Implementation of Behavior Change Techniques in Mobile Applications for Physical Activity

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Background: Mobile applications (apps) for physical activity are popular and hold promise for promoting behavior change and reducing non-communicable disease risk. App marketing materials describe a limited number of behavior change techniques (BCTs), but apps may include unmarketed BCTs, which are important as well.

Purpose: To characterize the extent to which BCTs have been implemented in apps from a systematic user inspection of apps.

Methods: Top-ranked physical activity apps (N=100) were identified in November 2013 and analyzed in 2014. BCTs were coded using a contemporary taxonomy following a user inspection of apps.

Results: Users identified an average of 6.6 BCTs per app and most BCTs in the taxonomy were not represented in any apps. The most common BCTs involved providing social support, information about others' approval, instructions on how to perform a behavior, demonstrations of the behavior, and feedback on the behavior. A latent class analysis of BCT configurations revealed that apps focused on providing support and feedback as well as support and education.

Conclusions: Contemporary physical activity apps have implemented a limited number of BCTs and have favored BCTs with a modest evidence base over others with more established evidence of efficacy (e.g., social media integration for providing social support versus active self-monitoring by users). Social support is a ubiquitous feature of contemporary physical activity apps and differences between apps lie primarily in whether the limited BCTs provide education or feedback about physical activity.
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Introduction

Mobile technology has captured the imagination of healthcare workers and patients as a promising vehicle for delivering health-related interventions with potentially greater reach and lower long-term cost than in-person interventions.[1] More than 50% of American adults own smartphones and half of those owners use their phone to search for health information.[2] Approximately 50% of mobile subscribers use a fitness application (app).[3,4] Apps that increase physical activity levels would be valuable because insufficient physical activity is the second-leading preventable cause of death in the U.S., with links to heightened risk for major non-communicable diseases.[5,6] Despite the popularity of fitness apps, their efficacy for increasing physical activity is largely unknown, in part because their dynamic and evolving nature presents a challenge to the slow pace of conventional evaluation methods.[7]

In the absence of high-quality evidence from RCTs, clinicians or patients can benefit from an informed review of app features to guide their selections of apps to increase physical activity and prevent health problems. Apps have previously been evaluated on the basis of their theoretical content, potential for behavior change, and consistency with evidence-based clinical practices.[8–11] Understanding which behavior change techniques (BCTs) are implemented can illuminate mechanisms by which using an app might facilitate behavior change as well as the types of patients for whom a given app may work best. One recent study[12] found that relatively few BCTs were identified in the marketing materials of fitness apps, and two types of apps—educational and

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motivational—were identified based on their BCT configurations. That study was limited by its focus on app descriptions in online marketing materials instead of inspecting apps to determine which BCTs were actually implemented. This study addresses this gap by auditing BCTs identified from a user inspection of apps.

Methods

Top consumer-rated physical activity apps in the “health and fitness” category of the Apple iTunes and Google Play marketplaces (N=100) were identified and downloaded for evaluation on November 22, 2013 (25 paid and 25 free apps from each marketplace) and analyzed in 2014. This set included apps from popular developers such as Endomondo, MapMyFitness, Nike, Noom, and Runtastic. Apps that appeared on both free and paid lists (n=8) or were available for both operating systems (n=6) were evaluated separately. All 100 apps were included in the apps for which online descriptions were previously evaluated.[12]

Trained coders (n=9) inspected each app and coded the presence/absence of BCTs implemented therein using the BCT taxonomy (v1).[13] Dyads coded an average of 22 apps each. Cohen’s κ was estimated based on the first five apps coded by each dyad and indicated moderate to substantial agreement (mean κ=0.62; range=0.57–0.66).[14] Both members of each dyad coded the remaining apps and resolved coding discrepancies via discussion. The graduate student who trained coders independently coded apps where disagreement about a technique existed and, in all cases, agreed with the consensus code achieved from discussion.

Descriptive statistics were used to estimate the prevalence of BCTs implemented in each app, and t tests were calculated to test for differences between free and paid apps. A latent class analysis was conducted to identify different types of physical activity apps based on the configuration of BCTs.

Results

Overall, 39 of 93 possible BCTs were observed in the coded apps. Apps incorporated between one and 21 BCTs with an average of 6.6 in each app (SD=3.3, median=6). Table 1 indicates that the most commonly observed techniques involved providing social support, information about others’ approval, instructions on how to perform a behavior, demonstrations of the behavior, and feedback on the behavior. The number of BCTs did not differ significantly between free and paid apps (t[98]=1.43, p=0.08, d=0.29).

A latent class analysis was conducted with techniques that appeared in $\geq$10% of the inspected apps. Fit indices from models with one to five latent classes suggested a two-class solution (G^2 [likelihood ratio]=959, Akaike information criterion=1,033, Bayesian information criterion=1,129). The two rightmost columns of Table 1 present item-response probabilities from this model. The first class comprised 48% of the apps and represented apps that provided support and feedback. These apps were characterized by the presence of features that provided (1) social support; (2) information about others’ approval; and (3) feedback on behavior. The second class comprised 52% of the inspected apps and represented apps that provided support and education. These apps were characterized by the presence of features that provided (1) social support; (2) information about others’ approval; (3) demonstrations of the behavior; and (4) instruction on how to perform the behavior.

Discussion

At present, BCTs have been only narrowly implemented in physical activity apps and most BCTs in the taxonomy were not observed in any apps. User inspection identified more BCTs in apps than did a review of marketing materials, although the rank ordering of BCTs from both sources was similar.[12] Different coding systems were used in these studies; thus, comparisons should be interpreted cautiously.

The most common BCTs in the apps involved social support via online communities (e.g., Facebook, Twitter). Social media integration is extremely common in weight-loss apps.[10,15] Some health problems, including obesity, may be “socially contagious” but evidence supporting online social networks as tools for promoting physical activity is modest to date.[10,16–18]

Unlike weight-management apps, self-monitoring was a relatively rare BCT in physical activity apps.[10,16] The sophisticated sensing capabilities of mobile devices with embedded accelerometers may contribute to this difference. Given the importance of self-monitoring for changing physical activity, it may be wise to rely less on passive monitoring via sensors in favor of active self-monitoring via retrospection and self-reporting when apps are intended to support behavior change.[19] Other techniques associated with increased physical activity include education (providing instruction or information about the general consequences of activity); action planning; time management; and reinforcing effort toward behavior.[20]

Two types of apps emerged based on their BCT configuration, and those classes roughly paralleled those identified from an analysis of online descriptions of app features.[12] User inspection revealed the ubiquity of social network integration across the two classes of apps, and the emphasis on feedback for motivation (as compared to techniques such as goal setting). These findings reinforce the conclusion that all apps are not created equal, and prospective users should consider their individual needs when selecting an app to increase physical activity.[12]

This user inspection provided a snapshot of BCT implementation in a sample of top-ranked physical activity apps at the end of 2013, but with the rapidly

Table 1. Prevalence and Item-Response Probabilities of Behavior Change Techniques in Latent Classes of Physical Activity Apps

		Item-response probabilities	
Behavior change technique	**Prevalence (%)**	**Class 1: Support and feedback apps**	**Class 2: Support and education apps**
Social support (unspecified)	79	.77	.81
Information about others' approval	64	.63	.65
Instruction on how to perform a behavior	49	.05	.90
Demonstration of the behavior	47	.01	.90
Feedback on behavior	42	.59	.26
Goal setting (behavior)	36	.20	.51
Prompts/cues	35	.24	.45
Graded tasks	33	.22	.44
Social reward	32	.20	.43
Self-monitoring of behavior	29	.51	.08
Social comparison	25	.37	.14
Self-monitoring of outcome(s) of behavior	22	.41	.04
Non-specific reward	22	.16	.27
Goal setting (outcome)	17	.29	.06
Review behavior goal(s)	17	.14	.20
Action planning	15	.14	.16
Material reward (behavior)	11	.08	.14
Monitoring outcome(s) of behavior by others without feedback	10	.16	.04

Note: Techniques appearing in less than 10% of the inspected apps included the following: discrepancy between current behavior and goal (8%); monitoring of emotional consequences (8%); review outcome goal(s) (6%); biofeedback (6%); material incentive (behavior, 6%); feedback on outcome (s) of behavior (5%); social support (practical, 5%); focus on past success (4%); credible source (3%); non-specific incentive (3%); reward (outcome; 3%); information about health consequences (2%); information about emotional consequences (2%); reduce negative emotions (2%); social support (emotional, 1%); behavioral practice/rehearsal (1%); social incentive (1%); incentive (outcome, 1%); behavior cost (1%); reward approximation (1%); situation-specific reward (1%). The 54 remaining techniques in the behavior change taxonomy were not observed.

evolving nature of the mobile health space, results may soon be outdated. Some BCTs idiosyncratic to mobile apps may not have been represented in the BCT taxonomy.[13] The prevalence of BCTs in apps does not speak to the degree to which each is incorporated, the usability of apps, or the efficacy of the apps for increasing physical activity.

In conclusion, this study was the first to characterize the prevalence of BCT implementation in physical activity apps based on user inspection. This approach revealed greater, but still limited, implementation of BCTs than reported in the recent review of online marketing materials. This information will be valuable for scientists and developers working cooperatively in the mobile health domain as well as physicians and other practitioners who seek low-cost interventions to increase their patients' physical activity.

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References

1. Klasnja P, Pratt W. Healthcare in the pocket: mapping the space of mobile-phone health interventions. J Biomed Inform 2012;45(1): 184–98.
2. Smith A. Smartphone ownership—2013 update [Internet]. Washington DC: Pew Research Center's Internet & American Life Project, 2013:12.pewinternet.org/Reports/2013/Smartphone-Ownership-2013.aspx.

3. Fox S, Duggan M. Mobile health 2012 [Internet]. Washington DC: Pew Research Center's Internet & American Life Project, 2012. www.pewinternet.org/Reports/2012/Mobile-Health.aspx.
4. Citrix. Mobile analytics report [Internet]. Santa Clara CA: Citrix, 2014. http://www.citrix.com/content/dam/citrix/en_us/documents/products-solutions/citrix-mobile-analytics-report-september-2014.pdf?accessmode=direct&_ga=1.42377445.1588170780.1425320050.
5. Mokdad AH, Marks JS, Stroup DF, Gerberding JL. Actual causes of death in the United States, 2000. JAMA 2004;291(10):1238–45.
6. Lee I-M, Shiroma EJ, Lobelo F, et al. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. The Lancet 2012;380(9838):219–29.
7. Mohr DC, Cheung K, Schueller SM, et al. Continuous evaluation of evolving behavioral intervention technologies. Am J Prev Med 2013;45(4):517–23.
8. West JH, Hall PC, Hanson CL, et al. There's an app for that: Content analysis of paid health and fitness apps. J Med Internet Res 2012;14(3):e72.
9. Cowan LT, Van Wagenen SA, Brown BA, et al. Apps of steel: Are exercise apps providing consumers with realistic expectations? A content analysis of exercise apps for presence of behavior change theory. Health Educ Behav 2013;40(2):133–9.
10. Pagoto S, Schneider K, Jojic M, et al. Evidence-based strategies in weight-loss mobile apps. Am J Prev Med 2013;45(5):576–82.
11. Eyler AA. Are diabetes self-management apps based on evidence? Transl Behav Med 2013;3(3):233.
12. Conroy DE, Yang C-H, Maher JP. Behavior change techniques in top-ranked physical activity apps. Am J Prev Med 2014;46(6):649–52.
13. Michie S, Richardson M, Johnston M, et al. The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. Ann Behav Med 2013;46(1):81–95.
14. Landis JR, Koch GG. The measurement of observer agreement for categorical data. Biometrics 1977;33(1):159–74.
15. Azar KMJ, Lesser LI, Laing BY, et al. Mobile applications for weight management: theory-based content analysis. Am J Prev Med 2013;45(5):583–9.
16. Maher CA, Lewis LK, Ferrar K, et al. Are health behavior change interventions that use online social networks effective? A systematic review. J Med Internet Res 2014;16(2):e40.
17. Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. N Engl J Med 2007;357(4):370–9.
18. Pagoto SL, Schneider KL, Oleski J, et al. The adoption and spread of a core-strengthening exercise through an online social network. J Phys Act Health 2014;11(3):648–53.
19. Michie S, Abraham C, Whittington C, et al. Effective techniques in healthy eating and physical activity interventions: a meta-regression. Health Psychol 2009;28(6):690–701.
20. Williams SL, French DP. What are the most effective intervention techniques for changing physical activity self-efficacy and physical activity behaviour—and are they the same? Health Educ Res 2011;26(2):308–22.

Appendix

Supplementary data

Supplementary data associated with this article can be found at http://dx.doi.org/10.1016/j.amepre.2014.10.010.