The Comparative Effectiveness of mHealth Interventions in Improving Health Outcomes:

A Meta-Analytic Review
Abstract

**Background:** As mobile technology continues expanding, researchers have been using mobile phones to conduct health interventions (mHealth interventions). The multiple features of mobile devices offer great opportunities to disseminate large-scale, cost-efficient, and tailored messages to participants. However, the interventions to date have shown mixed results, with a large variance of effect sizes (Cohen’s $d = -0.62$ to 1.65).

**Objective:** To generate cumulative knowledge that informs mHealth intervention research, the aims of the current study are twofold: (a) to calculate an overall effect magnitude for mHealth interventions compared to alternative interventions/conditions and (b) to analyze potential moderators of mHealth interventions’ comparative efficacy.

**Methods:** Comprehensive searches of the Communication & Mass Media Complete, PsycINFO, Web of Knowledge, Academic Search Premier, PubMed and Medline databases were conducted to identify potentially eligible studies in peer-reviewed journals and conference proceedings as well as dissertations and theses. Search queries were formulated using a combination of search terms: “intervention” (Title/Abstract) AND “health” (Title/Abstract) AND “*phone*” OR “black-berr*” (OR mHealth OR “application*” OR app* OR mobile OR cellular OR “short messag*” OR palm* OR iPhone* OR MP3* OR MP4* OR iPod*) (Title/Abstract).

**Results:** The search resulted in 3,424 potential studies, the abstracts (and full text, as necessary) of which were reviewed for relevance. Studies were screened in multiple stages using explicit inclusion and exclusion criteria, and citations were evaluated for inclusion of qualified studies. A total of 61 studies were included in the current meta-analysis. Results showed that mHealth interventions are relatively more effective than comparison interventions/conditions, with a small but significant overall weighted effect size ($d = 0.31$). Additionally, the effects of interventions
are moderated by theoretical paradigm, three engagement types (i.e., changing personal environment, reinforcement tracking, social presentation), mobile use type, intervention channel, and length of follow-up.

**Conclusions:** To the best of our knowledge, this is the most comprehensive meta-analysis to date that examined the overall effectiveness of mHealth interventions across health topics and is the first study that statistically tested moderators. Our findings not only shed light on intervention design using mobile devices, but also provide new directions for research in health communication and promotion using new media. Future scholarship is needed to examine the effectiveness of mHealth interventions across various health issues, especially those that have not yet been investigated (e.g., substance use, sexual health), engaging participants using social features on mobile devices, and designing tailored mHealth interventions for diverse subpopulations to maximize effects.

**Keywords:** meta-analysis, mobile devices, mHealth intervention, health outcomes, moderator analysis
Introduction

As mobile technology continues expanding and mobile devices become ubiquitous, with 73% of Americans actively using mobile devices [1] and approximately 7 billion mobile phone subscriptions worldwide [2], mobile phones have been increasingly used to conduct health interventions (mHealth interventions) to improve health conditions [3]. Studies have found several advantages of mHealth interventions compared to traditional approaches. Given the number of mobile device users, mHealth interventions have the potential to engage a large group of people at a relatively lower cost, making public health interventions more feasible and impactful [3-5]. As many mHealth intervention platforms (e.g., text-based, applications) have become available to benefit interventions in differing ways [1], mHealth can now address many issues including a limited workforce, finances, and accessing difficult-to-reach groups [6]. Overall, the use of mobile devices as part of health interventions has become an effective tool to potentially prevent and treat health issues [6].

Despite the promises of mHealth interventions, previous mHealth interventions have yielded conflicting results and inconsistent effect sizes (ESs), ranging from Cohen’s $d$ of -0.62 [7] to 1.65 [8]. Such large variance in ESs makes a comprehensive meta-analysis with moderator analyses imperative to provide a clearer picture of the effectiveness of mHealth interventions. However, previous syntheses either focused on a specific health issue [9, 10] or were constrained by small sample sizes and a lack of moderator analyses [3, 4], leaving what factors account for variance in ESs unanswered.

To fill the gap and provide insights into the effectiveness of harnessing mobile technology for health interventions, two questions will be addressed in the current study: first, whether mHealth intervention are comparatively more effective in general; second, whether the
comparative effects of mHealth interventions are moderated by theoretical, methodological and demographic variables. To answer these questions, meta-analysis was implemented as the research method, which enables researchers to conduct a more sophisticated synthesis of quantitative research literature [11]. Applying this innovative approach, we identify the overall effect of mHealth interventions and significant moderators to provide guidance for mHealth intervention design and implementation.

**Mobile Phone Use and mHealth**

With the growing technological culture, mobile phones have become the most popular and widespread personal technology, with 95% of the Americans owning a cell phone of some kind and 77% owning a smartphone [12]. Mobile technologies also include personal digital assistant (PDA) phones (e.g., blackberry), portable media players (e.g., MP3- and MP4-players), and handheld computers (e.g., iPad). As the use of mobile technology has increased, public health professionals have begun to take advantage of the multiple platforms provided by mobile phones to serve a wide variety of purposes, such as physical activity, weight loss, smoking cessation, mental health and chronic disease management.

“The use of mobile computing and communication technologies in health care and public health” [10] is referred to as mHealth, a rapidly expanding branch within eHealth. There are many effective strategies that utilize mobile devices to promote public health. In general, mobile phones have been used to share information about public health since it is economical, sustainable, and effective [13]. To benefit mobile phone users, public health professionals have begun to utilize mobile phone capabilities for prevention, management, and treatment of health issues [14]. Mobile phones have been primarily applied for health purposes through short-message service (SMS) and application (app) features of these technological devices. In
particular, text messages sent through mobile phones were found as a simple and efficient option for health services, which could be affordably used to send tailored health messages and reminders to improve delivery to patients [15-17]. Mobile apps are also widely used to promote public health, which can integrate a variety of built-in interactive features. Therefore, this allows for the potential to target heterogeneous audiences to address specific needs with diverse outcomes [15]. These apps offer great potential for dynamic engagement of patients and providers in health care and an innovative approach to improve health outcomes [18].

**mHealth Interventions**

Health interventions have utilized mobile technology in a variety of ways to increase health knowledge, promote health education, and change health behaviors. With the increasing use of mHealth interventions, several approaches have emerged for utilizing mobile technologies to implement health interventions. One primary approach to incorporating mobile phones into health interventions is focusing on the voice and text features that have achieved significant improvements in compliance with medication adherence, asthma symptoms, HbA\textsubscript{1c} levels, stress levels, smoking cessation, and self-efficacy [19]. Leveraging the advantages of mHealth interventions has improved public health outcomes in these areas as it has helped individuals become more aware and take accountability for their health issues. Other approaches to mHealth interventions include self-monitoring techniques and real-time surveillance features of the technology [20]. It is increasingly popular to utilize mobile phones to track individuals’ daily activity and provide reminders and motivational text-based messages to continue progression during the intervention [21]. As smartphones have become more popular, another approach is the social networking component that allows users to interact and share information using social media [22]. With the booming marketplace and the engaging features of mobile apps, mHealth
interventions have been increasingly based on mobile apps to deliver health information and modify health behavior, and have significant influence on youths’ health outcomes [1].

Mobile phones have become a source for interactive communication, providing numerous advantages in conducting health interventions, including widespread use of mobile technology across various socioeconomic groups, few geographical constraints compared to other media, and cost-effectiveness to reach a diverse and large population [2, 23]. A unique and noteworthy advantage of mHealth interventions is to target underdeveloped/underserved areas due to the enabling resources provided by mobile phones [14, 24]. A review of mobile phone-based health interventions for non-communicable disease management in sub-Saharan Africa reported that using apps on cellular devices can improve physical and mental health outcomes [14]. Incorporating mobile phones within public health education and promotion can be beneficial for a wide range of situations and populations.

**Mixed Effects of mHealth Interventions and Research Questions**

Despite mHealth interventions’ great potential to be superior to health interventions using traditional approaches, empirical research to date has generated mixed results in terms of the efficacy of mHealth interventions. For example, one successful mHealth intervention led to lower levels of perceived stress for intervention participants relative to a waitlist control group (Cohen’s $d = 1.02$) at 6-month follow up [25]. However, other mHealth interventions performed no better or worse than comparison conditions. For example, Biddle et al. [26] found that an mHealth intervention was less successful than a control condition ($d = -0.27$) at decreasing sedentary time among overweight/obese participants. Such inconsistent findings make the efficacy of mHealth interventions in improving health outcomes unclear and indicate the necessity for a meta-analytic review.
To assess the overall comparative effect of mHealth interventions, the first research question (RQ) was posed as follows:

*RQ1*: Are mHealth interventions more effective than comparison interventions/conditions at improving health outcomes?

To take a close examination of the large variation of ESs in the efficacy of mHealth interventions, the first potential moderating variable is the theoretical framework applied in these studies. Theory enriches and provides a roadmap for research practices [5]. Therefore, it is plausible to assume that theory-based mHealth interventions may be more efficacious than their counterparts. A wide variety of theories have been applied in the mHealth interventions to date, including behavioral theories (e.g., health belief model [HBM; 27], theory of planned behavior [TPB; 28]), cognitive theories (e.g., social cognitive theory [SCT; 29]), or behavioral and cognitive theories (e.g., cognitive behavioral therapy [CBT; 30]). However, which theoretical paradigm works best in mHealth interventions remains unclear.

Besides investigation of the theoretical framework, previous research [31-33] suggests that health topic, intervention designs (e.g., control group design, length of intervention and follow-up), and participants’ features (e.g., age, gender, health conditions) could moderate the effects of health interventions. Specifically, a meta-analysis on health interventions using social networking sites reported that studies using a “true” control condition without giving any intervention had a significantly higher weighted mean ES than studies giving an alternative intervention to the control group [33]. To examine the comparative effectiveness instead of the absolute effectiveness of mHealth interventions, it is crucial to take into consideration the control group design, including regular treatment [34], print-version [35] or computer-version [36] interventions, less intensive version of mHealth interventions [37], or interventions combining
In addition, several mobile-device-related features will also be analyzed as potential moderators. First, mobile devices have been applied in health interventions through different strategies. Some studies only used SMS [38, 39] or mobile apps [40, 41], while others combined both SMS and mobile apps [42, 43]. Second and relatedly, there are not only interventions that applied mobile phone as the only channel [7, 17] but also those that combined mobile phone with either face-to-face communication [39, 44], another type of media [8, 37], or both [34, 45]. Although some researchers suggested that unimodal interventions could provide participants with more exposure and be easier to manage [46, 47], leading to higher effectiveness, others advocated for multimodal interventions, which are more likely to engage participants and therefore function better in health promotion [48]. Furthermore, Sama and colleagues proposed a typology of eight types of mobile device engagement—changing personal environment, facilitating social support, goal setting, progress tracking, reinforcement tracking, self-monitoring, social presentation, and social referencing [18]. However, the types of engagement that improve the effectiveness of mHealth interventions remain unclear and will be examined in the current study.

RQ2: Are the relative effects of mHealth interventions moderated by (a) theoretical paradigm, (b) health topics, (c) types of engagement, (d) mobile use type, (e) intervention channel, (f) control group design, (g) length of intervention, (h) length of follow up, and (i) participants’ features?

Methods

Literature Search
To provide a clear picture of mHealth interventions’ effectiveness in improving health outcomes, comprehensive searches of the Communication & Mass Media Complete, PsycINFO, Web of Knowledge, Academic Search Premier, PubMed and Medline databases were conducted to identify potentially eligible studies in peer-reviewed journals and conference proceedings as well as dissertations and theses. Search queries were formulated using a combination of search terms: “intervention” (Title/Abstract) AND “health” (Title/Abstract) AND “*phone*” OR “black-berr*” (OR mHealth OR “application*” OR app* OR mobile OR cellular OR “short messag*” OR palm* OR iPhone* OR MP3* OR MP4* OR iPod*) (Title/Abstract).

The search was conducted on July 4th, 2016, without any limitations set for year of publication, resulting in 3,424 studies, the abstracts (and full text, as necessary) of which were reviewed for relevance. Studies were screened in multiple stages using explicit inclusion and exclusion criteria (see Figure 1), and citations were evaluated for inclusion of qualified studies.
Figure 1. Summary of selection process used in current study. RCT = randomized controlled trial. ES = effect size. Interventions using mobile phones only for data collection or making phone calls were excluded in this meta-analysis.

Overview of Meta-analysis

As generally recommended in the meta-analysis methodological literature [49, 50], Cohen's $d$ was computed as the basic unit of analysis for the meta-analytic review. The statistical analyses were based on methods proposed by Hedges and Olkin [51]. Since publication bias may exist when the publication status depends on the statistical significance of study results [52], multiple analytic approaches were implemented to check for publication bias. First, a funnel plot was used to examine whether ESs from smaller studies show more variability than those from
larger studies. Given that the funnel plot interpretation was open to subjectivity, Rosenthal’s failsafe $N$ and Duval and Tweedie’s trim and fill method were also applied to provide statistical evidence of publication bias.

The current meta-analysis used the variance-weighted analysis [51]: the overall weighted ES was computed by weighting the unbiased ES ($d$) by the inverse of its associated variance ($W_i = 1/V_i$). The overall homogeneity of ESs was tested using $Q$ statistics to determine whether all effects were from the same population. When $Q$ statistics are significant, the ESs are not from the same population, and the overall ES should be computed under the random effects models (REM), which incorporates between-studies uncertainty in the computation [53]. Otherwise, fixed-effect model (FEM) would be used.

In the moderator analysis, ANOVA-like categorical models were conducted to analyze categorical moderators (e.g., health topic, mobile use type) using mixed-effect models (MEM), since FEM with categorical moderator assumes that all studies in one subgroup share a common ES, while the MEM allows true variation of effects within subgroups of studies [54]. The same approach was applied when using meta-regression modeling to analyze continuous moderators (e.g., length of follow-up, participants’ age). In the cases where moderator analyses were statistically significant under the MEM, post-hoc analysis was conducted for pairwise comparison using Tukey contrasts with adjusted $p$-value. The analyses were conducted using Metafor and Multcomp package in R software.

Results

Study Description

A total of 61 studies were included in the current meta-analysis (see Table 1), with 127 ESs computed following Schmidt and Hunter’s approach [55].
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<thead>
<tr>
<th>Study</th>
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<th>Age</th>
<th>Subgroup</th>
<th>Topic</th>
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<td>SMS</td>
<td>HbA1c</td>
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<td>57.13</td>
<td>patients with poorly controlled diabetes</td>
<td>Diabetes - HbA1c</td>
<td>SCT, illness beliefs model, TAM</td>
<td>Telehealth</td>
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<td>0.06</td>
<td>64</td>
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<td>Overweight and obese individuals</td>
<td>Diabetes risk - sedentary behavior</td>
<td>SCT, behavioral choice theory, common sense model</td>
<td>Accelerometer</td>
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<td>0.01</td>
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<td>Diabetes risk - physical activity, healthy eating, weight loss</td>
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<td>App, SMS</td>
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<td>Cognitive apprenticeship model, situated learning theory</td>
<td>App, in-app texts, virtual visits</td>
<td>HbA1c</td>
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<tr>
<td>29</td>
<td>Hurling</td>
<td>2007</td>
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<td>Social comparison, decisional balance, ELM, goal theory</td>
<td>App</td>
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<td>30</td>
<td>Irvine</td>
<td>2015</td>
<td>0.21 0.01 398</td>
<td>Adults with back pain</td>
<td>low back pain</td>
<td>SCT, TPB</td>
<td>App</td>
<td>Back pain</td>
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<tr>
<td>31</td>
<td>Istepanian</td>
<td>2009</td>
<td>0.24 0.02 137 58.6</td>
<td>Diabetes patients</td>
<td>Diabetes self-management</td>
<td>SMT, SCT</td>
<td>Telemonitoring</td>
<td>HbA1c</td>
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</tr>
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<td></td>
<td>Study Reference</td>
<td>Effect Size</td>
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<td>N</td>
<td>Age Group</td>
<td>Intervention Details</td>
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<td>Outcome Measures</td>
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<tr>
<td>32</td>
<td>Johnson (2016)</td>
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<td>0.04</td>
<td>87</td>
<td>Adolescents</td>
<td>Medication adherence</td>
<td>SMT, SCT</td>
<td>QOL</td>
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<tr>
<td>33</td>
<td>Kamal (2015)</td>
<td>0.27</td>
<td>0.02</td>
<td>200</td>
<td>Stroke survivors</td>
<td>Medication adherence</td>
<td>HBM, SCT</td>
<td>SMS</td>
<td>Diastolic BP</td>
</tr>
<tr>
<td>34</td>
<td>Karhula (2015)</td>
<td>0.00</td>
<td>0.02</td>
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<td>Wagner's chronic care model</td>
<td>App for telemonitoring</td>
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<tr>
<td>35</td>
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<td>Diet/nutrition</td>
<td>SDT</td>
<td>App &amp; Text</td>
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<tr>
<td>36</td>
<td>Kirwan (2013)</td>
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<td>0.08</td>
<td>60</td>
<td>Patients with diabetes</td>
<td>Diabetes self-management</td>
<td>SMT, SCT</td>
<td>App &amp; Text</td>
<td>HbA1c</td>
</tr>
<tr>
<td>37</td>
<td>Laing (2014)</td>
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<td>0.02</td>
<td>162</td>
<td>Adults with BMI &gt; 25</td>
<td>Weight loss</td>
<td>SCT, SRT</td>
<td>MFP app</td>
<td>weight loss</td>
</tr>
<tr>
<td>38</td>
<td>Lappalainen (2013)</td>
<td>0.39</td>
<td>0.17</td>
<td>23</td>
<td>Males with stress exhaustion, or sleeping problems</td>
<td>Stress-related problems</td>
<td>mobile apps</td>
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</tr>
<tr>
<td>39</td>
<td>Lee (2014)</td>
<td>0.53</td>
<td>0.06</td>
<td>65</td>
<td>BPS/IC patients</td>
<td>alleviate pain and increase QOL</td>
<td>SMS</td>
<td>physical function role physical bodily pain general health vitality social function role emotion mental health</td>
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<tr>
<td>40</td>
<td>Levy (2015)</td>
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<td>0.14</td>
<td>60</td>
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<td>diabetes management</td>
<td>SMT, SCT</td>
<td>SMS</td>
<td>Reached optimal dose</td>
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<tr>
<td>41</td>
<td>Liguori (2016)</td>
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<td>0.11</td>
<td>39</td>
<td>children with a planned surgery</td>
<td>preoperative anxiety</td>
<td>mobile app</td>
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<td></td>
</tr>
<tr>
<td>42</td>
<td>Markowitz (2015)</td>
<td>0.27</td>
<td>0.04</td>
<td>90</td>
<td>YYAs with diabetes</td>
<td>diabetes management</td>
<td>SMS</td>
<td>PA and healthy food efficacy</td>
<td></td>
</tr>
<tr>
<td>43</td>
<td>Mauriello (2015)</td>
<td>0.44</td>
<td>0.02</td>
<td>219</td>
<td>Pregnant women at risk</td>
<td>risk management during pregnancy</td>
<td>TTM</td>
<td>iPad program</td>
<td>behavioral risk</td>
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<td>44</td>
<td>McGillicuddy (2013)</td>
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<td>0.24</td>
<td>19</td>
<td>recipients of a kidney transplant</td>
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<td>SDT</td>
<td>SMS</td>
<td>systolic BP diastolic BP</td>
</tr>
<tr>
<td>45</td>
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<td>0.25</td>
<td>0.04</td>
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<td>app ALICE</td>
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<td>46</td>
<td>Montes (2012)</td>
<td>0.28</td>
<td>0.02</td>
<td>251</td>
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<td>SMS</td>
<td>QOL</td>
<td></td>
</tr>
<tr>
<td>47</td>
<td>Newton (2014)</td>
<td>0.20</td>
<td>0.15</td>
<td>27</td>
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<td>physical activity</td>
<td>SCT</td>
<td>SMS</td>
<td>sedentary time</td>
</tr>
</tbody>
</table>
Note. The study was named by the first author’s last name and the publication year. The full list of meta-analyzed studies is not included in the references list but available upon request. SMS = short messaging service. SCT = social cognition theory, SMT= self-management theory, TPB = theory of planned behavior, TTM = transtheoretical model, HBM = health belief model, SDT= self-determination theory, SRT= self-regulation theory, CIPT = Consumer information processing theory, ELM = elaboration likelihood model, TAM = technology acceptance model, HTT = habituation-tedium theory, IMBSM = information-motivation-behavioral skills model, CVD = cardiovascular disease, QOL = QOL, BMI = body mass index, BP = blood pressure, YYA = youth and young adult
Publication Bias

Publication bias may exist when publication status depends on the statistical significance of study results [52]. We have applied multiple techniques to check for potential publication bias. First, a funnel plot can be used to examine whether ESs from smaller studies show more variability than those from larger studies. As shown in Figure 2, the funnel plot of ESs seems to be generally symmetric, which is consistent with the Regression Test for funnel plot asymmetry ($z = 1.51, p = .13$) and provides evidence for the absence of publication bias. Rosenthal’s Fail-safe $N$ was 17,539, which is much larger than the tolerance level ($5k + 10 = 660$), and no study
was found missing for symmetry using Duval and Tweedie’s Trim and Fill Method, which further confirmed the absence of publication bias.

**Figure 2.** Funnel plot of effect sizes to check publication bias for current study

**Overall Analysis**

Estimated under the FEM, the $Q$ statistic was significant ($Q_{\text{total}} (df = 129) = 443.30, p < .001$), indicating that the ESs were not homogeneous, and mean ES was estimated under the REM using Restricted Maximum Likelihood Estimation method. Under the REM, the sample weighted mean for standardized mean difference was 0.31 (95% CIs [.25, .37]), which is a small ES [98], but statistically significant ($p < .001$). In other words, there was a statistically significant mean difference between the mHealth intervention and control groups according to the overall analysis. $I^2$, an index representing the ratio of true heterogeneity to total variance across observed ESs, is 73.04%, indicating large between-study variance [99]. Similarly, Birge’s ratio, another index to quantify the magnitude of heterogeneity (computed as $Q/df = 443.30/129 = 3.44$), is larger than one (the ratio when all the variance comes from sampling error), indicating large
between-study heterogeneity. Sampling error variance ($S_e^2 = 0.0141$) only accounted for 19.58% of the total variance ($S^2 = 0.0720$), suggesting the presence of moderator(s). Therefore, the moderators proposed in RQ2 were analyzed.

**Moderator Analyses**

Moderator analyses were conducted by analyzing *theoretical paradigm* (1= no theory, 2= behavioral theory, 3= cognitive theory, 4= behavioral and cognitive theories combined), *health topic* (1= mental health, 2= nutrition and weight status, 3= physical activity, 4= health-related quality of life and well-being, 5= chronic disease management), *eight types of engagement* (Sama et al., 2014), *mobile use type* (1= text messages, 2= mobile app, 3= combined), *intervention channel* (1= mobile phone only, 2= mobile phone combined with other type of media, 3= mobile phone combined with face-to-face communication, 4= mobile phone combined with other type of media and face-to-face communication), *control group design* (1= no intervention, 2= intervention based on interpersonal communication (no media), 3= intervention using other type of media than mobile phone, 4= intervention using mobile phone, 5= intervention with multiple features), and *participants’ health condition*: (1= general healthy adults, 2= population at risk) as categorical moderators respectively. Moreover, *participants’ mean age, percentage of female participants* (to examine the influence of gender), *length of the intervention*, and *length of follow-up* were analyzed as continuous moderators.

**Theoretical Paradigm.** Under MEM, theoretical paradigm was significant as a moderator ($Q_{between} (df = 3) = 11.13, p = .01$). Post-hoc pairwise comparison indicated that mHealth interventions based on cognitive and behavioral theories combined ($d = .45$) had the highest weighted mean ES among the four categories and was significantly higher than
interventions not indicating a theory (\(d = .28, p = .049\)) or interventions applying behavioral (\(d = .24, p = .04\)) or cognitive theory only (\(d = .18, p = .002\)).

**Health Topic.** Under MEM, health topic was not a significant moderator (\(Q_{between} (df = 4) = 1.19, p = .88\)), with mHealth interventions on physical activity showing the lowest weighted mean ES (\(d = .23, SE = .08, 95\%\) CIs [.07, .38], \(p = .004\)) and interventions on nutrition and weight status showing the highest ES (\(d = .37, SE = .08, 95\%\) CIs [.21, .53], \(p < .001\)), which however are not significantly different from each other. The weighted mean ESs across all five topics were significantly larger than zero.

**Types of Engagement.** Among the eight types of engagement proposed by Sama and colleagues [18], only changing personal environment (\(Q_{between} (df = 1) = 9.24, p = .002\)), reinforcement tracking (\(Q_{between} (df = 1) = 10.43, p = .001\)), and social presentation or announcement (\(Q_{between} (df = 1) = 6.67, p = .01\)) were significant moderators. Specifically, the weighted mean ES of the mHealth interventions with the function of changing personal environment (\(d = .76, SE = .15, 95\%\) CIs [.47, 1.05], \(p < .001\)) was significantly higher than that of the interventions without this feature (\(d = .29, SE = .03, 95\%\) CIs [.24, .35], \(p < .001\)) at .01 level (\(z = 3.10\)). Similarly, the weighted mean ES of the mHealth interventions with the reinforcement tracking function (\(d = .44, SE = .05, 95\%\) CIs [.33, .54], \(p < .001\)) was significantly higher than that of the interventions without this function (\(d = .24, SE = .03, 95\%\) CIs [.17, .31], \(p < .001\)) at .01 level (\(z = 2.69\)). However, the weighted mean ES of the mHealth interventions with the social presentation/announcement function (\(d = .04, SE = .08, 95\%\) CIs [-.13, .20], \(p = .65\)) was significantly lower than that of the interventions without (\(d = .33, SE = .03, 95\%\) CIs [.27, .39], \(p < .001\)) at .05 level (\(z = 2.58\)).
Mobile Use Type. How the mobile device was applied in the intervention was found as a significant moderator ($Q_{\text{between}}$ ($df = 2$) = 13.57, $p = .001$). Post-hoc analysis indicated that the weighted mean ES of interventions combining SMS and mobile apps ($d = .53$, SE $=.11$, 95% CIs [.31, .75], $p < .001$) was significantly higher than the ESs of those using only SMS ($d = .33$, SE $=.04$, 95% CIs [.24, .41], $p < .001$) or mobile apps ($d = .22$, SE $=.03$, 95% CIs [.16, .28], $p < .001$) ($z_{\text{SMS}} = 2.41$, $z_{\text{App}} = 3.65$).

Intervention Channel. The channel through which mHealth interventions were implemented turned out to be another significant moderator ($Q_{\text{between}}$ ($df = 3$) = 8.69, $p = .03$). Pairwise comparison indicated that the weighted mean ES of interventions combining mobile phone with another type of media ($d = .38$, SE $=.05$, 95% CIs [.29, .47], $p < .001$) was significantly higher than that of interventions using mobile phone only ($d = .19$, SE $=.04$, 95% CIs [.12, .27], $p < .001$) ($z = 2.38$) or interventions combining mobile phone with face-to-face communication ($d = .19$, SE $=.04$, $K = 14$, 95% CIs [.10, .27], $p < .001$) ($z = 1.98$).

Control Group Design. Nonsignificant between-study variance under MEM ($Q_{\text{between}}$ ($df = 4$) = 6.13, $p = .19$) indicated that control group design did not show a significant difference in the comparative effectiveness of the interventions.

Participants’ Age, Gender, and Health Condition. The majority of mHealth interventions in the current sample were conducted with at-risk populations, except for six studies [61, 78, 7, 85, 42, 71]. However, whether the participants were healthy or at-risk populations was not a significant moderator of the ESs ($Q_{\text{between}}$ ($df = 1$) = 2.00, $p = .16$). Neither participants’ age ($Q_{\text{between}}$ ($df = 1$) = 1.54, $p = .21$) nor gender ($Q_{\text{between}}$ ($df = 1$) = 2.41, $p = .12$) was a significant moderator.
Length of Intervention and Follow-Up. Intervention length was a non-significant moderator ($Q_{\text{between}} (df = 1) = 1.79, p = .18$); however, when the follow-up measures were conducted did moderate the ESs ($Q_{\text{between}} (df = 1) = 7.49, p = .006$). Length of follow-up ranged from immediate [57] to nine months later [71], with an average follow-up period being 2.47 weeks ($SD = 6.43$). The weighted mean ES was significant immediately after the intervention ($d = .27, p < .001$), and increased by .011 for each additional week of follow-up ($p = .006$).

Discussion

Overall Effects

Findings from our current meta-analysis indicated that mHealth interventions are significantly more effective than comparison conditions at improving health outcomes ($d = 0.31$, 95%CIs [0.25, 0.37]), which is consistent with previous meta-analyses focusing on specific health issues [9, 100-101]. In particular, mHealth interventions have been significantly more effective than comparison conditions for physical activity (Hedge’s $g = 0.54$, 95%CIs [0.17, 0.91]) [9] and led to significant improvement in diabetes management (mean 0.5% reduction in HbA$_{1c}$) [101]. As it relates to SMS, text interventions were more effective for antiretroviral therapy adherence than control conditions ($OR = 1.39$, CI: 1.18, 1.64) [100]. Our finding related to the relative effectiveness of mHealth interventions shows not only consistency with previous research but extends current research by examining the effects across health contexts. In addition to the significant overall effect of mHealth interventions, several moderators were identified, which help explain the mechanisms behind the variance in mHealth interventions’ efficacy.

Effects of Engagement

Findings indicated several statistically significant moderators of mHealth intervention effects. One such moderator is the types of engagement (i.e., changing personal environment,
reinforcement tracking, and social presentation/announcement). mHealth interventions that included features for changing one’s personal environment and/or reinforcement tracking exhibited larger relative effects than mHealth interventions without those features. Changing a person’s personal environment directly enables people to engage in the desired behavior or a behavior that affects the desired health outcome (e.g., soothing sounds for meditating, which may help with stress) [18]. Resources that allow users to immediately engage in the desired behavior (or a behavior that affects the desired health outcome) may help to reduce barriers that may otherwise prevent them from engaging in healthy behaviors that improve health outcomes.

Theories of health behavior change (e.g., HBM, TPB) address the important role that perceived or actual barriers play, indicating that reducing perceived or actual barriers can enhance the likelihood of positive behavior change. Alternatively, mHealth interventions that included the feature of social presentation or announcement exhibited smaller relative effects than mHealth interventions without that feature. This finding is counterintuitive, as one might expect that a social presentation or announcement feature would have greater positive effects on health outcomes, as providing information to others about one’s accomplishments may increase motivation [102]. One possible explanation is that social presentation/announcement may serve as a distraction to participants. Previous research has found that features intended to draw in/engage audiences may actually distract them from the position advocated by messages [103]. Alternatively, the lower relative effects of mHealth interventions with a social presentation/announcement feature may be due largely to one study with this feature that contributed the largest negative ES in the meta-analysis [7].

**Effects of Intervention Channel**
mHealth interventions using both SMS and a mobile app were relatively more effective than interventions using either SMS or a mobile app. SMS were typically used to collect data about participants’ behavior [45], and/or provide reinforcement for desired behaviors [67, 85]. Furthermore, mHealth interventions that included other media were relatively more effective than interventions that included face-to-face components. Many of the mHealth interventions that included additional media channels used websites, emails, and/or print materials. Interventions with face-to-face communication as an additional channel typically used in-person health care/counseling or group workshops. mHealth interventions incorporating other media may be more effective because they provide additional content exposure, use complementary strategies, and/or drive people to the mobile intervention components, which is helpful in delivering messages to users with a variety of media use habits [104], especially for those whose preferred medium is not mobile device.

**Length of Follow Up**

MHealth interventions with longer follow-up exhibited greater effects than those with shorter follow-up. Previous research indicates that length of follow-up can serve as a moderator of relative intervention effects [31]; however, in previous research greater effectiveness was shown for shorter-term follow up [33], which is the opposite of the current finding. The finding may reflect the fact that some mHealth intervention studies used apps that are freely available, commercial apps [68], which participants could continue using after the intervention period. This finding highlights the promise of mHealth interventions in promoting positive long-term health outcomes. The easy accessibility and cost efficiency of mobile features may help prevent diminishing intervention effects compared to those that use other new media [33].

**Theoretical and Practical Implications**
Our moderator analyses found that studies based on both cognitive and behavioral theories were more effective than those based on no theory or behavioral/cognitive theory only. Cognitive theories, such as SCT [29] or self-regulation theory [105], mainly focus on psychological factors and inner thoughts. Although they are related to behavior, there is still a gap between intention and actual behavior due to internal and external barriers [28], and how to bridge this gap and eventually trigger behavioral change are not well-addressed. On the contrary, perceived and actual barriers are key variables in behavioral theories, such as HBM [27] or TPB [28], which acknowledge and emphasize reducing these barriers to achieve positive behavioral change. However, behavior is rooted in cognitions, which are considered precursors to behavioral change; positive behavioral change that is lacking a strong cognitive foundation may not have longitudinal effects. Therefore, the complementarity of cognitive and behavioral theories may explain the large ESs of studies that applied both types of theories [62, 94].

The convergence of cognitive and behavioral theories has observed success in CBT [106] and deserves further investigation by health communication researchers.

In terms of mHealth intervention design, given that tailored communication is effective in promoting health behavior change and health outcomes [31], it is important to enable users to change their personal environment using mobile devices and provide personalized reinforcement messages based on users’ progress on health outcomes. According to the Elaboration Likelihood Model [107], personally relevant messages are more likely to increase personal involvement and trigger central route message processing, which would achieve stable persuasive effects over time. Alternatively, health researchers and professionals should take caution when incorporating social presentation/announcement features to engage participants and to avoid distraction. More
research examining how to strategically integrate social engagement features [18] into mobile devices without affecting message exposure [46-47] to improve health outcomes is needed.

When designing mobile interventions, it is worth considering combining both SMS and app features, which are available on most smartphones. SMS is easier to implement while apps could afford multimedia interactive features; such features would complement each other to potentially maximize user engagement and health outcomes. According to channel complementary theory [104], people use multiple sources, which serve different niches and present unique information, to acquire information in certain health topics. Therefore, health researchers and professionals could also take advantage of other types of media when designing mHealth interventions, especially Internet, by which several studies have achieved high efficacy [8, 25, 36]. Lastly, due to the easy accessibility and cost efficiency of mobile devices, our finding also highlights the promise of mHealth interventions in achieving long-term health effects. Thus, researchers aiming to improve health outcomes over a long period of time could base interventions on existing low-cost mobile apps or free SMS to enable sustained use of the target mobile features and consequently maintain positive effects.

Limitations and Future Research

Despite this study’s pioneering efforts, several limitations should be noted. First, although the current study started from a comprehensive literature search and included more studies than previous reviews ([3-4, 10], the sample size of several specific categories remains small. For instance, none of the studies meeting inclusion criteria focused on reducing substance use, promoting sexual health, or preventing HIV/AIDS. Among the health issues in the current meta-analysis, only four studies focused on health-related quality of life [47, 61, 72, 86]. In the same vein, both the social presentation [7, 48, 61, 68] and social referencing [7-8, 48, 85] engagement
types have been applied in only four studies. The comparatively small sample size of RCTs, attributed to the recency of mHealth interventions and the long implementing and publishing process, could limit the reliability of statistical results in specific categories and increase the likelihood of chance differences. As such, more empirical evidence is needed to have a more reliable estimation of the moderating effects in mHealth interventions, especially in understudied areas.

Second, in an attempt to be as comprehensive as possible, the current study included not only published studies, but also conference papers and unpublished work, which makes the study vulnerable to including low quality studies, a general limitation for meta-analytic research [54]. Since studies included in one meta-analysis vary in quality, and fundamental errors in empirical studies cannot be corrected in meta-analysis, low-quality studies may contaminate the results.

Finally, despite efforts to include only the most relevant RCT studies, the current study is susceptible to the “apples and oranges” critique concerning the comparability of studies, a common concern for meta-analytic reviews [54]. Comparability refers to all of the studies included in one meta-analysis examining the same constructs or relationships. Because of the relatively small sample size in some categories, such as the variety of specific media that were used in combination with mobile devices in interventions, they were grouped in a larger category for moderator analyses.

**Conclusion**

Mobile health (mHealth) interventions have become increasingly common in recent years, given the ubiquity of mobile phone ownership, providing the possibility to disseminate tailored messages, cost efficiency of mobile delivery channels, and opportunity for large-scale dissemination. To the best of our knowledge, this is the most comprehensive meta-analysis to
date that examined the overall effectiveness of mHealth interventions across health topics and is the first study that statistically tested moderators. By analyzing 61 studies, we found that mHealth interventions have a small but significant weighted mean ES ($d = 0.31$), and effects are moderated by theoretical paradigm, three engagement types (i.e., changing personal environment, reinforcement tracking, social presentation), mobile use type, intervention channel, and length of follow-up. Our findings not only shed light on intervention design using mobile devices, but also provide new directions for research in health communication and promotion using new media. Future scholarship is needed to examine the effectiveness of mHealth interventions across various health issues, especially those that have not yet been investigated (e.g., substance use, sexual health), engaging participants using social features on mobile devices, and designing tailored mHealth interventions for diverse subpopulations to maximize effects.
References

* References marked with an asterisk indicate studies included in the meta-analysis.


75. *Holmen H, Torbjørnsen A, Wahl AK, Jenum AK, Småstuen MC, Årsand E, & Ribu L. A mobile health intervention for self-management and lifestyle change for persons with type 2 diabetes, part 2: One-year results from the Norwegian randomized controlled trial RENEWING HEALTH. *JMIR mHealth uHealth* 2014; 2(4): e57. doi:10.2196/mhealth.3882


