants. We delivered the messages via email to participant's GSU accounts to ensure the intervention was accessible to all participants. As a result, we had no way to determine to what degree participants engaged with the email messages. Further, the emails were only sent once per week, after the participant was non-compliant, meaning the opportunity to perform or record PA for that week had passed. Although the emails may have served to prevent future instances of non-compliance, emails sent during the week may have led to a greater reduction in non-compliance.

During week 5 of D2M, the university closed all campuses to students and non-essential employees due to COVID19 and many Metro Atlanta cities issued shelter-in-place orders for all residents during the remainder of the program. This likely impacted the amount of PA performed by participants, as well as their willingness or ability to record activity on MapMyFitness. Coincidentally, weeks 4 and 5 were traditionally when non-compliance levels increased during previous cycles of D2M (Davis et al., 2020). We delivered a treatment to specifically target non-compliance, so we expected overall non-compliance to be lower for year 7. Only a small percentage of email responses (11.7%) cited COVID19 related issues as reasons for non-compliance, however, participants impacted by campus closures and municipal shelter-in-place orders may have been less inclined to respond to emails. Encouragingly, the effects of COVID19 on D2M outcomes appeared to be minimal.

The present study was not designed to examine the impact of tailored messages on actual PA behavior. This points to a direction for future research. While we believed tailored emails reduce non-compliance, we do not know if that reduction corresponded to changes in amount of PA performed. These findings are meaningful because tailored email messages appeared to improve program implementation at the individual level, which was an initial step toward a change in PA behavior. However, future studies examining the impact of tailored messages on PA behavior change during a workplace HWBI are warranted.

There are several implications of the study findings on future D2M program cycles and similar eHealth HWBIs for PA. First, tailored or personalized messages should be used to encourage participants to implement the program. Many current technologies include features that make it easier to tailor PA programs and interventions (Dugas et al., 2020). Our study tailored on program goal, but other studies tailored on varying dimensions (i.e. theoretical frameworks, demographics) and demonstrated success (Albada et al., 2009; Lippke et al., 2010). More work is needed to determine which tailoring dimensions are more effective within an eHealth HWBI. Second, targeted messages may suffice as the first point of contact for more motivated participants. This would allow program deliverers to focus resources on participants who need the most attention to encourage program compliance. Lastly, future studies should consider measuring engagement with tailored messages, assessing the influence of the frequency of message delivery on non-compliance outcomes, and examining the relationship between program compliance and sustainable PA behavior change.

Conclusion

In summary, tailored email messages appeared to improve program compliance among participants in a HWBI for PA promotion, although targeted email messages may be sufficient for the first point of contact for some participants. Program developers should carefully consider the technology features of the delivery platform and can use program goal to tailor messages. Additional research is warranted to determine if the frequency of messages influences non-compliance and to better understand the relationship between program compliance and PA behavior change.

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Table 2.1

Participant Characteristics

Characteristics		TTM		TMO		DC		Total	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Age (years)		47.15	11.82	41.59	10.34	41.90	10.16	43.66	11.10
		N	*%*	*N*	*%*	*N*	*%*	*N*	*%*
Gender	Female	35	64.8	43	69.4	24	72.7	47	68.5
	Male	19	35.2	19	30.6	9	27.3	102	31.5
Employee Status	Administration	6	11.1	4	6.5	5	15.2	15	10.1
	Faculty	30	55.6	15	24.2	12	36.4	57	38.3
	Graduate Assistant	5	9.3	2	3.2	4	12.1	11	7.4
	Staff	13	24.1	41	66.1	12	36.4	66	44.3
Fitness App/Device	No	21	38.9	24	38.7	20	60.6	65	43.6
	Yes	33	61.1	38	61.3	13	39.4	84	56.4
PA Status	No	22	40.7	33	53.2	12	36.4	67	45.0
	Yes	32	59.3	29	46.8	21	63.6	82	55.0

[a]Meeting 150 minutes of MVPA per week
[b]Does participant use a fitness app or device outside of D2M

Table 2.2

Emails Sent by Week

		Week of D2M							
		1	2	3	4	5	6	7	Total
Group	Type of email sent								
TTM	Targeted	24	9	4	4	4	11	7	63
	Tailored	0	10	13	5	11	10	16	65
	Removal	0	0	0	6	0	0	0	6
TMO	Targeted	38	36	34	25	29	29	37	228
	Removal	0	0	0	11	0	0	0	11
DC	Targeted	16	3	6	3	2	1	0	31
	Removal	0	0	0	5	0	0	0	5
Total		78	58	112	59	46	51	60	409

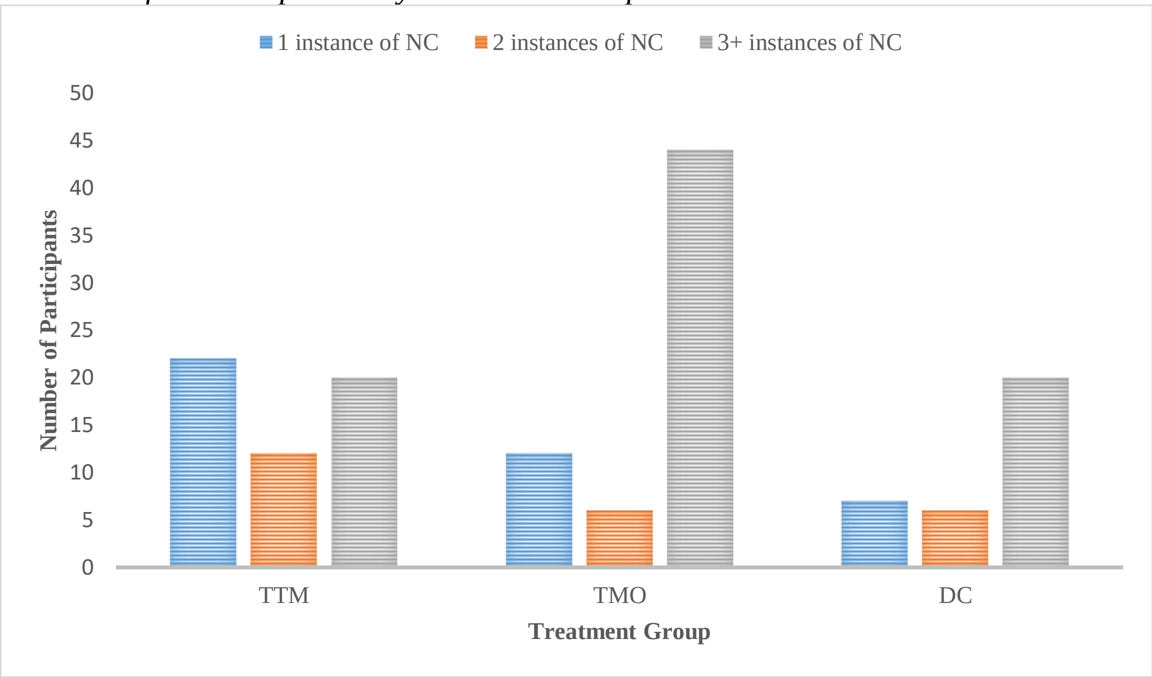
Table 2.3

Emails Responses by Group

	TTM		TMO		Total	
	n = 35		n = 25		N = 60	
	n	%	*n*	%	*n*	%
Technical Issue	7	20.0	11	44.0	18	30.0
Forgot/Too busy	10	28.6	4	16.0	14	23.3
Liaison Error	2	5.7	3	12.0	5	8.3
Forgot/Too busy - COVID	3	8.6	1	4.0	4	6.7
Logged after deadline	3	8.6	1	4.0	4	6.7
Did not specify	3	8.6	0	0	3	5.0
Lack of motivation	3	8.6	0	0	3	5.0
Medical	3	8.6	0	0	3	5.0
Withdraw	0	0	3	12.0	3	5.0
Participant thought program ended - COVID	1	2.9	1	4.0	2	3.3
Withdraw- COVID	0	0	1	4.0	1	1.7

Figure 2.1.

Instances of Non-compliance by Treatment Group.



APPENDICES

Appendix A

Targeted Email.

Hello D2M participant,

I noticed you didn’t log any minutes of physical activity on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging or need other support, I’m glad to assist you.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix B

Updated Targeted Email.

Hello D2M participant,

I noticed you didn’t log any minutes of physical activity on MapMyFitness this past week. Due to current circumstances, we are allowing participants to update minutes for weeks 5-8. If you experienced technical difficulties with logging or need other support, I’m glad to assist you.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix C

Final Contact Roster Removal Email.

Hello [insert participant name],

We noticed you didn’t log any minutes on MapMyFitness for the first half of D2M. Zeros pull down the team average, so we are going to remove you from the team roster unless we hear otherwise from you. However, we still want to support your efforts to be physically active. You will still have access to the resources of the program (weekly email tips, health coaches, etc.) but will no longer be listed as a member on the team.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix D

Example Tailored Emails for Social Support.

Appendix D.1

Hello [insert participant name],

I am checking in because I noticed you didn’t log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We want to help you reach your goal of [insert specific goal reference]. We know you and your teammates are busy. If you don’t have time to exercise together, try using walking meetings to get work done and be active at the same time. Another option is to walk over to your teammates instead of using phone calls or emails. Every extra minute of physical activity helps you and your team!

It is also not too late to sign up for health coaching. The health coaches can help you identify techniques to be more physically active. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix D.2

Hello [insert participant name],

I am checking in because I noticed you didn’t log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We want to help you reach your goal of [insert specific goal reference]. We know you and your teammates are busy. If you don’t have time to exercise together, try using walking meetings to get work done and be active at the same time. Another option is to walk over to your teammates instead of using phone calls or emails. Every extra minute of physical activity helps you and your team!

It is also not too late to sign up for health coaching. The health coaches can help you identify techniques to be more physically active. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix E

Example Tailored Emails for PA Adoption.

Appendix E.1

Hello [insert participant name],

I noticed you didn’t log any minutes on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging, I am glad to help you troubleshoot the problem.

During registration, you listed [insert specific goal reference] as something you would like to accomplish by participating in D2M. Consider setting a S.M.A.R.T. goal (specific, measurable, action oriented, realistic, and time oriented) to get you started. A goal can help you stay motivated throughout D2M!

Also, we offer health coaching to support your physical activity efforts during D2M. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix E.2

Hello [insert participant name],

I am checking in because I noticed you didn't log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We want to help you reach your goal of [insert specific goal reference]. We know you are busy, and it is easy to lose track of time. Consider using reminders to help you remember to do your workouts. Write your goal on Post-it notes and place them in your home or office. You can also set an alarm to remind you to go workout.

It is also not too late to sign up for health coaching. The health coaches can help you identify techniques to be more physically active. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix F

Example Tailored Emails for Health Outcomes.

Appendix F.1

Hello [insert participant name],

I noticed you didn’t log any minutes on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging, I am glad to help you troubleshoot the problem

During registration, you listed [insert specific goal reference] as something you would like to accomplish by participating in D2M. Physical activity is a great way to help with [insert health outcome]. Consider setting a S.M.A.R.T. goal (specific, measurable, action oriented, realistic, and time oriented) to get you started. A goal can help you stay motivated!

Also, we offer health coaching to support your physical activity efforts during D2M. If you are interested, I can help you set this up.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix F.2

Hello [insert participant name],

I am checking in because I noticed you didn’t log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We want to help you reach your goal of [insert specific goal reference]. We know you are busy, and it is easy to lose track of time. Consider using reminders to help you remember to do your workouts. Write your goal on Post-it notes and place them in your home or office. You can also set an alarm to remind you to go workout.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix G

Example Tailored Emails for Maintenance.

Appendix G.1

Hello [insert participant name],

I noticed you didn't log any minutes on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging, I am glad to help you troubleshoot the problem.

During registration, you listed [insert specific goal reference] as something you would like to accomplish by participating in D2M. Sticking to your physical activity routine can be challenging but don't get discouraged if you miss a workout. Instead, consider making a list of situations or issues that may have prevented you from being active and try to think about ways you can prepare for them in the future.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix G.2

Hello [insert participant name],

I am checking in because I noticed you didn’t log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We want to help you reach your goal of [insert specific goal reference]. We know you are busy, and it is easy to lose track of time. Consider using reminders to help you remember to do your workouts. Write your goal on Post-it notes and place them in your home or office. You can also set an alarm to remind you to go workout.

Best wishes,

Ashlee Davis

Assistant Program Coordinator

Desire2Move

Georgia State University

Appendix H

Example Tailored Email for Incentives.

Hello [insert participant name],

I noticed you didn’t log any minutes on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging, I would be glad to help you troubleshoot the problem.

During registration, you listed [insert specific goal reference] as something you would like to accomplish by participating in D2M. Rewards are a great way to push yourself to the end of the program and beyond. Consider setting a weekly goal and think about the [insert specific incentive] to encourage you to keep moving!

Also, we offer health coaching to support your physical activity efforts during D2M. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix I

Example Tailored Emails for Fitness/Performance Goals.

Appendix I.1

Hello [insert participant name],

I noticed you didn't log any minutes on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging, I would be glad to help you troubleshoot the problem.

During registration, you listed [insert specific goal reference] as something you would like to accomplish by participating in D2M. Consider setting a S.M.A.R.T. goal (specific, measurable, action oriented, realistic, and time oriented) to get you started. A goal can help you stay motivated throughout D2M!

Also, we offer health coaching to support your fitness efforts during D2M. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix I.2

Hello [insert participant name],

I am checking in because I noticed you didn't log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We want to help you reach your goal of [insert specific goal reference]. We know you are busy, and it is easy to lose track of time. Consider using reminders to help you remember to do your workouts. Write your goal on Post-it notes and place them in your home or office. You can also set an alarm to remind you to go workout.

It is also not too late to sign up for health coaching. The health coaches can help you identify techniques to be more physically active. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix J

Example Tailored Emails for Competition.

Appendix J.1

Hello [insert participant name],

I noticed you didn't log any minutes on MapMyFitness this past week. If you completed minutes of physical activity and forgot to log, you can back log up to 1 week. If you experienced technical difficulties with logging, I would be glad to help you troubleshoot the problem.

During registration, you listed [insert specific goal reference] as something you would like to accomplish by participating in D2M. Your team is currently in [insert team standing] place. Any additional minutes that you log can help pull your team ahead! I listed activities at the bottom of this email that you and your teammates may enjoy doing together.

<u>Occuring this week:</u>
[insert list of PA activities occurring at GSU]

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix J.2

Hello [insert participant name],

I am checking in because I noticed you didn’t log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

We know you want to help your team win the trophy! If you don’t have time to exercise together, try using walking meetings to get work done and be active at the same time. You can also set personal goals to help you stay motivated. Every extra minute of physical activity helps you and your team!

It is also not too late to sign up for health coaching. The health coaches can help you identify techniques to be more physically active. If you are interested, I can help you get started.

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix K

Example Updated Tailored Emails

Appendix K.1

Hello [insert participant name],

I hope you have been able to make time to be physically active. Any amount of physical activity will move you closer to your goal of making positive health changes. It is also a great way to relieve stress and improve mood during this unprecedented time we are experiencing. No amount is too small!

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University

Appendix K.2

Hello [insert participant name],

I am checking in because I noticed you didn’t log any minutes last week. As a reminder, if you completed minutes of physical activity and forgot to log, you can back log up to 1 week.

During registration, you listed [insert program goal] as something you would like to accomplish by participating in D2M. We know the current circumstances make it more challenging to exercise, but every extra minute of physical activity helps you and your team!

Best wishes,

Ashlee Davis
Assistant Program Coordinator
Desire2Move
Georgia State University