A Meta-Analytic Review of eHealth Interventions for Pediatric Health Promoting and Maintaining Behaviors

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Objective The current study quantitatively evaluated the impact of eHealth interventions on pediatric health promoting and maintaining behaviors believed to impact the development or worsening of a physical disease and their associated outcomes. Method PsycINFO, PUBMED/MEDLINE, Educational Resources Information Center (ERIC), and reference sections of identified articles were searched. Results An omnibus weighted mean effect size for all identified eHealth interventions revealed a small, but significant, effect (mean $d = .118$, 95% confidence interval [CI] = .066–.171). However, when considered independently, educational interventions demonstrated no significant effect on pediatric health behavior or health outcomes. Behavioral eHealth interventions produced relatively homogeneous effects that were small but significantly different from zero (mean $d = .354$, 95% CI = .232–.475). Conclusion eHealth interventions that incorporate behavioral methods (e.g., self-monitoring, goal setting, immediate feedback, contingency management) produce larger effect sizes for health behaviors and their associated outcomes than interventions that rely solely on education.

Key words adolescent; behavior change; child; eHealth; health behavior; meta-analysis.

Health behavior interventions that employ advanced technologies have increased dramatically in number and type in recent years. Technology can extend the reach of individual providers or function as an active ingredient in treatment; the latter use is termed “eHealth” (Boschen & Casey, 2008; Palermo, 2008; Palermo & Wilson, 2009). eHealth interventions derive from technologies as ubiquitous as cell phones, closed computer systems, and the Internet, to those that some clients have only seen on television or in an amusement park (e.g., virtual reality; Ritterband et al., 2003b; Palermo & Wilson, 2009).

eHealth interventions are applications of technology that seek to either improve a client’s understanding of health information or use technology as a surrogate for the clinician in treatment delivery (Palermo, 2008; Palermo & Wilson, 2009). Technology can be used to deliver the active ingredient in treatment and may take the place of some face-to-face meetings with a clinician. For example, Williamson et al. (2005) recruited a group of overweight and obese adolescent African–American females randomized to receive either a standard educational Internet intervention or an internet-delivered program that employed self-monitoring and tailored immediate feedback related to diet and exercise behaviors. This study demonstrates the ability of technology to serve as a proxy for clinicians in delivery of both knowledge and behavior modification components of a treatment program.

In a slightly more limited scope, eHealth technologies may be used as adjuncts to meetings with a clinician by providing reminders or additional information, reiterate program-specific messages, facilitate the completion of homework, and perform other tasks that take the resources of the clinician or educator in another context. For example, Franklin, Waller, Pagliari, and Greene (2006) used
automated text messages to communicate adherence goals agreed upon in session to children with Type 1 Diabetes Mellitus. This type of study provides an example of ways that technologies enrich face-to-face treatment even if only serving as an adjunct to treatment because of their inability to stand without clinician input.

Recently, a systematic review of Internet-based self-management interventions reported a generally positive effect for youth with health conditions (Stinson, Wilson, Gill, Yamada, & Holt, 2009). Specifically, Stinson and colleagues found that the current literature generally supports self-directed Internet interventions designed to improve disease knowledge, improve health outcome, decrease healthcare utilization, and improve quality of life. It is important to note that the authors narrowed their sample by excluding eHealth interventions that did not use the Internet. This approach allowed the authors to adequately describe the multitude of outcomes that are changeable through Internet delivery including knowledge, psychosocial variables, and health outcomes. However, even within such a narrowly defined and relatively small sample of studies (n = 9), Stinson et al. (2009) identified substantial variability in type of intervention, quality of design, and method of assessment. The observed variability may have contributed to the fact that while most interventions achieved positive results, there were several disconfirming examples throughout the sample of studies (e.g., Chan et al., 2007). This work provided an important step in understanding both behavioral processes and health outcomes that are malleable through the application of Internet interventions.

A number of moderating characteristics, some identified by Stinson and colleagues (2009) further explain the mechanism of action behind eHealth interventions. One method that has been used to synthesize face-to-face interventions is to classify individual interventions by the theory that underlies the primary intervention components (e.g., behavioral, cognitive, educational; Kahana, Drotar, & Frazier, 2008; Stinson, Wilson, Gill, Yamada, & Holt, 2009). The meta-analysis conducted by Kahana and colleagues (2008) employed this type of classification system to conclude that face-to-face interventions for adherence that incorporated behavioral components were more effective than those relying only on education/instruction. Unfortunately, due to the small number of effect sizes (n = 7) Kahana and colleagues (2008) were not able to apply their theoretical classification system to examine the differential effect sizes between educational and behavioral eHealth adherence interventions.

As stated previously, current reviews of pediatric eHealth interventions have been limited primarily to the examination of pediatric web-based modalities or as a subset of interventions for a specific health behavior (e.g., adherence). The expanding landscape of eHealth interventions and the interest in the field (viz. special issue of Journal of Pediatric Psychology, 34(3), devoted to this new mechanism of treatment delivery) necessitate work at this early stage to empirically synthesize the existing intervention literature and provide clinicians and researchers with a summary that might guide research and clinical interventions in a field “still in its infancy” (Ritterband & Palermo, 2009, p. 435). The current study fills a gap in the literature by empirically examining the impact of different types of eHealth interventions across various health promoting and maintaining behaviors and their associated outcomes.

Thus, the first aim of the current study is to advance the literature by providing a quantitative review of the pediatric eHealth literature to statistically determine the impact of eHealth interventions on health promoting and maintaining behaviors and what, if any, moderating intervention characteristics lead to intervention success. Specifically, the current review aims to extend the literature on pediatric eHealth interventions by examining the differential impact of educational versus behavioral eHealth interventions on child and adolescent health promoting and maintaining behaviors and their associated outcomes. In light of findings in the health behavior literature (e.g., Kahana et al., 2008), we hypothesized that eHealth interventions that adopt a primarily educational/instructional approach will have a significantly smaller aggregate effect size for health behavior change than eHealth interventions that incorporate behavioral principles into the intervention framework.

The current study examines only eHealth interventions that target a child or adolescent’s health promoting or maintaining behavior or a theoretically associated outcome. For the purposes of the current review, interventions were determined to examine health behavior/outcome if the intervention impacted a health promoting or maintaining behavior believed to affect the development or worsening of a physiological disease state. Outcomes of interest included both behavioral process variables that may lead to health improvement (e.g., diet and exercise) and health outcomes that were targeted with behavioral process interventions (e.g., participant weight in a diet and exercise intervention).

The decision to target health promoting and maintaining behaviors was made because this conceptualization
provides a framework for sampling studies with similar theoretical mechanisms of action. For example, interventions for health promoting behaviors (e.g., self-monitoring of adherence) work through a different theoretical mechanism than virtual reality distraction during IV placement (e.g., Gold, Kim, Kant, Joseph, & Rizzo, 2006) or cognitive coping for headache (e.g., Connelly, Rapoff, Thompson, & Connelly, 2006). An additional goal is to report on the impact of interventions that use technology as a treatment component rather than as an extension of the treatment provider’s ability to directly communicate with a client (as is the case in telehealth). Thus, we excluded telehealth interventions that simply use technology as a method of communication between a client and a treatment provider.

**Methods**

**Literature Search**

The current review of the literature excludes telehealth interventions and adopts a slightly modified definition of eHealth based on Palermo and Wilson (2009): eHealth is an application of intervention technology, in a primary or secondary capacity, to promote or modify health behavior in children or adolescents. Under this definition, we identified a number of potential technology-based intervention delivery mechanisms. These include Internet, cell phones, PDAs, CD-ROM, pagers, computer games, and virtual reality.

Literature searches from a number of electronic medical and psychological databases were undertaken, in addition to manual reference searches of identified empirical and review articles. Databases searched include PsycINFO, PUBMED/MEDLINE, and Educational Resources Information Center (ERIC). Search terms included: Internet, eHealth, multimedia, cell phone, PDA, virtual reality, pager, and CD-ROM. The wildcard symbol (*) was used to ensure that variations of each keyword would be retrieved. We combined each of the above search terms with the secondary search terms pediatric or health for a total of 48 searches across three databases. Searches retrieved articles published during or before 2009. We applied search limiters to exclude studies with samples of individuals with ages greater than 18 or those written in a language other than English. In addition, we examined reference sections of review articles and book chapters addressing pediatric eHealth for relevant articles (e.g., Kahana et al., 2008; Palermo & Wilson, 2009; Stinson et al., 2009). Our search yielded 884 peer-reviewed articles for further screening after removing 59 duplicates.

**Inclusion Criteria**

Studies were included in the current review if they used quantitative methods to evaluate the impact of an eHealth intervention on a pediatric disease state (e.g., asthma, diabetes, etc.) with a known health behavior moderator of outcome (e.g., adherence to medication) or a health behavior that can have a deleterious effect on child or adolescent health (e.g., poor diet, lack of exercise, smoking, etc.). Only English language articles were included and only interventions targeting the health behavior of children or adolescents (i.e., age ≤ 18 years) were included.

**Exclusion Criteria**

Exclusion criteria were applied in the order that follows, thus, a study could meet criteria for exclusion on more than one criterion, but would only count toward the n-size for the first criterion in the list. Articles were excluded because: (a) the article was not an intervention study (n = 708); (b) the study did not employ technology as a component of a health intervention (n = 37); (c) the use of technology did not fit the definition of eHealth stated previously (n = 18); (d) no health behaviors that affect a disease state were targeted for intervention (n = 58); (e) the study focused purely on using technology for assessment or tracking (n = 7); (f) the outcome means included participants that were age 18 or over, or drew a mixed sample of adults and children or adolescents (n = 18); (g) the study utilized a small-n or case-report design (n = 1); or (h) the article failed to include sufficient statistical information to compute an effect size (n = 5; a list of excluded studies is available from the authors on request). We decided to exclude single-n studies because the analyses must account for changes in both level and slope to accurately reflect the impact of single- or small-n treatments. It is impossible to represent both level and slope with a single number and, therefore, it is impossible to convert results to a standard mean difference. One article was excluded because it reported data from a sample that was already included. After applying the exclusion criteria, we identified a total of 31 empirical articles for review. However, two of these articles reported on two independent studies each (e.g., Study 1 and Study 2), yielding a total of 33 independent studies contributing effect sizes to this meta-analysis.

**Classification of Interventions**

We classified interventions as either educational or behavioral using criteria from Kahana et al. (2008) modified to
be applicable to eHealth. Educational interventions were those that primarily focused on communicating some form of knowledge about health behavior to children or adolescents. This includes knowledge about disease control, replacement behaviors, information about the positive impact of a program-specific behavior, or normative feedback about a particular behavior. We classified interventions as behavioral if they used technology to provide some behavioral intervention (i.e., self-monitoring, immediate feedback, reinforcement schedules, or goal setting/goal review) or if technology served as an adjunct to a behavioral intervention. Note that behavioral interventions may have used more than one particular behavioral strategy, and could have included education as part of the intervention framework.

Data Analysis Plan

If results from the same sample at the same time point appeared in more than one study, the data were only included once in the effect size aggregation procedure. If an article reported results from two independent samples, the data were treated as independent for each sample. When a study reported multiple health behavior change variables or associated outcomes, these were averaged to create an aggregate effect size for the study. When findings were described as non-significant with no associated values, an effect size of zero was used (Lipsey & Wilson, 2001).

Only variables measuring a health behavior or a measure of disease functioning that could be reasonably associated with health behaviors (e.g., z-BMI) were coded. Consistent with the intent of the article, behavior change outcomes were coded first with disease outcome being coded only if the article did not report a behavior change variable. A total of 56 effect sizes were calculated from 33 studies. As noted above, the number of studies (33) exceeds the number of articles (n = 31) because two articles reported on two independent studies with independent samples.

Consistent with other meta-analyses of interventions appearing in the pediatric health literature (e.g., Pai, Drotar, Zebracki, Moore, & Youngstrom, 2006; Kahana et al., 2008), post-test data were gathered when studies employed a comparison of two or more groups. When group comparisons were not the focus of the study or insufficient data were presented to calculate an effect size based on group differences, pretest to posttest mean differences were calculated (Lipsey & Wilson, 2001). However, we identified only one study reporting pretest to posttest differences (i.e., Long & Stevens, 2004); thus, aggregate effect sizes should be interpreted as the impact of an intervention group compared to a control or comparison group rather than an overall effect of treatment.

All effect sizes were converted to Cohen’s d in order to allow comparisons of individual effect sizes. Cohen (1988) provided guidelines for interpreting the d effect size; he recommended assigning qualitative descriptors as follows: .20–.49 as small, .50–.79 as medium, and .80 and above as large. Studies were weighted by their sample size. A weighted least squares approach was used to emphasize findings from studies with larger samples and smaller variances (Hedges & Olkin, 1985). The more conservative random effects model was calculated to account for random heterogeneity among the samples. This was accomplished by reestimating the mean effect size and confidence intervals, incorporating the random effects variance as an adjusted inverse variance weight (Lipsey & Wilson, 2001).

Q-statistics were calculated to test the homogeneity of the effect sizes. A significant Q-statistic indicates more variability between effect sizes than can be accounted for by study-level sampling error (Lipsey & Wilson, 2001). In the current study, it was hypothesized that variability in individual effect sizes could be accounted for by the classification system described above. Using the classification system, the Q-statistic allows variability among effect sizes to be parsed into between and within group variability (Lipsey & Wilson, 2001). When such a statistical comparison reveals a significant between-groups difference (i.e., educational vs. behavioral) and the resulting groupings each have non-significant Q-statistics, then the variability in effect sizes has been explained and no further testing of moderators is necessary.

Results

Description of Studies

Of the 33 included studies, 14 (42.4%) employed interventions for diet or exercise with a focus on weight control or overall nutritional health, 9 (27.3%) focused on symptom control in children with asthma, 6 (18.2%) targeted smoking cessation, 2 (6.1%) targeted encopresis, 1 (3%) targeted healthy sun behavior, and 1 (3%) targeted diabetes care behaviors. Twenty-nine (87.9%) of the included studies were randomized controlled trials; two studies (6.1%) employed a nonrandomized between-groups design, two studies (6.1%) employed a nonrandomized single-group pre- posttest methodology (see Table I).
<table>
<thead>
<tr>
<th>Author</th>
<th>Health concern</th>
<th>Methodology</th>
<th>Total n</th>
<th>Male</th>
<th>Ethnicity</th>
<th>Class.</th>
<th>Intervention type</th>
<th>Sessions/duration</th>
<th>Face-to-face sessions</th>
<th>Post-Tx assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baranowski et al. (2003)</td>
<td>Nutrition</td>
<td>RCT</td>
<td>1578</td>
<td>50%</td>
<td>17% AA; 44% W; 30% H; 9% O</td>
<td>Bx</td>
<td>Computer game</td>
<td>10 sessions/25 min each</td>
<td>NA</td>
<td>5 weeks</td>
</tr>
<tr>
<td>Baranowski et al. (2003)</td>
<td>Obesity</td>
<td>RCT</td>
<td>35</td>
<td>0%</td>
<td>100% AA</td>
<td>Bx</td>
<td>Internet</td>
<td>Eight modules/1 per week</td>
<td>4-week day camp</td>
<td>12 weeks</td>
</tr>
<tr>
<td>Bartholomew et al. (2000)</td>
<td>Asthma</td>
<td>RCT</td>
<td>171</td>
<td>65%</td>
<td>42.1% H; 52.9% AA; 5% O</td>
<td>Ed</td>
<td>CD-ROM</td>
<td>One 40 min tutorial and 4–15 mo self-paced</td>
<td>NA</td>
<td>16–62 weeks</td>
</tr>
<tr>
<td>Buller et al. (2008)</td>
<td>Smoking</td>
<td>RCT</td>
<td>1510</td>
<td>52%</td>
<td>65% W; 12% H; 7% O</td>
<td>Ed</td>
<td>Internet</td>
<td>Six modules/45–60 min. each</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Burnett et al. (1989)</td>
<td>Weight &amp; Nutrition</td>
<td>RCT</td>
<td>76</td>
<td>56%</td>
<td>Bx Computer feedback</td>
<td></td>
<td></td>
<td>Five sessions of computer assisted feedback</td>
<td>NA</td>
<td>12 weeks</td>
</tr>
<tr>
<td>Chan et al. (2003)</td>
<td>Asthma</td>
<td>RCT</td>
<td>10</td>
<td>50%</td>
<td>Bx</td>
<td></td>
<td>Internet</td>
<td>Once daily recording/128 days</td>
<td>NA</td>
<td>25 weeks</td>
</tr>
<tr>
<td>Chan et al. (2007)</td>
<td>Asthma</td>
<td>RCT</td>
<td>120</td>
<td>66%</td>
<td>Bx</td>
<td></td>
<td>Internet</td>
<td>Six modules</td>
<td>2 phone calls per week</td>
<td>52 weeks</td>
</tr>
<tr>
<td>Chen et al. (2006)</td>
<td>Smoking</td>
<td>Exp vs. Ctl</td>
<td>77</td>
<td></td>
<td>Bx</td>
<td></td>
<td>Internet</td>
<td>Six sessions/1 hr each</td>
<td>6 weekly group therapy sessions</td>
<td>6 weeks</td>
</tr>
<tr>
<td>Doyle et al. (2008)</td>
<td>Diet</td>
<td>RCT</td>
<td>83</td>
<td>37%</td>
<td>50% W; 26% AA; 13% H; 11% O</td>
<td>Bx</td>
<td>Internet</td>
<td>16 weeks with 1–2 hrs of intervention per week</td>
<td>NA</td>
<td>16 weeks</td>
</tr>
<tr>
<td>Franklin et al. (2006)</td>
<td>Diabetes</td>
<td>RCT</td>
<td>92</td>
<td>40%</td>
<td>96.6% W</td>
<td>Bx</td>
<td>Cell phone</td>
<td>One to two daily texts for 12 months</td>
<td>NA</td>
<td>52 weeks</td>
</tr>
<tr>
<td>Frenn et al. (2003)</td>
<td>Diet &amp; PA</td>
<td>Exp vs. Ctl</td>
<td>79</td>
<td>39%</td>
<td>26% AA; 44% H; 5% W; 5.8 O</td>
<td>Bx</td>
<td>Internet</td>
<td>Eight modules/40 min each for one month</td>
<td>NA</td>
<td>4 weeks</td>
</tr>
<tr>
<td>Goran et al. (2004)</td>
<td>PA</td>
<td>RCT</td>
<td>307</td>
<td>40%</td>
<td></td>
<td>Bx</td>
<td>CD-ROM</td>
<td>Eight modules/45 min each for 8 weeks</td>
<td>4 classroom and 4 family lessons</td>
<td>8 weeks</td>
</tr>
<tr>
<td>Guendelman et al. (2002)</td>
<td>Asthma</td>
<td>RCT</td>
<td>134</td>
<td>57%</td>
<td>76% AA; 10% W; 14% O</td>
<td>Bx</td>
<td>Phone/Internet</td>
<td>One to two brief intervention(s) per day for 90 days</td>
<td>NA</td>
<td>6 weeks</td>
</tr>
<tr>
<td>Homer et al. (2000)</td>
<td>Asthma</td>
<td>RCT</td>
<td>137</td>
<td>59%</td>
<td>60% AA; 5% H</td>
<td>Ed</td>
<td>Computer Game</td>
<td>Three visits to guide character through six levels</td>
<td>NA</td>
<td>36 weeks</td>
</tr>
<tr>
<td>Hornung et al. (2000)</td>
<td>Sun behavior</td>
<td>RCT</td>
<td>192</td>
<td>56%</td>
<td>73% W; 4% AA; 13% H; 10% O</td>
<td>Ed</td>
<td>CD-ROM</td>
<td>One session</td>
<td>9-weekly sessions at Boy Scout Troop meetings</td>
<td>28 weeks</td>
</tr>
<tr>
<td>Jago et al. (2006)</td>
<td>PA</td>
<td>RCT</td>
<td>473</td>
<td>100%</td>
<td>Bx</td>
<td></td>
<td>Internet</td>
<td>Asked to log in two times per week for 9 weeks</td>
<td>NA</td>
<td>9 weeks</td>
</tr>
</tbody>
</table>

(continued)
Table I. Continued

<table>
<thead>
<tr>
<th>Author</th>
<th>Health concern</th>
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<th>Total n</th>
<th>Male</th>
<th>Ethnicity</th>
<th>Class.</th>
<th>Intervention type</th>
<th>Sessions/duration</th>
<th>Face-to-face sessions</th>
<th>Post-Tx assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan et al. (2007)</td>
<td>Asthma</td>
<td>RCT</td>
<td>164</td>
<td>38%</td>
<td>100% Taiwanese</td>
<td>Bx</td>
<td>Internet</td>
<td>Daily self-monitoring for 12-weeks</td>
<td>physician contact for treatment recommendations</td>
<td>12 weeks</td>
</tr>
<tr>
<td>Jones et al. (2009)</td>
<td>Diet</td>
<td>RCT</td>
<td>105</td>
<td>63%</td>
<td>33.5% W; 17.5% AA; 11% H; 4% O</td>
<td>Bx</td>
<td>Internet</td>
<td>16 modules/1 module per week</td>
<td>NA</td>
<td>16 weeks</td>
</tr>
<tr>
<td>Joseph et al. (2007)</td>
<td>Asthma</td>
<td>RCT</td>
<td>314</td>
<td>37%</td>
<td>98% AA</td>
<td>Bx</td>
<td>Internet</td>
<td>Four modules</td>
<td>NA</td>
<td>52 weeks</td>
</tr>
<tr>
<td>Krishna et al. (2003)</td>
<td>Asthma</td>
<td>RCT</td>
<td>228</td>
<td>63%</td>
<td>85% W</td>
<td>Ed</td>
<td>CD-ROM</td>
<td>44 lessons for total of 1 hr 20 min</td>
<td>3 visits with healthcare professional</td>
<td>3 months</td>
</tr>
<tr>
<td>Long et al. (2004)</td>
<td>Diet</td>
<td>PP</td>
<td>121</td>
<td>48%</td>
<td>47% W; 41.5% H; 11.5 AA</td>
<td>Ed</td>
<td>Internet</td>
<td>5 hr self-paced over 3 weeks</td>
<td>10 hours of classroom curriculum over 30 days</td>
<td>4 weeks</td>
</tr>
<tr>
<td>Mangunkusumo et al. (2007)</td>
<td>Diet</td>
<td>RCT</td>
<td>486</td>
<td>47%</td>
<td>87% W</td>
<td>Ed</td>
<td>Internet</td>
<td>One session</td>
<td>One 5-min session with healthcare professional</td>
<td>7 weeks</td>
</tr>
<tr>
<td>Marks et al. (2006)</td>
<td>PA</td>
<td>RCT</td>
<td>319</td>
<td>0%</td>
<td>38% W; 50.5% AA; 11.5% H/O</td>
<td>Ed</td>
<td>Internet</td>
<td>14 days of access with four sessions recommended</td>
<td>NA</td>
<td>2 weeks</td>
</tr>
<tr>
<td>McPherson et al. (2005)</td>
<td>Asthma</td>
<td>RCT</td>
<td>101</td>
<td>54%</td>
<td>88% W</td>
<td>Ed</td>
<td>Computer Game</td>
<td>Eight modules</td>
<td>NA</td>
<td>4 weeks</td>
</tr>
<tr>
<td>Mermelstein et al. (2006)</td>
<td>Smoking</td>
<td>RCT</td>
<td>351</td>
<td>46%</td>
<td>74.4% W; 13.4% B; 5.1% H; 6.8% O</td>
<td>Bx</td>
<td>Internet</td>
<td>Unrestricted access to website</td>
<td>10 group therapy sessions</td>
<td>12 weeks</td>
</tr>
<tr>
<td>Nemire et al. (1999)</td>
<td>Smoking</td>
<td>RCT</td>
<td>72</td>
<td>61%</td>
<td>H</td>
<td>Ed</td>
<td>Virtual reality</td>
<td>Eight sessions/30 min in VR environment</td>
<td>8 sessions/10 min for goal setting</td>
<td>2 weeks</td>
</tr>
<tr>
<td>Patten et al. (2006)</td>
<td>Smoking</td>
<td>RCT</td>
<td>139</td>
<td>50%</td>
<td>88% W; 4% O; 3% H</td>
<td>Ed</td>
<td>Internet</td>
<td>Unrestricted access to website</td>
<td>NA</td>
<td>24 weeks</td>
</tr>
<tr>
<td>Ritterband et al. (2003a)</td>
<td>Encopresis</td>
<td>RCT</td>
<td>24</td>
<td>79%</td>
<td>87.5% W; 12.5% AA</td>
<td>Bx</td>
<td>Internet</td>
<td>27 modules/5–10 min each</td>
<td>NA</td>
<td>3 weeks</td>
</tr>
<tr>
<td>Ritterband et al. (2008)</td>
<td>Encopresis</td>
<td>PP</td>
<td>22</td>
<td>59%</td>
<td>100% W</td>
<td>Bx</td>
<td>Internet</td>
<td>22 modules/5–10 min each</td>
<td>NA</td>
<td>2 weeks</td>
</tr>
<tr>
<td>Southard et al. (2006)</td>
<td>PA</td>
<td>RCT</td>
<td>120</td>
<td>63%</td>
<td>88.9% W; 7.4% AA; 3.7% O; 1.2% H</td>
<td>Ed</td>
<td>Computer game</td>
<td>No restrictions</td>
<td>NA</td>
<td>12 weeks</td>
</tr>
<tr>
<td>Williamson et al. (2005)</td>
<td>Diet &amp; PA</td>
<td>RCT</td>
<td>50</td>
<td>0%</td>
<td>100% AA</td>
<td>Bx</td>
<td>Internet</td>
<td>Unrestricted access to website</td>
<td>4 face-to-face sessions 24 weeks &amp; follow-up emails</td>
<td></td>
</tr>
</tbody>
</table>

Note: All author lists have been abbreviated to one name in an effort to conserve page space. W, White; AA, African–American; H, Hispanic; R, Randomized; O, Other; RCT, randomized controlled trial; PP, Pretest Posttest Design; Exp, Experimental; Ctl, Control; PA, Physical Activity.

*aThe intervention used face-to-face or teledmedicine contact as well as technology delivered intervention.

*bThe article contributed two studies with effect sizes.
Studies were categorized by type of intervention. Twenty studies (60.6%) were classified as incorporating behavioral techniques into an eHealth intervention. Thirteen studies (39.4%) were classified as using only educational techniques in eHealth interventions. In order to evaluate the intervention classification system, the first author and a trained research assistant independently coded all of the identified studies. Coders demonstrated acceptable agreement using the coding system (percent agreement = 84%). Disagreements were remedied by discussion until 100% consensus was reached for all studies.

### eHealth Intervention Outcomes

The random effects weighted-mean effect size (Table II) for all eHealth interventions revealed a small, but significant, effect size (mean $d = .118$, 95% CI = .066 – .171). The omnibus test revealed a significant associated Q-statistic (Table II) indicating a significant amount of heterogeneity across effect sizes ($Q = 62.851$, $p < .001$). The significant Q-statistic suggests that further analyses are necessary to interpret the current sample of effect sizes.

### Difference between Educational and Behavioral Interventions

The random effects model of effect sizes for eHealth interventions that incorporated a behavioral component had a small, but significant, effect size (mean $d = .354$, 95% CI = .232 – .475). However, the effect size for educational eHealth interventions was not significantly different from zero (mean $d = .033$, 95% CI = -.037 – .103). There was a significant difference in the between-groups (i.e., behavioral vs. educational) Q-statistic ($Q_B = 24.16$, $p < .05$). The within-groups Q-statistics associated with both behavioral and educational interventions indicated independent homogeneous samples of effect sizes. Thus, the type of intervention employed explained all of the heterogeneity in the overall sample. As such, no further moderational analyses (e.g., demographic characteristics, quality of study design, etc.) were necessary. See Figures 1 and 2 for forest plots of study effect sizes for behavioral and educational interventions (respectively).

### Fail Safe n-Size Calculation

The current investigation excluded studies that had not passed the peer review process. This decision was made to reduce the potential variability in methodological quality that unpublished investigations could introduce (Lipsey & Wilson, 2001). Studies with null findings are more likely to remain unpublished, particularly in social science research (Dickersin, 1990). To acknowledge the existence of unpublished work and to determine the potential impact on the current study, it is necessary to know how many studies with a null finding would have been required to reduce the weighted-mean effect size to zero. Due to the nonsignificant finding for educational interventions, this calculation is omitted for the omnibus test and educational interventions. Based on the collected data for behavioral interventions, approximately 230 studies with null findings would be required to negate the observed findings (Rosenthal, 1979).

### Discussion

The current study is a data-driven review examining the role of eHealth interventions for pediatric health behavior change or disease outcome. The present results indicate that, to date, eHealth interventions, when examined together, can produce small effect sizes for health behavior change or their associated outcomes. Upon closer inspection, however, the current findings reveal that interventions using behavioral principles such as self-monitoring, goal setting, and immediate feedback are responsible for the significant effect size, while purely educational interventions did not significantly contribute to health behavior change or disease outcomes. After examining the Q-statistics associated with the study groupings, it was clear that other important moderators (e.g., demographic

<table>
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<tr>
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<th>Number of studies</th>
<th>Mean weighted-effect size</th>
<th>95% CI</th>
<th>Q</th>
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</thead>
<tbody>
<tr>
<td>Omnibus test</td>
<td>33</td>
<td>.118</td>
<td>.066–.171</td>
<td>62.85**</td>
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<tr>
<td>Behavioral interventions</td>
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<td>.354</td>
<td>.232–.475</td>
<td>25.416</td>
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<tr>
<td>Educational interventions</td>
<td>13</td>
<td>.033</td>
<td>-.037–.103</td>
<td>13.275</td>
</tr>
</tbody>
</table>

**p < .01.

1We examined a number of alternative moderators to determine if the variability in effect sizes could be explained due to: the use of eHealth as primary or adjunctive intervention; age of the participant; study methodology; and type of physiological disease targeted. None of these potential moderators explained the variability in effect sizes.
variables, quality of study design, etc.) could not have contributed significant variability beyond what was accounted for by the categorization system.

The current study advances the literature by applying a coding system (i.e., educational vs. behavioral) to pediatric eHealth interventions. Aggregate effect sizes indicate that eHealth interventions incorporating behavioral components produced a significant effect size. This finding provides encouraging support for continued application of behavioral principles such as self-monitoring, goal setting, and immediate feedback through a computer or an independent electronic device such as a pager (e.g., Williamson et al., 2005; Franklin et al., 2006). As noted above, clinicians and researchers desiring to impact health behavior should take care to ensure that stand-alone devices or programs interface with a client in a way that incorporates the behavioral techniques mentioned previously.

In contrast to behavioral interventions, studies that relied on educational interventions did not produce a significant weighted mean effect size. Generally speaking, eHealth interventions in our sample that used education only did not significantly impact health behaviors such as adherence to medication. One reason for this finding may be that educational interventions do not necessarily target health behavior as the primary dependent variable. Rather, the goal of educational interventions may be to increase

Figure 1. Forest plot of effect sizes and their 95% CI for behavioral interventions. The square representing each effect size is proportional to its weight in the meta-analysis. Studies with an asterisk provided effect sizes for multiple outcomes which were aggregated in the analysis. HbA1c = glycated hemoglobin; PA = physical activity; BMI = body mass index.
knowledge in a particular domain which is hypothesized to then produce behavior change. Obviously, improving knowledge may be a helpful step toward disease control or outcome; however, the current findings suggest that it may be an incomplete intervention toward producing behavior change. Consistent with this view, a close examination of the individual studies that make up the Kahana et al. (2008) effect-size for technology-based adherence interventions revealed that the included interventions were primarily educational (i.e., according to Kahana et al.’s coding scheme).

Perhaps more importantly, our findings of significant effects for behavioral interventions delivered via eHealth applications mirror those in the face-to-face behavioral adherence interventions identified by Kahana et al. (2008) effect-size for technology-based adherence interventions revealed that the included interventions were primarily educational (i.e., according to Kahana et al.’s coding scheme).

From a clinical perspective, our results suggest that interventionists should carefully consider the way that their eHealth interventions incorporate strategies such as goal setting, self-monitoring, and immediate feedback. If the technology does not come from a behavioral framework, the clinician should take care to employ behavioral techniques in their face-to-face meetings with clients. That is, eHealth interventions that employ education only should not be used as the sole mechanism of action in behavior change programs.

**Future Directions**

During the review of the literature, variability in the deployment of behavioral modalities within eHealth was apparent from study to study. The fact that we did not find heterogeneity in effect sizes within behavioral eHealth interventions (i.e., the nonsignificant Q-statistic) suggests that it is possible to produce behavior change using different combinations of face-to-face time and technology utilization. However, the ideal combination of face-to-face contact and technology-driven intervention components across
specific health conditions, populations, and setting is not yet clear. Component analyses of future eHealth interventions may help to identify causal mechanisms within different modalities and have the potential to streamline interventions thereby reducing cost or maximizing the benefit of each expenditure.

It has been suggested that eHealth interventions make health-related goals more attainable because such interventions (a) break treatment goals into smaller more manageable pieces, (b) automatically assess success, and (c) modify previously attained goals in response to program success (Norman et al., 2007). Mobile devices may be a way to take full advantage of these ideas. For example, one study in the current sample used a mobile device to promote behavior change (Franklin et al., 2006). In addition to improving HbA1c levels, the Sweet Talk program also improved diabetes self-efficacy and participant’s sense of connectedness to their treatment team. Despite the impressive design of the Sweet Talk program, mobile devices still have a great deal of untapped potential. The results of the Sweet Talk program evaluation, and the ubiquity of hand-held mobile devices among adolescents (Lenhart, Madden, & Hitlin, 2005) underscores the value of further investigation of similar interventions.

This review does not represent a comprehensive list of the areas where eHealth interventions can be effective. Nor does it cover the scope of eHealth interventions used in pediatric psychology. In fact, the decision to narrowly define behavior change research excluded, for example, the large field of pediatric pain research. Pain researchers often elegantly employ technology to distract children during painful procedures or teach coping skills (e.g., Connelly et al., 2006; Mott et al., 2008). Thus, future work in eHealth might examine the aggregate impact of electronic interventions on pain ratings or, perhaps preferably, the cognitive processes underlying coping, as well as other areas that make use of eHealth technologies (e.g., anxiety interventions).

**Limitations**

We acknowledge a number of limitations to the conclusions that we draw from our results. The methodology limits what we know about eHealth interventions to those targeting behavior changes. It is not possible to know the impact of face-to-face contact with clinicians in the current sample of effect sizes. It is possible that there is an additive effect of contact with a clinician. Future studies attempting to address this limitation would need to examine the interaction between level of training and face-to-face contact.

The current study was not designed to assess gains in knowledge as an outcome. Future studies are needed to determine the effectiveness of educational interventions (i.e., changes in knowledge) and how they might be used in treatment sequencing. In fact, some of the studies collected for the current review did achieve effect sizes significantly different from zero on measures of knowledge while behavior remained unchanged (e.g., Homer et al., 2000; Krishna et al., 2003). Furthermore, Barak, Hen, Boniel-Nissim, and Shapiro (2008) used a more inclusive set of outcomes in their analysis of eHealth interventions and found that psychoeducational interventions can produce medium effect sizes when examining more knowledge-oriented outcomes in samples of adults and children. Future studies could advance the literature by quantitatively examining the impact of pediatric eHealth education interventions on dependent variables such as knowledge. If future work demonstrates significant effects, it is possible that clients could receive empirically supported eHealth interventions to improve knowledge before a behavioral session with a clinician who could focus more on motivation or barriers as needed.

**Conclusion**

eHealth is a promising mechanism for delivering health behavior change interventions. Evidence from this meta-analytic review supports the use of behavioral eHealth interventions in the treatment or prevention of pediatric physical health problems that involve health behaviors (e.g., sun exposure, diabetes, obesity, smoking, etc.). Additionally, this review supports the view that the success or failure of an eHealth intervention is likely to be driven by the same factors that contribute to success in face-to-face interventions. Thus, we echo Ritterband et al. (2003b) in their recommendation that researchers carefully consider the existing evidence for a face-to-face intervention for a particular problem before developing a novel eHealth intervention.

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**Conflicts of interest:** None declared.
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*References marked with an asterisk indicate studies included in the meta-analysis.


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