Using mobile health interventions to promote physical activity: A mixed methods study

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BHlth

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Abstract

Introduction: Mobile technologies (e.g. mobile applications, wearable trackers) and online social networks have emerged as potential facilitators of physical activity. To date, few studies have examined the integration of these technologies in an intervention, users' perceptions about them, and their combined efficacy on physical activity.

Methods: This study adopted a mixed method design within a pre-post, one-arm quasi-experiment to evaluate the efficacy and acceptability of a mobile social networking application, connected with a wearable tracker, to promote physical activity. Quantitative results were analyzed using descriptive and inferential statistics. Interviews and focus groups were conducted before and after the intervention to explore users' perspectives.

Results: Fifty-five participants were enrolled in the study (mean age=23.6 years, 50.1% female). Quantitative analysis revealed a non-statistically significant increase in average daily step count between baseline and 6 months (mean change = 14.5 steps/day, $P = 0.98$, 95% confidence interval [-1136.5, 1107.5]). Post-hoc subgroup analysis comparing the higher and lower physical activity groups at baseline showed that the latter had a statistically significantly higher increase in their daily step count (group difference in mean change from baseline to 6 months = 3025 steps per day, $P = 0.008$, 95% confidence interval [837.9, 5211.8]. Qualitative analysis indicated users' preference for self-regulation techniques, social comparison with similar or existing connections, and personalization features.

Discussion: The study demonstrated the feasibility of a mobile social networking app, connected with a wearable tracker for physical activity promotion. A one-size-fits-all approach to behavior change was deemed insufficient by users, calling for the development of personalized interventions in future research.

Statement of originality

This thesis is the result of my own work and to the best of my knowledge it contains no materials previously published or written by another person. Any contribution made to the research by others, with whom I have worked with at Macquarie University or elsewhere, is explicitly acknowledged in the thesis. This work has not been submitted for the award of any other degree or diploma at Macquarie University or any other educational institution.

Signed:

Date: 10/10/2018

Dedication

To my wonderful parents who have always supported me in my dreams, even though they might not always understand them. Thank you for your unwavering encouragement and for this beautiful life I am given.

To my husband Duy Hung Nguyen who bravely uprooted his life and moved across the world for me. Thank you for your courage, kindness and patience.

To my dear friend and mentor – the fabulous Ms. Rachael Neale who passed away this year. Thank you for teaching me how to write in English, for fighting so courageously, and for continuing to inspire me every day.

Though she be but little, she is fierce.

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First and foremost, I would like to thank my supervisor, mentor and friend—Dr Liliana Laranjo for her constant support and encouragement throughout my candidacy. Liliana has been exceptional in everything she does; while managing multiple projects and duties, she has always found time for our weekly meetings, for reviewing my many drafts and responding promptly with stimulating and thought-provoking comments. Liliana has truly gone over and beyond for me, and I am deeply grateful to have her on my team.

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Thank you to my colleagues and co-authors—Ms. Paige Martin, Dr William Tong and Dr Ying Wang; without your contribution, this thesis would not be possible. My deepest thanks go to everyone at Centre for Health Informatics and Australian Institute of Health Innovation for creating such a supportive environment which allowed me to grow both professionally and personally.

Finally, no words can express my gratitude for the unwavering support from my family and friends. Your encouragement has inspired me to keep on trying every day, even when, especially when the going gets tough.

List of abbreviations

COM-B	Capability Opportunity Motivation—Behavior
mHealth	Mobile health
apps	applications
RCT	Randomized controlled trial
npj	Nature Partner Journal
N	Number
SUS	System Usability Scale
d	Cohen’s d effect size

List of outputs

Publications arising from this candidacy

Paper I: **Tong HL**, Laranjo L. The use of social features in mobile health interventions to promote physical activity: a systematic review. *npj Digital Medicine*. 2018;1(1):43. doi: 10.1038/s41746-018-0051-3.

Paper II: **Tong HL**, Coiera E, Tong W, Wang Y, Quiroz JC, Martin P, Laranjo L. Efficacy of a mobile social networking intervention in promoting physical activity: Quasi-experimental study. *Journal of Medical Internet Research mHealth uHealth*. [In Press; accepted on 31/01/2019]

Paper III: **Tong HL**, Coiera E, Laranjo L. Using a mobile social networking app to promote physical activity: A qualitative study of users' perspectives. *Journal of Medical Internet Research*. 2018, 20(12). doi:10.2196/11439.

Other publications achieved during this candidacy

Laranjo L*, Dunn AG*, **Tong HL**, Kocaballi AB, Chen J, Bashir R, Surian D, Gallego B, Magrabi F, Lau AY, Coiera, E. Conversational agents in healthcare: a systematic review. *Journal of the American Medical Informatics Association*, 2018, 25(9), pp.1248-1258.

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Specific contributions in co-authored articles

HLT – Huong Ly Tong; LL – Liliana Laranjo; EC – Enrico Coiera; PM – Paige Martin; WT – William Tong; YW – Ying Wang; JCQ – Juan C Quiroz

	Paper I	Paper II	Paper III
Conception & design	HLT, LL	HLT, LL, EC	HLT, LL, EC
Planning & implementation	HLT	HLT	HLT
Data collection	HLT	HLT, LL, PM	HLT, LL
Analysis & interpretation	HLT, LL	HLT, LL, WT, YW, EC	HLT, LL
Writing the article	HLT, LL	HLT, LL, EC, PM, WT, YW, JCQ	HLT, LL, EC
Overall responsibility	HLT	HLT	HLT

The student's contribution

The systematic review (Paper I) is conceptualized by HLT and LL. HLT was responsible for data collection and analysis, and writing the first draft, with critical feedback from LL.

The pilot study (paper II and III) formed a part of a bigger mixed-methods feasibility study, which was conceptualized by LL & EC. HLT is a co-author on the published protocol of the larger study. HLT was responsible for conceptualizing, collecting and analyzing the data associated with the two papers presented in this thesis.

Chapter 1. Introduction

1.1 The importance of physical activity

Physical inactivity has been widely targeted as a domain for behavior change, in order to reduce the worldwide epidemic of obesity and chronic diseases [1]. Physical activity has many benefits for both physical and mental wellbeing. Previous research has demonstrated the important role of physical activity in the prevention and treatment of many chronic conditions, most notably type 2 diabetes, hypertension, colon cancer, depression and anxiety [2, 3]. Moreover, there is a dose-response relationship between physical activity and several health outcomes [4]. People of all ages can benefit from regular physical activity, and the World Health Organization has issued different recommendations for different age groups, such as at least 150 minutes of moderate- to vigorous-intensity physical activity per week for adults [5]. Despite the importance of physical activity, 31% of adults and 80.3% of adolescents worldwide fail to meet these recommended levels of physical activity [6]. A similar pattern of physical inactivity is observed in Australia, where more than 50% of adults reported insufficient physical activity levels [7]. This highlights the importance of finding effective ways to change behavior and promote physical activity, to reduce morbidity and mortality.

1.2 Behavior change theories and challenges

It is well established that behavior change is a challenging process. A key element to behavior change success is the use of behavior change theories, models and techniques to better understand the casual mechanisms and influencing factors of the behavior, and the context of the intervention [8]. Particularly, physical activity behaviors are affected by factors operating at several levels, such as personal (biological and psychological attributes), social (family and work factors), and environmental (infrastructure and policy factors) . To accommodate for this complexity, many behavior change theories have suggested that the success of physical activity interventions depends not only on the individual, but also on a variety of social and environmental factors. For example, both Social Cognitive Theory and the Capability Opportunity Motivation—Behavior (COM-B) model have proposed that while people can regulate their own behavior (such as through self-monitoring), external opportunities can arise from the physical or social environment to prompt or support the behavior [9, 10]. Additionally, in recent years, researchers have encouraged intervention developers to describe their interventions in terms of the specific behavior change techniques [11]. A behavior change technique is an “observable, replicable and irreducible component” of an intervention, intended to alter causal processes that regulate behavior [12]. Behavior change techniques can be linked to existing theories and models, and provide a more transparent, replicable approach to the design and evaluation of behavior change interventions [8, 12].

To date, researchers have identified several promising approaches that can lead to acceptable increases in physical activity. Specifically, some behavior change techniques such as self-monitoring of behavior, goal setting and behavioral reinforcement through rewards have been incorporated in several programs [13, 14]. These techniques have been shown to be effective in increasing physical activity, and often deemed as acceptable by users, highlighting their potential.

Additionally, there seems to be an important link between social factors and health-related behavior. Specifically, researchers have demonstrated that existing networks of friends and family exert great influence on individual health behavior[15, 16], suggesting the potential of leveraging social networks to deliver physical activity interventions [17]. Social networks refer to the webs of an individual's relationships, which give rise to various functions such as social influence, social companionship, social support and social comparison [18]. To date, several studies have found strong evidence that behavior change techniques such as social support and social comparison can encourage physical activity [19-21]. Though these interventions seem promising, their potential can be missed when they are not easily disseminated or accessible to a large audience.

1.3 The role of technological interventions

Due to rapid innovation and development, technology has recently emerged as a potential solution to facilitate behavior change interventions and their dissemination. In particular, mobile health (mHealth) technologies and online social networks hold great promises in promoting intervention success and diffusion. mHealth can be defined as "the use of mobile telecommunication technologies for the delivery of health care and in support of wellness" [22], including both mobile applications (apps) and wearable devices. mHealth interventions offer many advantages over traditional interventions [8], as they can reach and be used by individuals continuously in their natural environment [23, 24], and provide real-time feedback and recommendations [25]. mHealth technologies are increasingly being used in physical activity interventions, with encouraging results [26]. However, like other health informatics interventions, mHealth interventions often encounter the "law of attrition" problem—the phenomenon of participants stopping usage and/or being lost to follow up [27].

Studies have suggested that integrating social features into mHealth technologies can help address the attrition problem, as well as facilitate the social processes related to behavior change [17, 28]. Social features can be defined as those enabling the interaction of an individual with other people (e.g. online social networks) and/or the delivery of social behavior change techniques (e.g. social support, social comparison) [29]. Online social networks are a specific type of social features, which allow users to create and display a personal profile and build connections with other users [30]. Previous meta-analyses have found that online social networks can improve retention rates, as well as have positive effects on behavior change [28, 31]. Thus, interventions integrating online social networks and mHealth technologies could potentially help engage users and result in positive health outcomes.

1.4 Rationale for this research project

Despite their potential, to date, few studies have examined how social features can be successfully delivered in mHealth interventions. Even though studies have looked at the impact of social support or social comparison on physical activity [20, 32, 33], few have examined the combination of both mHealth and online social networks, posing the question of whether such interventions yield effectiveness on physical activity promotion. Furthermore, researchers have also highlighted that understanding users' perspectives are essential to address the attrition problem in health informatics interventions [34]. Particularly, users can provide insight into which social features and mHealth components are considered the most engaging and acceptable. Users' preferences of social features seem to be mixed, but evidence is still scant [35-40]. In summary, while the use of social features in mHealth interventions seem promising, it is unclear whether these technologies can be combined within an intervention and work in synergy to produce a significant increase in physical activity, as well as what are users' perceptions and acceptability of such interventions. Understanding these aspects is essential in future research, as it will inform the development and implementation of next-generation mHealth interventions that can translate to long-term usage and positive health benefits.

1.5 Thesis aims

The overarching aim of this project was to evaluate the efficacy and acceptability of mHealth interventions with social features in promoting physical activity. Firstly, I conducted a systematic review and meta-analysis to critically review existing studies of mHealth interventions with social features for physical activity (Paper I). Subsequently, a social networking mobile application, connected with a wearable tracker, was pilot-tested to evaluate its efficacy on physical activity. This study adopted a mixed methods intervention design, which involved the collection, analysis and integration of both quantitative and qualitative data within an intervention trial. Particularly, quantitative analysis (i.e. descriptive and inferential statistics) was used to compute the efficacy of the intervention on physical activity (i.e. steps/day), as well as its usability and participant engagement (Paper II). To assess acceptability and users' perceptions, semi-structured interviews and focus groups with participants were used to gather information about which features were deemed important to their engagement and physical activity promotion, as well as explore the advantages and disadvantages of different components of the intervention. Data was subsequently analyzed using thematic analysis techniques [41] (Paper III).

1.6 Organization of the thesis

The core of this thesis comprises three publications.

Table 1.1 below outlines the link between thesis chapter, research questions and specific methods. Chapter 2 presents Paper I, which is a systematic review of the literature. The Methods chapter (Chapter 3) then provides an overview of the mixed methods intervention study, including setting and participants, research procedures and study design, data collection and analysis. Chapter 4 and 5 (Papers II and III) present the findings of the quantitative and qualitative components, respectively, of the mixed methods intervention study. Finally, the Discussion and Conclusion chapter (Chapter 6) summarizes and integrates the findings of the three papers, discusses the unique contribution of the research in comparison with the existing literature, outlines the strengths and limitations of this study, and provides directions for future research.

Table 1.1 Summary of chapters, aims, and corresponding methods

Chapter	Aims	Methods
1. Introduction	Present background information and identify research gaps	N/A
2. Paper I: The use of social features in mobile health interventions to promote physical activity: a systematic review	1) Characterize the use of social features in mHealth interventions for physical activity promotion 2) Explore the extent of user engagement and satisfaction, and users' perspectives	Narrative synthesis
	3) Assess the effectiveness of mHealth interventions with social features on physical activity outcomes	Meta-analysis
3. Methods	Present the overarching methodology of the study	N/A
4. Paper II: Efficacy of a mobile social networking intervention in promoting physical activity: Quasi-experimental feasibility study	1) Assess the efficacy, participant engagement and usability of a mobile social networking intervention, connected with a wearable tracker to promote physical activity 2) Investigate the effects of social features on physical activity levels, and the association between engagement with the mobile app and physical activity levels	Descriptive and inferential statistics
5. Paper III: Using a mobile social networking app to promote physical activity: A qualitative study of users' perspectives	Explore users' perspectives on the facilitators and barriers to their engagement with the intervention and physical activity	Qualitative interviews and thematic analysis
6. Discussion and conclusion	Summarize and integrate the study findings, discuss research contribution, study strengths and limitations, and outline directions for future research.	N/A

Abbreviation: N/A: not applicable

Chapter 2. Paper I—The use of social features in mobile health interventions to promote physical activity: a systematic review

2.1 Chapter background

The article in this chapter reviews the existing literature on the use of social features in mHealth interventions for physical activity. mHealth technologies have increasingly been used in interventions to promote physical activity, yet, they often have high attrition rates. Integrating social features into mHealth has the potential to engage users; however, little is known about the efficacy and user engagement of such interventions. Thus, this systematic review included a narrative synthesis and a meta-analysis to characterize and evaluate the impact of interventions integrating social features in mHealth interventions to promote physical activity.

This article provides much-needed insights into the current state of the literature, and lays foundation for the integration and interpretation of the mixed-methods intervention study. The article was published at Nature Partner Journal (npj) Digital Medicine on 4th September 2018.

2.2 Article content

The article content included in this chapter is permitted under Journal Author Rights within npj Digital Medicine's copyright agreement. The original article can be found at the publisher's website: https://www.nature.com/articles/s41746-018-0051-3. The appendices mentioned in this article can be found in Appendix 2 of the thesis.

Author contributions: HLT conceptualized the study, carried out the search, screened the studies, conducted data analysis, and wrote the first draft of the manuscript. LL assisted with the study design, screened the studies, provided guidance on data analysis, and critical feedback on the manuscript.

REVIEW ARTICLE OPEN

The use of social features in mobile health interventions to promote physical activity: a systematic review

Huong Ly Tong[1] and Liliana Laranjo[1]

Mobile health (mHealth) technologies have increasingly been used in interventions to promote physical activity (PA), yet, they often have high attrition rates. Integrating social features into mHealth has the potential to engage users; however, little is known about the efficacy and user engagement of such interventions. Thus, the aim of this systematic review was to characterize and evaluate the impact of interventions integrating social features in mHealth interventions to promote PA. During database screening, studies were included if they involved people who were exposed to a mHealth intervention with social features, to promote PA. We conducted a narrative synthesis of included studies and a meta-analysis of randomized controlled trials (RCTs). Nineteen studies were included: 4 RCTs, 10 quasi-experimental, and 5 non-experimental studies. Most experimental studies had retention rates above 80%, except two. Social features were often used to provide social support or comparison. The meta-analysis found a non-significant effect on PA outcomes [standardized difference in means = 0.957, 95% confidence interval −1.09 to 3.00]. Users' preferences of social features were mixed: some felt more motivated by social support and competition, while others expressed concerns about comparison, indicating that a one-size-fits-all approach is insufficient. In summary, this is an emerging area of research, with limited evidence suggesting that social features may increase user engagement. However, due to the quasi-experimental and multi-component nature of most studies, it is difficult to determine the specific impact of social features, suggesting the need for more robust studies to assess the impact of different intervention components.

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INTRODUCTION

Regular physical activity (PA) is associated with many physical and mental health benefits. Previous studies have demonstrated that PA can be effective in the prevention and treatment of a wide range of diseases, such as hypertension, stroke, type 2 diabetes, several types of cancer, depression, and anxiety.[1–3] The World Health Organization recommends that adults should do at least 150 min of moderate intensity or 75 min of vigorous intensity PA, throughout 1 week.[4] Notably, there is a dose-response relationship between PA and cardiovascular outcomes, with higher levels of PA leading to greater health benefits.[5] Despite the importance of PA, a third of adults and four-fifths of adolescents worldwide fail to meet the recommended levels of PA.[6] This highlights the importance of finding effective ways to promote PA to reduce morbidity and mortality, as well as health care costs.

The growing availability of mobile health (mHealth) technologies, such as activity trackers or mobile applications (apps) has given rise to new opportunities to influence PA behavior. Specifically, they can be used by individuals at any time and in any environment, enabling the collection of objective, reliable data on PA measures.[7,8] mHealth technology is increasingly being used in PA interventions, with encouraging results.[9] However, so far, these interventions have not been adopted by large number of users and often have high attrition rates.[10] A meta-analysis has found that online social networks (OSNs) can improve intervention retention rates, as well as have a significant positive effect on health behavior change.[11] Thus, integrating some social features from OSNs (e.g., social support, social comparison) into mHealth technologies could help engage users and result in positive health outcomes.

Several systematic reviews examined the use of mHealth technologies to promote PA, but they were often limited to a single mode of mHealth technology, or a specific setting.[12–18] No systematic review has examined the use of social features across mobile apps or wearable PA trackers, which limits the ability of researchers and developers to assess the impact of such features on efficacy and user engagement. Thus, the aim of this study was to characterize the use of social features in mobile health (mHealth) interventions to promote physical activity, as well as their effectiveness and impact on users' preferences and engagement. Specifically, our research questions were:

(1) What are the characteristics and effectiveness of mobile health interventions with social features in promoting PA, for both patients and healthy consumers?
(2) What are the experimental studies' retention rates, and what is the extent of users' engagement and satisfaction with these interventions?
(3) What are users' perspectives on the use of social features in mHealth interventions to promote PA?

RESULTS

The database search retrieved 1393 citations (Fig. 1); 200 duplicates were removed. After title and abstract screening, 1161 articles were excluded. Full-text screening was conducted for

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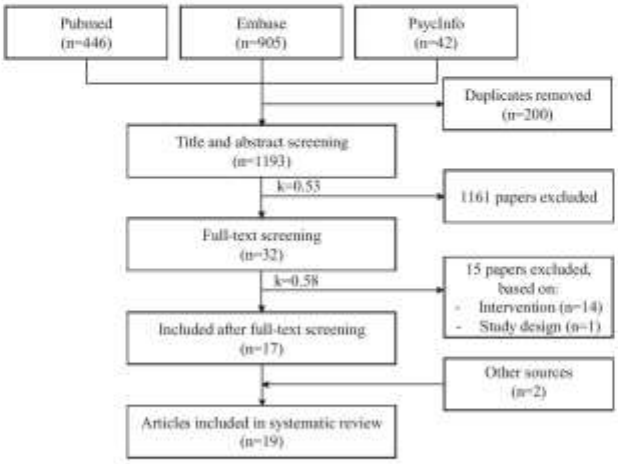

Fig. 1 Flow diagram of included studies in which 19 studies were identified from 1393 articles in the initial database search (January 2018). Search updates were conducted until April 2018. Two additional papers were identified: one from the reference list of the included studies, one from gray literature search

the remaining 32 papers, and a further 15 papers were excluded (reasons for exclusion are included in Supplement 1). Two additional papers were identified: one from the reference list of the included studies, one from gray literature search, leading to the inclusion of 19 studies for final analysis. The kappa statistic was 0.53 (fair agreement) for the title and abstract screening and 0.58 (fair agreement) for the full-text screening, before consensus agreement was reached.[19]

Description of included studies

The final 19 studies included four RCTs,[20–23] 10 quasi-experimental studies[24–33] and five non-experimental studies (i.e., surveys and interviews).[36–38,39,40] Tables 1 and 2 present a detailed characterization of the included studies. Nearly half of the studies were from the US.[21–25,29,30,32,39] Most studies targeted healthy individuals,[20,22,23,25,27,29,31–33,36,37,39,40] and five studies targeted specific conditions, such as chronic obstructive pulmonary disease,[38] attention deficit hyperactivity disorder,[24] prostate cancer,[30] childhood cancer survivors,[21] and stroke survivors.[26] Publication year ranged from 2012 to 2017. Study duration in experimental studies ranged from 1 week to 6 months. Participants were diverse in age; five studies involved adolescents and young adults.[20,21,24,27,29] Twelve studies reported no conflict of interest[20–27,31,32,38,40] and seven studies did not include a conflict of interest statement[28–30,33,36,37,39] (Supplement 2).

mHealth technologies

Mobile apps were the most utilized technology. In experimental studies, mobile apps were used either in isolation,[22,26,28,32,33,27] or as part of a more complex intervention with other components (e.g., wearable PA trackers).[21,23–25,29,20,31] In two non-experimental studies, mobile apps were examined in isolation.[36,38] Authors of seven studies developed their own apps,[22,23,26,27,32,33,38] while the rest used the Fitbit app.[21,24,25]

Five experimental studies used wearable activity trackers as part of a multi-component intervention.[20,21,24,25,29] Fitbit devices, such as the Fitbit Flex and Zip, were the most mentioned wearable PA trackers.[21,24,25,29,30] Additionally, three non-experimental studies examined the use of wearable PA trackers.[37,39,40]

Social features

In the included studies, social features were often delivered via OSNs. Specifically, four studies used Facebook,[21,24,29,31] one used Twitter,[25] one used WhatsApp,[28] and one used a health-specific OSN (i.e., iWell).[23] One study examined a fitness OSN—Strava.[36] Social features were primarily used to deliver social support[20–22,24,25,27–32,38] and provide social comparison.[22,25–27,32,33,38,23] Interestingly, OSNs were also frequently used to deliver non-specific rewards (e.g., badges for PA achievements) if there has been progress in PA performance.[24,26,27,29,31]

In two experimental studies, participants mentioned that other users did not actively make use of the social features in OSNs (e.g., several users viewed posts but did not comment) and that they would like to see more engagement and contribution from others in Facebook groups.[21,29] Other social media platforms (e.g., Snapchat, Instagram) were suggested by some younger participants as a replacement for Facebook, because they were not frequent users of the latter.[21,24]

Users' perspectives on social features were mixed. Participants in several studies reportedly felt more motivated from social support and social comparison because they perceived a sense of membership and belonging in the group[29,32] or because they liked the competition aspects.[27,29,33,38–40] Meanwhile, some users said that they did not like social comparison for many reasons: (1) they were only interested in their own progress,[27,32] (2) they thought competition might promote an unhealthy desire to win and have detrimental effects on the users' emotions if they lose,[38] (3) they were concerned about privacy issues.[37] Chatroom features in mobile apps were seen as redundant in one study because the users already had other preferred communication platforms.[27] However, they were deemed important by other participants, as they liked to have a direct way to message their friends from the app.[33]

Behavior change techniques (BCTs) and theories

Our review found that overall, 20 of 93 possible BCTs were observed in the interventions. All interventions incorporated between 2[33] and 14 BCTs,[20] with a median of five BCTs per intervention. In experimental studies, self-monitoring of PA behavior was the most popular BCT, facilitated via wearable PA trackers.[20,21,23–27,29–33] Social support was delivered in all interventions, except for two.[26,33] Goal setting was used in six interventions.[20,24,26,30–32] Intervention components other than the mobile technology (e.g., emails) were also used to review PA goals with participants, based on previous performance.[20,21,24] Three experimental studies used interviews to examine which features were preferable from participants' perspectives. The findings included goal setting, reward for progress in performing PA[24,27] and personalized feedback.[27,30] A complete classification of BCTs is provided in Supplement 3 (experimental studies) and Supplement 4 (non-experimental studies).

The theory of reasoned action/planned behavior was the most mentioned in the included studies,[31–33,39] followed by self-determination theory.[20,21,36] Social networks were mentioned twice.[20,28] Most studies used solely one behavior change theory to inform the intervention design.[20,22,23,25–28,31–33,38] Two non-experimental studies used behavior change theories to analyze the results.[36,39]

Usage and acceptability

The lowest retention rate in experimental studies was 46.7% over 2.5 months.[28] Other studies had retention rates between 68% (6-month period) and 100% (2-week period). Four studies did not report retention rates.[24–26,29] In order to encourage participants to comply with study procedures, six studies provided incentives ranging from \$10 to \$25;[20–23,26,27] three studies reported incentives of more than \$50 (Table 1).[24,30,32] Two studies did not provide any incentives,[25,28] and three studies did not report whether they provided any incentives to participants.[29,31,33] Chung et al. did not provide incentives for study compliance,

Table 1. Characteristics of included experimental studies

First author, year, location	Study type	Study duration	Participants N (I; C); N women; other characteristics	Intervention/study arms description	Description of social features and associated BCTs	Outcomes[a] (*denotes significant results)	Theories and models of behavior change[b]	Retention rates I; C N (%)	Incentives for study compliance
Ashton, 2017, Australia[20]	RCT	3 Months	50 (26; 24); 0; Young men	2 arms I: Website + Jawbone wearable tracker + app + Facebook group + face-to-face sessions + healthy lifestyle materials C: no intervention	Facebook group *Social support*	• Steps/day • Self-reported MVPA[c] • Feasibility	Social cognitive theory, Self- determination theory	24 (92.3%) 23 (95.8%)	Control participants received incentives for returning to the follow-up session (e.g., $10 voucher to cover travel expenses)
Mendoza, 2017, US[21]	RCT + interviews	2.5 Months	59 (29; 30); 35; childhood cancer survivors	2 arms I: Fitbit Flex tracker + Fitbit app + Facebook group + SMS C: no intervention	Facebook group *Social support*	• MVPA • Sedentary time • Motivation for PA[d] • Enjoyment of PA[e] • Engagement • Acceptability	Self-determination theory	29 (100%) 30 (100%)	Gift cards of "modest value" were provided to participants for completing the assessments
King, 2016, US[22]	RCT	2 Months	95 (I: 22 for analytic app, 24 for affect app, 22 for social app; C:27); 67; Inactive older adults	4 arms I: *Analytic app, Affect app, Social app* C: diet-tracker app	Social app *Social support Social comparison*	• MVPA* • Sedentary time* • EMA of brisk walking and sedentary time	*Analytic app:* Social Cognitive Theory, *Affect app:* Operant conditioning principle + Gamification, *Social app:* Social influence	Analytic app: 21 (95.5%), Affect app: 22 (91.7%), Social app: 22 (100%) Control: 24 (88.9%)	"Participants received a $20 gift card for participating"
Greene, 2012, US[23]	RCT	6 Months	513 (265; 248); NR	2 arms I: iWell OSN + wireless accelerometer + wireless scale; C: printed educational materials	iWell OSN *Social support Social comparison*	• Leisure time walking* • All physical activity • Engagement	Social network	180 (68%) 169 (68%)	Participants were compensated with a cookbook at their 3-month follow-up and a $25 Amazon.com gift card at the 6-month follow-up
Muntaner-Mas, 2017, Spain[28]	Quasi-experimental	2.5 Months	48 (I: 20 for training group, 15 for mobile group; C: 13); NR; Older adults	3 arms:I: *Training group:* in-person exercise program, *Mobile group:* WhatsApp-delivered exercise program + Chat group; C: no intervention	Mobile group: WhatsApp *Social support*	• Self-reported PA levels[f] • Balance test • Aerobic capacity	Social network	Training group: 16 (80%); Mobile group: 7 (46.7%); Control: 9 (69.2%)	None
Schoenfelder, 2017, US[24]	Quasi-experimental + Interviews	1 Month	11 (n/a); 6; Adolescents with ADHD	1 arm: Fitbit Flex tracker + Fitbit app + Facebook group + daily text messages	Facebook group *Social support*	• Step counts* • Engagement • Acceptability[g]	NR	NR	Participants received incentives of $5/week for each online survey completed (2 per week) and $20 for the post-study interview – totaling up to $60 for adolescent and $20 for parents
Chung, 2016, US[25]	Quasi-experimental	2 Months	12 (n/a); NR; BMI = 22 – 35 kg/m^2	1 arm: Fitbit Zip tracker + Fitbit app + Twitter	Twitter *Social support* Fitbit app *Social comparison*	• Step counts • Duration and intensity of activity • Satisfaction • Engagement	Gamification	NR	None
Paul, 2016, UK[26]	Quasi-experimental	1.5 Months	23; 12; Stroke survivors			• Step counts • Sedentary time,	Behavior change techniques	NR	Participants were given compensation for travel

Table 1 (continued)

First author, year, location	Study type	Study duration	Participants N (I; C); N women; other characteristics	Intervention/study arms description	Description of social features and associated BCTs	Outcomes[a] (*denotes significant results)	Theories and models of behavior change[b]	Retention rates I; C N (%)	Incentives for study compliance
				2 arms I: Starfish app; C: no intervention	Starfish mobile app *Social comparison*	upright time and walking time • Gait speed[h]			expenses for assessment visits
Rosenberg, 2016, US[30]	Quasi-experimental + Interviews	1 week	31; 0; Prostate cancer patients	1 arm: Fitbit Zip tracker	Wearable activity trackers, i.e., Fitbit Zip *Social support*	• Acceptability	NR	26 (83.9%)	Participants kept their Fitbit and were paid $10 for completing the study
Middelweerd, 2015, Netherlands[27]	Quasi-experimental + Focus group	3 weeks	30 (n/a); 20; Dutch university students	1 arm: Nexercise app	Nexercise app *Social support* *Social comparison*	• Preferences, attitudes • Acceptability	NR	30 (100%)	The incentive for completing the focus groups was either an arm holder for a smartphone or voucher for free entrance to the university sports center
Pumper, 2015, US[29]	Quasi-experimental + Interviews	1 month	30 (n/a); 18; Adolescents	2 arms Group 1: Facebook group + Fitbit Flex tracker ($n = 17$) Group 2: Fitbit Flex tracker ($n = 13$)	Facebook group *Social support*	• Acceptability	NR	NR	NR
Kernot, 2014, Australia[31]	Quasi-experimental	1 month	29; 29; Women with young children	1 arm: Facebook group + pedometer	Facebook group *Social support*	• Self-reported walking*, MVPA[i] • Feasibility • Usability • Engagement	Theory of planned behavior, Fun theory	25 (86.2%)	NR
Al Ayubi, 2014, US[32]	Quasi-experimental + Interviews	1 month	14 (n/a); NR; BMI = 18.5–43 kg/m^2	1 arm: Persuasive Social Network for Physical Activity (PersonA) mobile app 1st week: PersonA 2nd–4th week: PersonA + social menu	PersonA mobile app *Social support Social comparison*	• Step count and distance • Usability, usefulness, feasibility, willingness to use • Accuracy	10 theories[j]	13 (92.9%)	"Participants were compensated $50 for participating"
Khalil, 2013, United Arab Emirates[33]	Quasi-experimental + Survey	2 weeks	8; 8; Pre-existing social connections	1 arm 1st week: Step up app 2nd week: Step up app + social component	Step up app *Social comparison*	• Step count • Acceptability • Satisfaction	Theory of reasoned action	8 (100%)	NR

I intervention, *C* control, *BCTs* behavior change techniques, *RCT* randomized control trial, *app* application, *MVPA* moderate to vigorous physical activity, *SMS* short message service, *PA* physical activity, *EMA* ecological momentary assessment, *NR* not reported, *OSN* online social network, *n/a* not applicable, *ADHD* attention deficit hyperactivity disorder, *BMI* body mass index (kg/m^2)

[a]Outcomes reported include PA-related outcomes (e.g., steps, cognitive or psychological outcomes such as intention to exercise), engagement, acceptability, and satisfaction with the intervention. For other outcomes, see Supplement 4. [b]As reported by the authors in the papers. Measured by: [c]Godin Leisure-Time Exercise Questionnaire, [d]Behavioral Regulation in Exercise Questionnaire-2, [e]Physical Activity Enjoyment Scale, [f]International Physical Activity Questionnaire [IPAQ]; [g]Client Satisfaction Questionnaire [CSQ-8], [h]Ten-Meter Walking Test (10MWT), Active Australia Survey. [i]pre-intervention survey was developed by the authors; no validation study was published); [j]10 theories: The Health Belief Model, the theory of reasoned action/theory of planned behavior, the Elaboration Likelihood Model, the social cognitive theory, the social support and health link theory, the uses and gratifications theory, the common bond and common identity theory, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Fogg Behavioral Model

but provided material incentives and rewards as BCTs to encourage PA behavior (i.e., complete a step challenge to get a water bottle).[25]

Measures of engagement with intervention components differed between studies, including OSN usage (e.g., liking a post on a Facebook group, sharing PA data),[21,23,24,31] and duration of use of wearable PA trackers.[23–25,31] Two studies found that the Fitbit tracker was worn for at least 70% of the time.[24,25] Interestingly, Chung et al. noted that overweight participants tended to wear the Fitbit tracker 99% of the time, while normal weight participants only wore it 73% of the time (p-value not reported).[25]

Two non-experimental studies examined factors that influence long-term use of mHealth interventions. One study compared novice and experienced users of Strava and found that social support and social comparison were the main drivers of long-term use of the application.[36] Another study interviewed long-term users of wearable PA trackers, and found that goal setting, reward systems, and self-monitoring were the major drivers for engagement and use.[37] One study reported technical issues as a perceived barrier to long-term usage.[30]

User acceptability was examined in four experimental studies[21,24,27,33] and in one non-experimental study.[38] Even though all studies reported high levels of acceptability, only one study used a validated questionnaire;[24] the others used interviews or surveys designed by the authors.

Study outcomes and meta-analysis

In most studies, PA outcomes were objectively measured by a wearable tracker/pedometer[21,23–25,29–31] or smartphone built-in accelerometers.[22,26,27,32,33] PA outcomes were self-reported in two studies using validated questionnaires.[28,31] One study used a pedometer to objectively measure steps per day, and used a validated questionnaire to measure self-reported moderate-to-vigorous physical activity.[20] Six studies reported physiological outcomes (e.g., weight, Body Mass Index, blood pressure) other than PA levels (Supplement 3); one study reported cognitive and psychological outcomes (e.g., motivation for PA, enjoyment of PA).[21]

Amongst quasi-experimental studies, four reported significant increase in PA;[24–26,31] one reported non-significant increase.[28] Two studies also reported an increase in PA, but it was not reported if the change was statistically significant.[32,33]

We included four RCTs in the meta-analysis, all with continuous outcomes.[20–23] There was no statistically significant effect of mHealth interventions with social features on PA outcomes [standardized difference in means = 0.957 (95% confidence interval −1.09 to 3.00)] (Fig. 2). Heterogeneity was high (I^2 99.6%).

Risk of bias assessment

Out of four included RCTs, two studies were deemed as having the lowest risk of bias according to Cochrane's tool (low risk of bias in five out of six categories,[20] and four out of six categories[22]) (Supplement 5). All studies had a low risk of bias for random sequence allocation, and a high risk of bias for blinding of participants and personnel. Two studies lacked sufficient information for risk assessment in allocation concealment,[21,23] and blinding of outcome assessment.[21] Even though all four studies mentioned trial registration, one failed to provide the registration identification number,[23] and another had very limited information on the registration,[21] which made it difficult to assess "selective reporting". Included studies other than RCTs had a higher risk of bias; detailed assessment was not possible due to the quality of reporting.

DISCUSSION

Main findings

The integration of social features in mHealth for PA promotion appears to be in an early stage of development due to the recent timing of publication of included studies (all published after 2010), and the predominance of quasi-experimental studies. Social features were often delivered via OSNs and used to provide social support or social comparison. From users' perspectives, preferences and use of social features were mixed: some users felt more motivated because of social support and competition aspects, while others expressed concerns about engaging in social comparison.

Comparisons with existing literature

Our systematic review focuses on the integration of social features in mHealth technology to promote PA. Several systematic reviews examined the use of mHealth technology to promote PA;[12–18] however, none has focused on social features.

Two recent systematic reviews have looked at the effectiveness of OSNs on health behavior change,[11,35] and found modest effects on health outcomes. These two systematic reviews differ from our study in several ways. Firstly, this study focuses solely on PA, while other studies looked at a range of health behaviors. Secondly, instead of examining OSNs (which can be web-based or delivered as a software application), we examined social features providing BCTs (e.g., social support, social comparison) in mHealth. Thirdly, rather than including only experimental studies, our review also included non-experimental studies such as surveys and interviews to capture users' perspectives on the use of social features. Notably, even potentially efficacious interventions can fail to have an impact if users do not adopt the technology or use it over a long period of time. Thus, it is important to understand users' perspectives on engagement with mHealth to inform intervention development and implementation.

The use of social features and BCTs in mHealth

Our study found that social features were most often used to deliver social support and social comparison. We also observed that self-monitoring of behavior was the most commonly used BCT in the included studies, which is in line with findings from previous literature.[12,13,15] Self-monitoring of behavior can be seen as an important starting point to provide other BCTs,[13] such as social comparison, or provision of feedback. A previous meta-analysis has shown that PA interventions that included self-monitoring and at least another self-regulatory technique (e.g., goal setting, feedback, on behavior) were significantly more effective than other interventions.[41] While these findings shed light into the common use of BCTs in health interventions, due to the quasi-experimental nature of most studies, it remains unclear whether specific bundles of BCTs are more effective than others. An interesting hypothesis (which remains untested) is that different BCTs might be effective in different stages of behavior change,[42] indicating the promises of adaptive interventions, tailored to individual progress.

Additionally, from users' perspectives, preferences for social features were mixed amongst the participants in several included studies,[27,29,32,33,37,38,40] which could be linked to differences in individual characteristics. For example, some participants acknowledged that they liked social comparison because of their own competitive nature.[38] In contrast, other users showed interest in self-comparison only, preferring to follow their own goals and plans, and seeing little benefit in comparing themselves with other people.[32] This indicates that while some BCTs (e.g., self-monitoring) might be suitable for most users, others (e.g., social comparison) might be more controversial, and thus, users' preferences and characteristics should be taken into account

Table 2. Characteristics of non-experimental studies

First author, year, location	Methods	Participants N^a; N women; other characteristics	Aims	Description of mHealth technology[b]	Theories and model of behavior change mentioned[c]	Main findings
Maher, 2017, Australia[40]	Survey	237; 168; Former (n = 37) and current (n = 200) wearable tracker users	Explore users' experience of activity trackers, including usage patterns, sharing of data to social media, perceived behavior change, and technical issues	Wearable PA trackers	NR	65% of participants said they did not use social features and 77% did not share their activity data on a social media platform. The prime motivation for using social features was reportedly "to compete with friends"
Zhu, 2017, US[39]	Survey	238; 67; Wearable trackers users	Explore the association between social competing & sharing, and intention to exercise	Wearable PA trackers	Theory of planned behavior	Social sharing and competing can directly influence attitudes towards exercise, subjective norms, and perceived behavioral control, which in turn influence intention to exercise
Stragier, 2016, Belgium[36]	Survey	394; 43; Strava (a fitness OSN) users	Test whether users' self-regulatory motives, social motives, or enjoyment motives for fitness OSN use will predict perceived usefulness, and habitual use	Fitness OSN i.e., Strava *Social support Social comparison*	Self-determination theory	Self-regulatory motives both directly and indirectly predicted habitual use. Social motives directly predicted habitual use, while enjoyment indirectly predicted habitual use. The study also found that for new users, self-regulatory motives are the main drivers of using Strava; for experienced users, social motives and enjoyment are the main drivers
Fritz, 2014, Switzerland[37]	Interviews	30; 16; Wearable tracker users for at least 3 months	Explore factors that influence long-term use of wearable activity trackers.	Wearable PA trackers	NR	Some participants used the social features of the system but struggled to find the right community to share data with. Most users expressed the desire to share data with someone who had similar goals or interests, rather than existing social connections
Bartlett, 2017, UK[38]	Convergent mixed methods: Interviews + Survey	Interviews 28; 16; People with COPD, carers & HCPs Survey: 87; 59; People with COPD	Develop 3 prototypes of mobile apps (i.e., virtual coach system, music and maps system, online community system) and test how acceptable and persuasive each prototype is in increasing PA amongst people with COPD	Online community app *Social support Social comparison*	Persuasive System Design · Dialogue support (virtual coach) · Primary task support (music and maps) · Social support (online community)	Interviews: Opinions on social features varied between users. Some participants liked social features because of the competitiveness and communication with others who had similar experiences, while others viewed competition as unhealthy. HCPs stated that online community would be best for immobile people, but the approach would only work if the users chose it themselves. Survey: The virtual coach system was rated as most persuasive, while the online community system was rated as least persuasive. The most useful feature was instruction on how to perform behavior; while the least useful features were prompts/cues, non-specific reward and social comparison

BCTs behavior change techniques, *PA* physical activity, *NR* not reported, *OSN* online social network, *COPD* chronic obstructive pulmonary disease, *HCPs* health care providers
All surveys were developed by the authors; no validation studies were published. [a]Total number of participants, [b]behavior change techniques were classified where applicable; [c]as reported by the authors

Author, year	Statistics for each study						
	Std diff in means	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
Ashton, 2017	0.375	0.286	0.082	-0.184	0.935	1.315	0.189
Mendonza, 2017	0.026	0.260	0.068	-0.484	0.537	0.101	0.920
Greene, 2012	0.227	0.124	0.015	-0.016	0.471	1.833	0.067
King, 2016	3.170	0.020	0.000	3.131	3.209	158.500	0.000
	0.957	1.044	1.090	-1.089	3.003	0.916	0.359

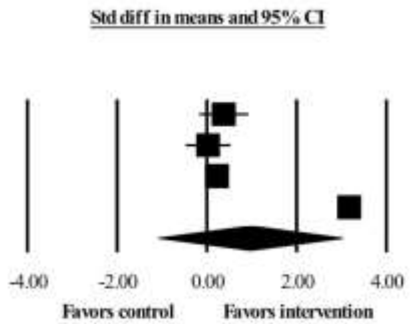

Fig. 2 Forest plot of effect sizes and 95% confidence intervals (CI) representing the effect of mobile health interventions with social features on physical activity outcomes (random effects model)

when delivering an intervention, rather than adopting a one-size-fits-all approach.

User engagement and retention

Retention rates of included studies were generally high. Specifically, four studies reported a 100% retention rate,[21,22,27,33] and four studies reported at least 80%.[20,30–32] The only exception is the Muntaner-Mas study with a retention rate of <50%.[28] The use of social features in the Muntaner-Mas was considerably limited (i.e., only the chat function of WhatsApp was used), and no incentives for study completion were provided, which might explain the lower retention rate.

The high retention observed in most included studies suggests that integrating social features into mHealth interventions could potentially increase user engagement and retention, addressing the common attrition problem in health informatics studies.[43] Other systematic reviews have reported high retention rates for behavioral informatics interventions that incorporated general OSNs (e.g., Facebook).[11,35] A recent longitudinal study has examined a large dataset of six million users over 5 years to determine whether social networking features influence user engagement, or change behavior within the application, as well as in real life. By comparing social network users to matched control non-users, the study observed a 17% increase in user retention for social network users, with the long-lasting effect of over 1 year.[44]

Another aspect worth considering is the use of incentives and rewards. It is important to draw the distinction between incentives for study compliance (e.g., compensation of $10 for traveling to the research center) and incentives used as BCTs, targeting a particular behavior (e.g., offering a prize when a certain number of steps is achieved).[45] In terms of incentives for study compliance, research has shown that these can influence retention rates.[46,47] In this review, due to the multi-component nature of the included interventions and the study designs used, it is not possible to distinguish between the different impact of social features and compliance incentives on retention rates. In terms of incentives targeting behavior, several studies have demonstrated their potential effectiveness.[48–50] However, researchers have questioned whether providing material incentives may undermine the development of intrinsic motivation and impact autonomy in decision-making[51–53]—factors which are strongly predictive of long-term exercise adherence.[54] Questions have also been raised about the scalability and sustainability of material incentives, highlighting the need to explore sustainable incentive procedures in future research.[55]

Strengths and limitations

There are several strengths in our study. Prior to the study commencement, we developed and registered a protocol in the PROSPERO database, which we followed systematically throughout the study. The screening form was also pre-tested and piloted before screening began. Furthermore, all the studies were independently screened by two researchers; a kappa score of 0.53 (first round) and 0.58 (second round) revealed a fair level of agreement. Lastly, BCTs were coded using a pre-tested and validated taxonomy,[45] which provided an objective way to examine how BCTs have been used in social features and mHealth. The BCTs were coded and reviewed by two researchers who have achieved coding competence in the use of BCTTv1.

Our findings should be interpreted in light of some limitations. Firstly, through our database search, we were unable to find a complete and sound definition of social features. Instead, we developed our own definition of social features based on the literature. Secondly, we excluded papers that were not in English. Even though this was done to ensure that the authors could fully understand and make an informed decision in the screening phase, we might have missed some important papers. Thirdly, for our review, we classified BCTs according to the intervention description provided in the papers and did not infer the presence of BCTs, potentially leading to a lower overall number of BCTs found compared to other reviews.[12,13] Fourthly, the short study duration and the incentives provided by some included studies could potentially influence the observed retention rates. Finally, the predominance of low-quality experimental studies and the heterogeneity of the RCTs reflected the emerging nature of this field, which limited our ability to draw strong conclusion regarding the intervention effectiveness on PA.

Implications for research

Our study highlights several important implications on potential research areas and study design. Firstly, our findings suggest that self-monitoring of behavior seems to be prevalent and relevant in PA interventions. While social features appear to be important to user engagement and retention, due to the limited number of RCTs and the multi-component nature of the interventions, it was difficult to ascertain their impact on retention, or their effectiveness on PA outcomes. It is important to note that material incentives could also contribute to high retention or be used as a BCT. However, questions about the sustainability of material incentives remain, suggesting the need to explore other kinds of incentives (e.g., social, verbal encouragement or virtual prizes).[55] Users' mixed preferences regarding social features and BCTs suggest that a one-size-fits-all approach might be inadequate, highlighting the need to personalize interventions based on individual characteristics and preferences.

To develop and assess personalized interventions with multiple components and BCTs (e.g., incentives, social features), future studies should consider using factorial and adaptive study designs. The Multiphase Optimization Strategy and the Sequential Multiple Assignment Randomized Trial may be particularly useful to determine which intervention components or combinations are most effective, what is the optimal sequence for delivering these components, and which tailoring variables should be used.[56]

Furthermore, authors are urged to follow the Consolidated Standards of Reporting Trials for electronic and mobile health applications and online telehealth (CONSORT-EHEALTH),[57] and the Transparent Reporting of Evaluations with Nonrandomized Designs (TREND) statement when reporting their findings, in order to increase evidence quality and facilitate future reviews and meta-analyses.[58]

METHODS

For the purpose of this systematic review, we defined social features within mHealth PA interventions as those that enable the interaction of an individual with other people (e.g., OSNs), and/or the delivery of *social* BCTs (e.g., social support, social comparison).[45] As the domain of mHealth is broad, we specifically focused on the use of mobile apps and wearable PA trackers.

Search strategy

A systematic search of the literature was performed in January 2018, and updated in April 2018, using PubMed, Embase, and PsycInfo. Search strings included several terms related to mobile health and social features (a complete search strategy is provided in Supplement 6). No restrictions were placed in the search according to the year of publication. We also searched the reference lists of relevant articles and gray literature (e.g., dissertations, theses, conference proceedings). Authors were contacted when additional information about the studies was needed.

Study selection criteria

We included any primary research studies that involved patients or healthy consumers who used or were exposed to a mobile health intervention with social features, where the primary aim was to promote PA (e.g., increase step counts, intention to exercise). As we wished to examine both intervention effectiveness and users' perspectives on mHealth interventions with social features, we included both quantitative and qualitative studies.

Studies were excluded if they: (1) did not incorporate social features in the mHealth component of the intervention; (2) involved only short message service (SMS), web (i.e., applications that are solely web-based), telephone, telemonitoring or telemedicine, or static pedometers (i.e., not able to transmit data to a consumer interface); (3) only reported PA as a secondary outcome or did not mention PA at all; (4) were not in English.

Screening, data extraction, and synthesis

Two investigators piloted the screening procedure and independently conducted two-phase screening: (1) title and abstract and (2) full-paper screening. Cohen's kappa was used to measure intercoder agreement in each screening phase. Disagreements were resolved through discussion and consensus.

One investigator extracted information from the included studies into a standardized form; another investigator examined the form for consistency. The following data were collected for each study: first author, year of publication, location, study duration, type of mHealth technology, social features, intervention components and characteristics, participants and setting information, reported outcomes, incentives for study compliance, conflicts of interest and funding sources. For each intervention component, BCTs were coded according to the BCT Taxonomy v1[45] and reviewed by two researchers with coding competency. Decisions on coding were made based on the authors' description of the interventions. Though there is a specific CALO-RE taxonomy on physical activity and healthy eating,[59] we chose the BCT Taxonomy v1 as it is the most comprehensive and up-to-date classification. For randomized controlled trials (RCTs), study quality was assessed using Cochrane's risk of bias tool.[19]

We conducted a narrative synthesis of results for all studies, and a meta-analysis for RCTs. We transformed all effect sizes to a common metric comparable across studies—the bias-corrected standardized difference in means—and classified it as positive when in favor of the intervention and negative when in favor of the control. We used a random effects model to combine the results in a more conservative way. As suggested in the literature, we did not avoid conducting a meta-analysis based on heterogeneity.[60–62] Instead, we assessed the presence of heterogeneity using I^2 statistics and cautioned readers in the interpretation of the results.[61,62] Due to the small number of included RCTs, a subgroup analysis was not conducted. Comprehensive Meta-Analysis V.2.2 was used for computations.

The study protocol was registered with PROSPERO (International prospective register of systematic reviews) with number CRD42018086067. This systematic review is compliant with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement.[63]

CONCLUSION

The integration of social features in mHealth interventions for PA is a new field of research that has potential to increase user engagement and physical activity. Future research should adopt innovative research designs to develop and evaluate multi-component personalized interventions for PA promotion.

DATA AVAILABILITY

The authors declare that the data supporting the findings of this study are available within the paper and its supplementary information files.

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AUTHOR CONTRIBUTIONS

H.L.T. conceptualized the study, carried out the search, screened the studies, conducted data analysis, and wrote the first draft of the manuscript. L.L. assisted with the study design, screened the studies, provided guidance on data analysis, and critical feedback on the manuscript.

ADDITIONAL INFORMATION

Supplementary information accompanies the paper on the *npj Digital Medicine* website (https://doi.org/10.1038/s41746-018-0051-3).

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Chapter 3. Methods

The following chapter will discuss the methods used in the mixed-methods intervention study. This chapter begins by describing the study setting and the intervention, then presenting the mixed methods intervention design and explaining its rationale. Specific details on the methods of the quantitative and qualitative components are outlined in the results publications (Chapters 4 and 5 [Paper II and III], respectively).

3.1 Study setting and participants

This study was conducted at Macquarie University, Sydney, Australia. Fifty-five staff members and students were recruited using purposive sampling techniques. The sample size was pragmatically chosen to enable comprehensive pilot-testing of the intervention [42]. To be eligible for participation, participants had to be healthy adults with sufficient English to understand and participate in the study; aged between 19 and 35 years old; who planned to be living in Sydney for the duration of the study; and owned a mobile phone (iOS or Android) with internet access. Exclusion criteria included pregnancy; BMI below 17; prior history of eating disorders; or having co-morbid conditions that could impact on study participation.

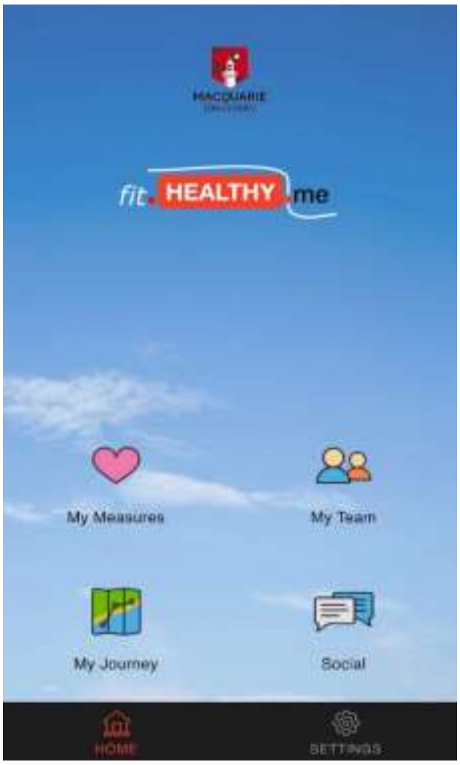
3.2 Intervention description

The intervention bundle included a mobile social networking app (fit.healthy.me), a fitness tracker (Fitbit Flex 2), and text messages and emails (Table 3.1). Specifically, the fit.healthy.me app incorporated several BCTs, such as self-monitoring of physical activity, social support and social comparison. In the app, the social features (i.e. app functions) were composed of 'My team', 'Social forum' and 'Private message'. 'My team' allowed participants to visualize and compare their steps against others, and 'follow' other people, while 'Social forum' and 'Private message' allowed participants interact and provide social support. In order to enable the automation of self-monitoring of PA, the fit.healthy.me app was integrated with the Fitbit Flex 2 fitness tracker. Additionally, prompts and cues (i.e. text messages and emails) were sent every 2 weeks to remind users to wear the fitness tracker, and check fit.healthy.me. Screenshots of the mobile app are provided in Figure 3.1.

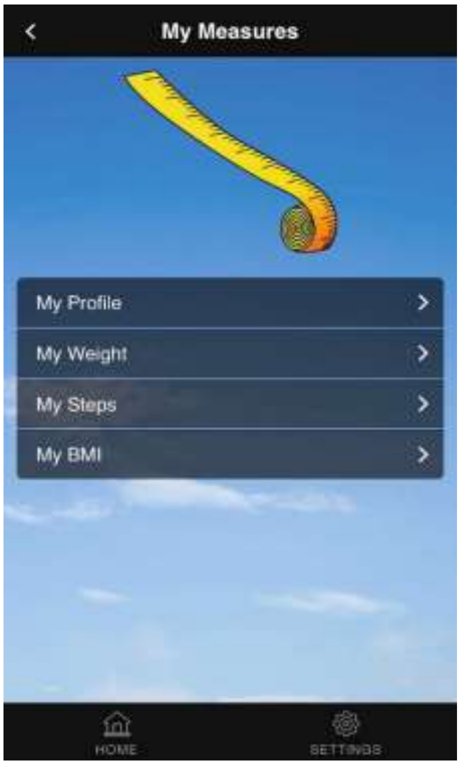
Table 3.1 Intervention description

Modes of delivery	Features	Behavior change techniques[a]
fit.healthy.me app	My measures	Self-monitoring of behavior (i.e. physical activity)
	My team	Social comparison
	Social forum	Social support Social comparison
	Private message	Social support Social comparison
	My journey	Instruction on how to perform the behavior
Fitbit Flex 2	Fitness tracker	Self-monitoring of behavior (i.e. physical activity)
Texts/emails	Reminders	Prompts/cues

[a]Classified according to the BCT taxonomy developed by Michie et al.[12]



Chapter 1. Homepage



b) My measures

c) Social features

Figure 3.1 Screenshots of fit.healthy.me app

3.3 Study design

This study adopted a mixed methods intervention design, which involved the collection, analysis and integration of both quantitative and qualitative data within an intervention trial [43]. This approach was well suited to this research project, which aimed to pilot test a mobile social networking intervention for physical activity promotion, and assess its efficacy, usability, user engagement and perspectives. In this pre-post, one-arm quasi-experiment, participants were subjected to the intervention for a six-month period. Additionally, semi-structured interviews and focus groups were added before and after the intervention in order to explore users' perspectives on the potential barriers and facilitators to engagement with the intervention. This qualitative component enabled a better understanding of the quantitative results (i.e. why the intervention may or may not have worked) [43, 44], to inform the design and implementation of future mHealth interventions.

3.4 Study procedure, data collection and analysis

The study procedure is presented in Figure 3. Participants were recruited using several channels such as posters around university campus, website information and social media (i.e. Facebook); an online survey was used to screen eligibility. Eligible participants were invited to attend the pre-intervention session, where they received information about the study, signed the consent form and filled in a questionnaire about their demographic characteristics and smartphone usage. Their weight and height were also measured. The participants then attended brief individual interviews to talk about perceived facilitators and barriers to physical activity, and their views on the potential advantages and disadvantages of the fit.healthy.me app and wireless devices (Fitbit tracker and scale). The content of the pre-intervention interviews was summarized and used as prompts for discussion in the post-intervention session. During the intervention, physical activity data and app usage were collected; preliminary data exploration and analysis occurred at the end of the study. At the post-intervention sessions, participants completed the System Usability Scale survey [45], and their weight was measured again. Participants chose to attend either individual interviews or focus groups to talk about their experiences and make suggestions on the intervention. Data integration occurred by embedding qualitative data into the intervention design [43, 44]. Specifically, both quantitative and qualitative data were analyzed separately. Qualitative data were then used to explain the quantitative results of the intervention, and the integration of both data enabled me to draw recommendations for future research.

3.5 Ethics approval

Prior to implementation of the research design, approval was granted by Macquarie University's Human Research Ethics Committee for Medical Sciences (Reference 5201600716 approved 3/11/2016, see Appendix 1).

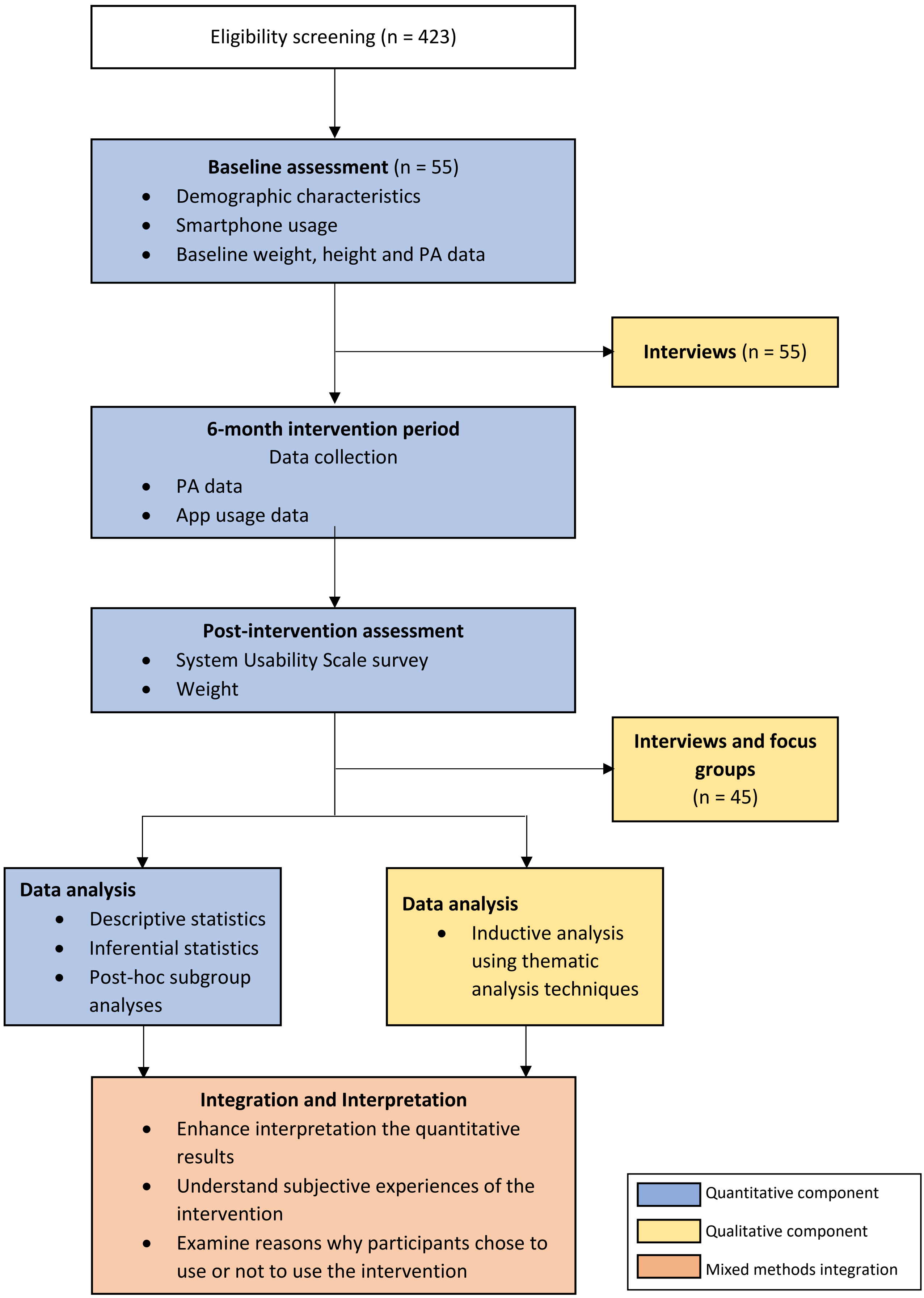


Figure 3.2 Diagram of study procedure

Chapter 4. Paper II—Efficacy of a mobile social networking intervention in promoting physical activity: Quasi-experimental study

4.1 Chapter background

This paper presents the quantitative results from the mixed methods intervention study. Specifically, the paper reports on three aspects: (1) the preliminary efficacy of the intervention on physical activity (i.e. daily step count), (2) participant engagement with the intervention and (3) the usability of the fit.healthy.me app. Descriptive and inferential statistical tests were conducted, as well as post-hoc subgroup analyses for participants with different levels of steps at baseline, app usage and social features usage.

4.2 Article content

This article was accepted at Journal of Medical Internet Research mHealth uHealth on 31/01/2019. The appendices mentioned in this article can be found in Appendix 3 of the thesis.

Author contributions: Study conceptualization: HLT, EC, LL. Data collection: HLT, LL, PM. Data analysis: HLT, EC, WT, YW, JCQ, LL. First draft: HLT, LL. All authors critically revised the manuscript and approved the final version.

Efficacy of a mobile social networking intervention in promoting physical activity: Quasi-experimental study

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Abstract

Background: Technological interventions such as mobile applications (apps), online social networks and wearable trackers have the potential to influence physical activity; yet, few studies have examined the efficacy of an intervention bundle combining these different technologies.

Objectives: To pilot test an intervention composed of a social networking mobile app, connected with a wearable tracker and investigate its efficacy in improving physical activity, as well as explore participant engagement, and the usability of the app.

Methods: Pre-post quasi-experimental study with one arm, where participants were subjected to the intervention for a six-month period. The primary outcome measure was the difference in daily step count between baseline and six months. Secondary outcome measures included engagement with the intervention and system usability. Descriptive and inferential statistical tests were conducted; post-hoc subgroup analyses were carried out for participants with different levels of: steps at baseline, app usage and social features usage.

Results: Fifty-five participants were enrolled in the study; the mean age was 23.6 years and 28 (50.9%) were female. There was a non-statistically significant increase in average daily step count between baseline and 6 months (mean change = 14.5 steps/day, *P* = 0.98, 95% confidence interval [-1136.5, 1107.5]). Subgroup analysis comparing the higher and lower physical activity groups at baseline showed that the latter had a statistically significantly higher increase in their daily step count (group difference in mean change from baseline to 6 months = 3025 steps per day, *P* = 0.008, 95% confidence interval [837.9, 5211.8]). At six months, the retention rate was 81.8% (45/55); app usage decreased over time. The mean System Usability Score was 60.1 (SD 19.2).

Conclusions: Our study showed the preliminary efficacy of a mobile social networking intervention, integrated with a wearable tracker to promote physical activity, particularly for less physically active subgroups of the population. Future research should explore how to address challenges faced by physically inactive people to provide tailored advice. Additionally, users' perspectives should be explored to shed light on factors that might influence their engagement with the intervention.

Keywords: "Mobile Applications"[Mesh], "Fitness Trackers"[Mesh], "Exercise"[Mesh], "Social Networking"[Mesh]

Introduction

There is strong evidence of the effectiveness of regular physical activity in the prevention of several chronic diseases and associated premature death [1, 2]. Furthermore, there appears to be a dose-response relationship between physical activity and health status [3, 4]. Yet, despite the importance of physical activity, 27.5% of adults worldwide are insufficiently active [5], highlighting the need for interventions to promote physical activity.

Behavioral informatics interventions (i.e. using health information technology to facilitate behavior change) have become increasingly popular in recent years [6]. A key element to behavior change success is the use of behavior change theories, models and techniques to better understand the causal mechanisms and influencing factors of the behavior, and the context of the intervention [6]. Additionally, in recent years, researchers have encouraged intervention developers to describe their interventions in terms of the specific behavior change techniques [7]. A behavior change technique is an "observable, replicable and irreducible component" of an intervention, intended to alter causal processes that regulate behavior [7]. Behavior change techniques can be linked to existing theories and models, and provide a more transparent, replicable approach to the design and evaluation of behavior change interventions [7, 8].

To date, several behavior change theories and models have indicated the importance of the link between social factors and health-related behaviors [9-11]. Specifically, researchers have demonstrated that existing networks of friends and family exert great influence on individual health behavior [12, 13], suggesting the potential of leveraging social networks to deliver physical activity interventions [14]. Social networks refer to the webs of an individual's relationships, which give rise to various functions such as social influence, social companionship, social support and social comparison [15]. To date, several studies have found strong evidence that behavior change techniques such as social support and social comparison increase physical activity levels [16-18]. Though these interventions seem promising, their potential can be missed when they are not easily disseminated or accessible to a large audience [19]. A potentially useful way to disseminate social network interventions for physical activity is through the use of online social networks. Online social networks, which are now ubiquitous in our lives, allow users to create a personal profile, and connect with other users [20]. Several meta-analyses have found that online social networks can have positive, significant effects on behavior change [21, 22].

In addition to social aspects, many studies have also highlighted the importance of other behavior change techniques, such as self-monitoring or goal setting, in physical activity [23, 24]. Mobile health (mHealth) technologies such as mobile applications (apps) and wearable trackers offer new opportunities to deliver these behavior change techniques. Specifically, recent mHealth technologies can reach individuals continuously, allowing users to self-monitor their physical activity [25] and providing real-time feedback [26]. mHealth interventions have increasingly been used in physical activity interventions, reporting significant, moderate improvements in step counts [27-29]. Given their potential, interventions combining mHealth technologies and online social networks might be particularly effective in promoting physical activity.

To date, researchers have largely examined the effects of mHealth and online social networks on physical activity in isolation [30-37]. There are a few studies that evaluated the feasibility and effectiveness of interventions with both mHealth and online social networks components, showing user acceptability and moderate increases in physical activity levels [38-42]. However, these studies often examine online social networks as an additional feature (e.g. a Facebook group), not integrated within a mobile app. Additionally, it is also essential to examine usage metrics and usability determinants of mHealth interventions, as these factors reflect true user engagement, and can largely influence the effects of the intervention [43]. Thus, the aim of this study was to pilot test a social networking mobile app, connected with a wearable tracker to promote physical activity. Specifically, we investigated (1) the intervention efficacy on physical activity and (2) participant engagement and usability of the intervention. The secondary aims were to explore the effects of social features on physical activity levels, and the association between engagement with the mobile app and physical activity levels.

Methods

Study design

This study is part of a larger mixed-methods feasibility study on the use of a social networking mobile app to promote physical activity and weight management [19]. Specifically, this paper reports on the quantitative results related to the physical activity outcomes of a pre-post, one-arm quasi-experiment where participants were subjected to the intervention for a six-month period. Results related to weight outcomes of the study will be reported in a forthcoming publication. The design and conduct adhered to the CONSORT 2010 statement—extension to randomized pilot and feasibility trials [44], where applicable. Ethics approval was granted by Macquarie University's Human Research Ethics Committee for Medical Sciences (ethics reference number 5201600716).

Study settings and participants

Fifty-five participants (mean age 23.6 years, 50.9% female), mostly Macquarie University students and staff (Sydney, Australia) were recruited using purposive sampling techniques [19]. Given the nature of this study, the sample size was pragmatically chosen to enable a comprehensive assessment of the feasibility of the intervention before conducting a randomized controlled trial [44]. Recruitment channels included posters around university campus, website information, and Facebook. Eligible participants were healthy adults with sufficient English to understand and participate in the study; who planned to be living in Sydney for the duration of the study; and owned a mobile phone (iOS or Android) with internet access. Exclusion criteria were pregnancy; BMI below 17; prior history of eating disorders; or having diabetes or other co-morbid conditions that could impact on study participation (e.g. severe mental illness, end-stage disease). Participants were screened for eligibility via an online questionnaire.

Eligible participants were invited to attend the initial study session at the research centre, where they received information about the purpose of the study and signed the consent form. Subsequently, participants filled in a questionnaire about their demographic characteristics and smartphone usage (e.g. type of smartphone used, hours per day using the smartphone), and their baseline measurements (i.e. weight, height) were assessed. At the end of the study, participants were invited to attend a post-intervention session in which they completed the System Usability Scale survey [45], and their weight was measured again.

Intervention description

The intervention bundle involved three components, including a mobile app (named fit.healthy.me), a wearable tracker, and texts/emails. Specifically, the fit.healthy.me app was developed based on several behavior change techniques, such as self-monitoring of physical activity, social support and social comparison. In the app, the social features were composed of 'My team', 'Social forum' and 'Private messages'. 'My team' allowed participants to visualise and compare their step counts against others, and ‘follow’ other people, while ‘Social forum’ and ‘Private messages’ allowed participants to interact and provide social support to each other.

In order to enable the automation of self-monitoring, the fit.healthy.me app was integrated with the Fitbit Flex 2 wearable tracker [19]. Specifically, the Fitbit Flex 2 was wirelessly synced with fit.healthy.me (via the Fitbit Application Programming Interface). Fitbit Flex 2 uses accelerometer technology to measure acceleration signals, which are then converted to step count—a common indicator of physical activity. Research has demonstrated good reliability and validity in using Fitbit Flex 2 for measuring step count in free-living conditions [46, 47].

Additionally, prompts and cues (i.e. text messages and emails) were sent every 2 weeks to remind users to wear the fitness tracker during waking hours, and check fit.healthy.me at least once every day. A detailed description of the modes of delivery and features of the intervention is presented in Box 1. Screenshots of the mobile app are provided in Appendix 1.

Prior to the study commencement, the fit.healthy.me app underwent development testing [48] within the research centre. Participants were provided access to the intervention by downloading the app from the Apple app store or Google Play. During the study, participants could email or call the study team if they required any technical assistance. A research team member with clinical expertise also regularly monitored the study and responded to any concerns raised by participants. As an incentive for participation in the study, individuals were offered to keep the tracker at the end of the 6-month period.

Box 1: Intervention features and behavior change techniques

Modes of delivery	**Features**	**Behavior change techniques[a]**
fit.healthy.me app	My measures	Self-monitoring of behavior (i.e. number of steps per day)
	My team	Social comparison
	Social forum	Social support (emotional) Social comparison
	Private messages	Social support (emotional) Social comparison
	My journey	Instruction on how to perform the behavior
Fitbit Flex 2	Fitness wearable tracker	Self-monitoring of behavior (i.e. physical activity)
Texts/emails	Reminders	Prompts/cues

[a]Classified according to the Behavior Change Techniques taxonomy developed by Michie et al [7]

Measures

This study specifically reports on three aspects of the study results: (1) the efficacy of the intervention on physical activity measures, (2) participant engagement with the intervention, and (3) the usability of the fit.healthy.me app.

Efficacy in promoting physical activity

The primary outcome measure for this study was the difference in daily step count between baseline and six months, which was measured using the Fitbit Flex 2 (minute-by-minute data was retrieved via the Fitbit Application Programming Interface). To enable the collection of baseline daily step count, participants underwent a seven-day period after the initial study session where they were not able to login to fit.healthy.me but were asked to use the Fitbit Flex 2 every day; the baseline measure was obtained by averaging the number of steps per day the first seven days. The final step count was determined by computing the average number of steps per day on the last week where participants had at least four valid days [49]. A valid day of step count was defined as at least 10 hours of wear time during that day [47] (Box 2). Wear time was calculated by subtracting non-wear time from 24 hours; non-wear time was defined if no step counts were detected over a period of at least 60 continuous minutes, allowing for two minutes of counts between 0 and 100 [49, 50].

Post-hoc subgroup analysis was carried out for participants with different physical activity levels at baseline (≥10,000 steps per day versus <10,000 steps per day). Ten-thousand steps per day was used as a threshold as this goal is acknowledged as a reasonable target for healthy adults [51-53].

Participant engagement

Participant engagement with the intervention was assessed using multiple measures (Box 2). Specifically, retention was defined as attendance at the 6-month final session. Participants who came to the final sessions were considered 'completers'; participants who did not come were considered to have dropped out of the study. For the Fitbit Flex 2, engagement was measured by the mean number of days a valid step count was logged (participants were considered to have a valid step count if they wore the Fitbit for at least 10 hours in any given day). For the fit.healthy.me app, engagement was measured by both the length of usage (i.e. the mean number of days of usage), and frequency of usage (i.e. the number of times participants used the app/each feature). A participant was considered to have used the app in a day if he/she used any features of the app at any time of that day. Similarly, a participant was considered to have used a social feature if he/she clicked on any of 'My team', 'Social forum' and 'Private messages' features at any time. Every time a participant used an app feature, the timestamp and the name of that feature was automatically saved into our local database. These data were summarized to show participant engagement with the fit.healthy.me app at the end of the study.

Box 2. **Definition and calculation of engagement measures**

Retention[a]	
Completers	Participants who came to the final sessions
Non-completers	Participants who did not come to the final sessions (dropout attrition)
Retention rate	Percentage of completers out of all 55 participants
Fit.healthy.me app usage	
Length of usage	The mean number of days of usage
Frequency of usage	The mean number of times participants used the app/ each feature
Non-usage attrition	Participants who did not use the app at all in the last month of the study
Fitbit Flex 2 tracker usage	
Length of usage	The mean number of days a valid step count was logged
A valid day of step count	Having at least 10 hours of wear time
Wear time	Calculated by subtracting non-wear time from 24 hours
Non-wear time	Defined if no step counts were detected over a period of at least 60 continuous minutes, allowing for two minutes of counts between 0 and 100 [49, 50]

Abbreviation: app: application. [a]Adapted from Eysenbach (2005) [43]

Usability

Participants completed the System Usability Scale (SUS) [45] to assess the usability of the fit.healthy.me app. The SUS is a validated questionnaire comprising of a standard set of 10 statements that seeks users' opinions on the usability of a system [45]. SUS has been widely used to evaluate usability within commercial and research studies (including mobile apps) for over 30 years [54-56]. Participants were asked to rank the statements on a 5-point Likert scale from strongly disagree (scored as 1) to strongly agree (scored as 5). Final scores of the SUS can range from 0 to 100, with higher scores indicating better usability [57]. A study collecting 10-year worth of SUS data from over 200 studies found that the average score is around 70, suggesting that a SUS score of 70 might be considered acceptable [57]. A list of the statements and explanation for calculation of the SUS scores is provided in Appendix 2.

Statistical analysis

Participants' demographic characteristics, intervention usage data and engagement metrics were analysed descriptively using means, standard deviations (SD) and frequency counts. Wilcoxon signed-rank test was used to determine whether the number of days participants used the fit.healthy.me app differed between the first and last (sixth) month of the study. SUS score was calculated to determine the usability of the fit.healthy.me app [45].

To investigate the efficacy of the intervention, the difference between average step count at baseline and final weeks was assessed using a paired t-test. Three participants did not have valid data for at least four days at the end of the study, and thus, were excluded from the analysis. Kendall's tau b test was used to measure the correlation between total engagement with the fit.healthy.me app and changes in daily step count.

Post-hoc subgroup analyses were carried out for participants with different levels of: steps at baseline, app usage, and social features usage. As mentioned above, in terms of physical activity, 10,000 steps per day was used as a cut-off point to define high versus low level [51-53]. In terms of app usage and social features usage, the median was used as a cut-off point to determine frequent vs non-frequent usage. Independent two-sample t-tests were used for normally distributed numerical data; for non-normal data, the Wilcoxon rank-sum test was used. Chi-square tests were used for categorical data. For statistically significant results, effect sizes (i.e. Cohen's *d*) were calculated [58].

Data were analysed using R version 3.5.0 [59-63]. The significance level for all statistical tests was set at $P < 0.05$, two tailed, and 95% confidence intervals (CIs) were calculated where applicable.

Results

Participant flow and recruitment

Recruitment occurred from April to May 2017. Four hundred and twenty-three people completed an online questionnaire to assess their eligibility; 55 of them met the eligibility criteria, consented to participate, and attended the pre-intervention session. The most common reasons for ineligibility were pregnancy and chronic diseases. After each participant completed the six-month period, they were sent an automatic email, inviting them back for the final sessions. Out of 55 initial participants, 45 participants returned for the final session (i.e. completers). Step data were collected for all 55 participants during the 6-month intervention period. Given our definition of valid days and the condition that at least four valid days were needed to compute the weekly average, not all participants had the final step count in week 26 (median final week number: 21; interquartile range: 10-25).

Sample characteristics

A summary of the differences in baseline characteristics between enrolled participants and completers is presented in Table 1. At baseline, participants had a mean age of 23.6 years (SD 4.6). Twenty-eight (50.9%) were female, and 42 (76.4%) were university students. The average BMI was 26.5 kg/m^2 (SD 6.8), with nearly half of the participants (24/55, 43.6%) in the normal weight range. Participants reported using a smartphone for 5.6 hours (SD 3.4) per day, on average; most users (36/55, 65.5%) had an iPhone. The majority of participants (49/55, 89.1%) said that the most used apps in their phones were social media, while 10% (6/55) said fitness apps. There were no statistically significant differences between enrolled participants and completers.

Table 1: Differences in baseline characteristics between enrolled participants and completers

		Enrolled participants (N=55)	**Study completers** (N=45)	***P***
Age	mean (SD)	23.6 (4.6)	24.2 (4.7)	0.51[a]
Female	N (%)	28 (50.9)	22 (49.9)	0.52[b]
Weight (kg)	mean (SD)	78.1 (22.3)	77.8 (21.2)	0.997[a]
BMI (kg/m^2)	mean (SD)	26.6 (6.8)	26.7 (6.5)	0.94[a]
BMI categories[c]	N (%)			
18 – 18.49		3 (5.5)	1 (2.2)	0.14[b]
18.5 – 24.99		24 (43.6)	22 (48.9)	0.19[b]
25 – 29.99		15 (27.3)	10 (22.2)	0.16[b]
≥30		13 (23.6)	12 (26.7)	0.48[b]
Steps/day		10967.2 (3907.4)	10896.3 (4206.2)	0.93[a]

Abbreviations: BMI: body mass index, kg: kilogram, m: meter, N: frequency count, *P*: p-value, SD: standard deviation. [a]Assessed using two-sample t-tests, [b]Assessed using chi-square tests, [c]According to the World Health Organization, a BMI of less than 18.5 is classified as underweight, 18.5 – 24.9 is normal, 25 – 29.9 is pre-obese, ≥30 is obese [64].

Physical activity measures

On average, daily step count did not change between baseline and 6 months (mean difference = 14.5, P = 0.98, 95% CI [-1136.5, 1107.5]). A post-hoc subgroup analysis comparing the higher physical activity group with the lower physical activity group (at baseline) showed that the lower physical activity group experienced a statistically significant increase of 3025 steps in daily step count between baseline and post-intervention (P = 0.008, 95% CI [837.9, 5211.8], *d* = 0.80) (Table 2 and Figure 1). Appendix 3 shows boxplots for participants' daily step count at each week of the study. There were no statistically significant changes in average daily step count between different levels of app usage (P = 0.42) (Appendix 4), or different levels of social feature usage (P = 0.25) (Appendix 5). Total engagement with the fit.healthy.me was not directly associated with change in daily step counts (Kendall's tau b = -0.11, P = 0.25).

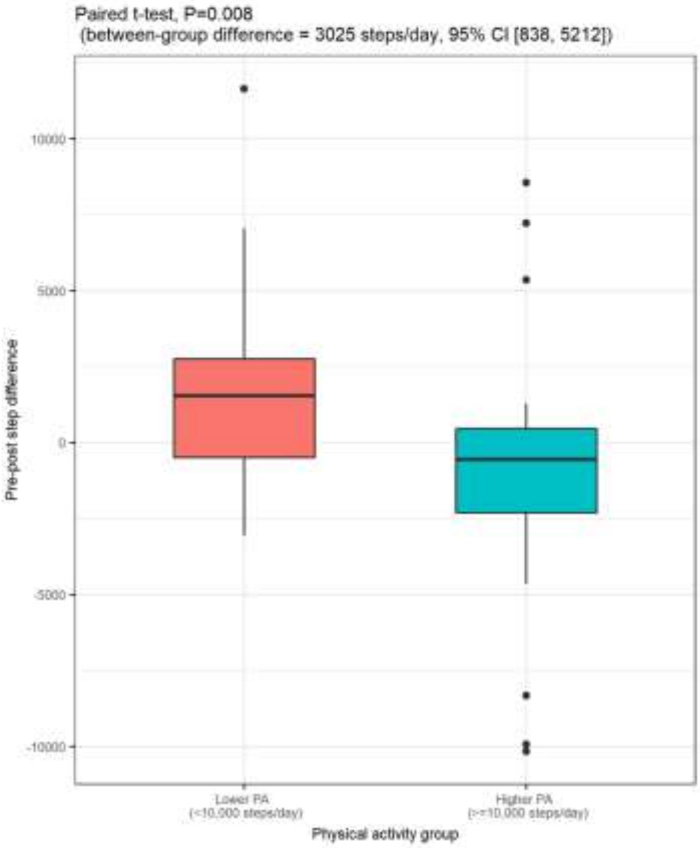

Figure 1: Boxplots of the differences in pre-post daily step count between the lower and higher physical activity groups. **Abbreviations:** PA: physical activity.

Table 2: Differences in characteristics between lower and higher physical activity subgroups at baseline

	<10,000 steps/day (N=20) mean (SD)	**≥10,000 steps/day (N=35) mean (SD)**	***P* (95% CI)**
Baseline weight (kg)	77.0 (26.3)	78.6 (20.1)	0.80[a] (-14.3, 11.0)
Baseline BMI (kg/m²)	26.4 (7.8)	26.6 (6.2)	0.91[a] (-4.1, 3.6)
Baseline steps/day	7441 (2921.1)	12982 (2825.8)	<0.005 [a] (-7179.0, 3904.3)
Duration of app usage (days)	16.1 (15.3)	15.4 (17.0)	0.51[b] (-4.0, 7.0)
Intensity of app usage (times)	1487.0 (1244.7)	1719.1 (1561.6)	0.79[b] (-559, 860)
Pre-post intervention step difference	1992.3 (3598.3)	-1032.6 (3894.7)	**0.008**[a]* **(837.9, 5211.8**)

Abbreviation: N: frequency count, SD: standard deviation, *P*: p-value, CI: confidence interval, kg: kilogram, m: metre; **Notes**: [a] Assessed using two-sample t-test, [b]Assessed using Wilcoxon rank-sum test, *denotes statistical significance

Participant retention and engagement

The retention rate was 81.8%. Overall, the length of usage of the Fitbit Flex 2 tracker was higher than app and social features. 'My Team' and 'My Measures' had a higher level of engagement compared to 'Social Forum' and 'Private Messages' (Table 3). In general, app usage decreased over time (Figure 2). Particularly, the number of days participants used the app in the last month of the study significantly decreased from the first month of the study ($P<0.001$, 95% CI [-5.5, -4]). Four participants did not use the app at all throughout the study. Subgroup analyses showed that there were no statistically significant differences in any characteristics between frequent and non-frequent app users (Appendix 4).

Table 3. Length and frequency of usage of the Fitbit Flex 2, fit.healthy.me app and social features[a]

	Usage data	Mean (SD)	Range
Fitbit Flex 2 usage	Days valid step count were logged via Fitbit (days)	66 (48.7)	(5 – 183)
App usage	Length (days)	15.7 (16.2)	(0 – 63)
	Frequency (times)	1634.7 (1446.8)	(0 – 6317)
App features usage	Frequency (times)		
	My measures	44.2 (47.8)	(0 – 228)
	My team[b]	59.0 (51.6)	(0 – 203)
	Social forum[b]	21.8 (37.5)	(0 – 213)
	Private messages[b]	9.2 (20.8)	(0 – 88)
	My journey	17.0 (13.0)	(0 – 63)

Abbreviations: SD: standard deviation. **Notes:** [a]Study duration was 183 days, [b]Social features included 'My team', 'Social forum' and 'Private messages'.

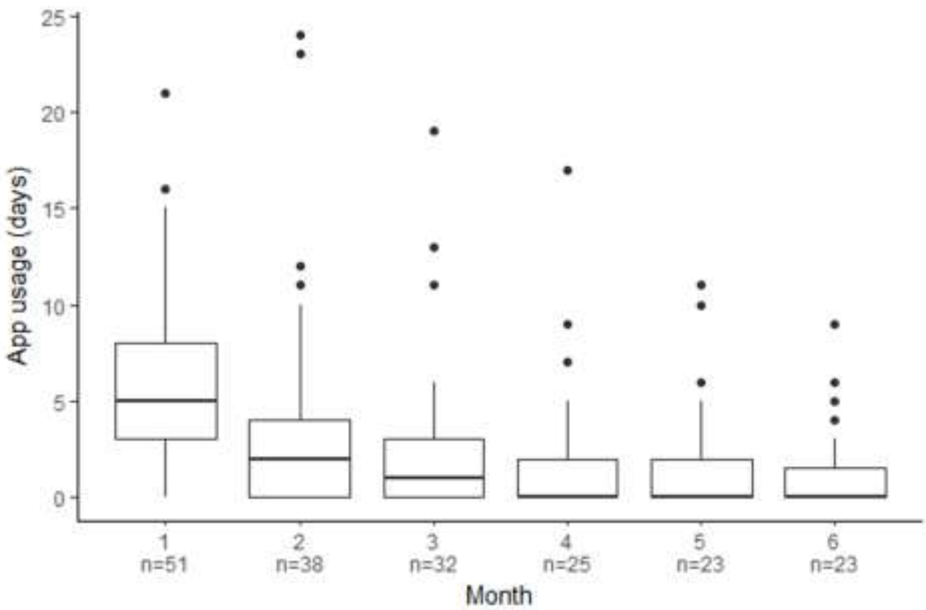

Figure 2: Boxplots of the number of days participants used the fit.healthy.me app, by month

System Usability Scale

Out of 55 participants, only 45 returned to the post-intervention sessions and completed the SUS. The mean SUS score was 60.1 (SD 19.2). Two-thirds of the participants (N=30) gave a SUS score lower than 70, indicating low usability [57]. Seven participants rated the app's usability as moderate; 8 participants rated it as having high usability. Appendix 2 presents responses to individual system usability scale statements. Post-hoc subgroup analysis indicated that frequent app users gave a higher SUS score than non-frequent users (*P* = 0.04, 95% CI [0.6, 25.3]) (Appendix 4).

Discussion

Main findings

There was a non-statistically significant increase in average daily step count between baseline and 6 months. Post-hoc subgroup analysis comparing the higher and lower physical activity groups at baseline showed that the latter experienced a statistically significant increase in average daily step count between baseline and post-intervention, suggesting the app might be more beneficial for specific subgroups of the population (e.g. less physically inactive individuals). At six months, the retention rate was 81.8%; 41.8% participants used the fit.healthy.me app at least once during the last month of the study.

To the best of our knowledge, our study is the first to evaluate a mobile social networking intervention integrated with a wearable tracker. Other studies have examined interventions composed of either mobile technologies [30-33] or online social networks [34-37] in isolation, and thus, evidence on the efficacy and feasibility of an intervention combining both was limited until now. Even though several studies have incorporated social features in mHealth interventions, these features were often included as an additional component (e.g. Facebook group), rather than being fully integrated with the mobile app [38, 39, 41, 42, 65, 66].

Efficacy in promoting physical activity

Our study found that compared to the higher physical activity group, the lower physical activity group at baseline experienced a significant increase of 3025 steps in daily step count, suggesting that specific populations (e.g. less physically active people) might benefit more from the use of a mobile social networking app. Previous research has outlined the importance of considering particular challenges and barriers that inactive people might face when designing fitness technology. For example, several studies have suggested that while self-regulation techniques (i.e. goal setting, self-monitoring and feedback on behavior) and social support are often present in fitness technology, other behavior change techniques such as action planning or environment restructuring are present less often and might be particularly useful for inactive people [67, 68]. It is worth noting even increases of 2000 steps per day are associated with reduced risk of cardiovascular disease, given the dose-response relationship between physical activity levels and health benefits [69]. Altogether, the use of behavioral informatics such as ours seem promising and should be confirmed by fully powered randomized controlled trials.

User retention, engagement, and usability

The retention rate of our study was 81.8%, which is consistent with the reported retention rates of around 70% to 90% in other mHealth and online social networks interventions [21, 38, 39, 70-72]. Our study also revealed that app usage declined over time—a phenomenon frequently observed in other apps for physical activity [29, 73, 74]. It is known that initially, users tend to be attracted to new technologies; over time, disengagement can be triggered by either internal factors such as lack of time, or external factors such as usability issues, technological problems [75]. A possible explanation for the decline in usage of our app could be usability issues. In fact, two-thirds of our users gave a SUS score lower than 70 to the fit.healthy.me app, indicating low usability [57]; non-frequent users were more likely to give a lower SUS score. Indeed, when a user experiences a usability flaw, the negative experience might outweigh other positive features of the technology (a phenomenon known as 'negativity bias')[76], and subsequently lead to lower engagement. The link between usability and engagement has been frequently demonstrated in previous research [75]. Notably, the Technology Acceptance Model highlights the importance of perceived usefulness and perceived ease of use (concepts overlapping with many aspects of usability [45, 77-79]) in users' acceptance and adoption of technology [80, 81]. Hence, it is important to address usability in order to maximise user engagement.

We also found that usage levels varied amongst different features. Specifically, 'My team' attracted a significantly higher level of engagement compared to 'Social forum' and 'Private messages'. This difference could possibly be due to the format and content presented in each feature: 'My team' supports social comparison via displaying summary statistics and graphs, while the 'Social forum' and 'Private messages' features support discussion amongst users. It can be hypothesised that users found more utility in the numerical and graphical social comparison aspects of 'My team' to the discussion-based nature of other social features, suggesting the need to explore how to effectively deliver social behavior change techniques to maximise engagement.

Strengths & Limitations

This study has several strengths. Firstly, we assessed a range of features supporting different behavior change techniques to examine the individual aspects of this multi-component intervention. Secondly, we reported different measures of engagement, including retention rate, non-usage attrition, and engagement metrics with different intervention components to shed light into attrition problems in behavioral informatics interventions [43, 82]. Finally, the intervention was fully integrated with wireless tracking devices, and thus, eliminated the reliance on self-reported data.

The findings of this study must be interpreted in light of some limitations. Given that this was a quasi-experimental study with a single-arm pre-post design, we cannot infer causation from our results. Possible confounders might have been at play and thus, the results should be interpreted with caution. Moreover, we had a purposely small and homogenous sample, which affects generalizability of the study. Another limitation is related to the handling of missing data in daily step count. Due to our definition of valid days of step count, and the condition that participants needed to have at least four valid days of daily step count within a week in order to compute the weekly average, not all participants had the final step count in the last month of the study, and hence, we calculated the final step count based on the last week where participants had at least four valid days. While this method allowed us to include more participants in the analysis (and thus avoid selection bias resulting from excluding participants from the analysis), it can potentially bias the results in other ways (e.g. overestimation of final step count in the case where daily step count decreases over the study duration). Additionally, as the fit.healthy.me app was developed for research purposes, it lacked the advanced features and design aspects that would be available in commercially available fitness apps. Usability testing was assessed using the SUS and not done extensively. All post-hoc subgroup analyses were exploratory and might be subject to type I error. Specifically, in our analysis comparing different physical activity subgroups, our focus was on the difference between baseline and final weeks, and the analysis did not take into account all 26 weeks (as shown in Appendix 3). Future work exploring the time series nature of physical activity data, and analysing and modelling weekly trends, might reveal more in-depth information about users' behavioral patterns and provide more robust results. Finally, in this study, we only used step count as a measure of physical activity. Future research might consider other measures, such as intensity of physical activity (light, moderate, vigorous) or sedentary time [83, 84].

Implications

Our study highlights several important implications regarding the design and implementation of behavioral informatics interventions for physical activity. Firstly, our findings suggest that wearable devices and mobile social networking apps can work in synergy to facilitate behavior change, particularly in physically inactive groups. Specifically, wearable trackers can automate self-monitoring—an important task in behavior change [23, 85], whereas mobile apps can provide a platform to support other relevant behavior change techniques, such as providing feedback on behavior, goal setting, or social comparison [86]. Several studies have also suggested that social interaction can enhance engagement [28, 87], highlighting the potential of integrating social features in technological interventions.

Furthermore, it is important to note that physically inactive groups might face additional challenges, and thus, future research should also consider the potential of other behavior change techniques in these interventions. Perhaps fitness technology could prompt individuals to identify the particular barriers they face regarding physical activity [67], and facilitate the tailoring of specific recommendations accordingly. Tailored advice can be more helpful and relevant to users [88, 89], potentially leading to more effective interventions in this subgroup of the population. Additionally, future research should also explore users' preferences and perspectives on factors that might influence their engagement, to maximise the effectiveness of mHealth interventions in promoting physical activity.

Conclusion

Our study showed preliminary evidence that mobile social networking interventions, integrated with wearable trackers can help to promote physical activity. Future research needs to explore how to best support barriers faced by physically inactive people and provide tailored recommendations accordingly to maximise intervention effectiveness.

List of abbreviations

Apps	Applications
Mobile health	mHealth
CONSORT	Consolidated Standards of Reporting Trials
SUS	System Usability Scale
SD	Standard deviation
BMI	Body mass index
PA	Physical activity

Appendix 1: Screenshots of fit.healthy.me app

Appendix 2: Responses to individual system usability scale statements

Appendix 3: Boxplots of the 55 participants' daily step count over 26 study weeks

Appendix 4: Differences in characteristics between frequent app users and non-frequent app users

Appendix 5: Differences in characteristics between frequent users and non-frequent users of the social features in the fit.healthy.me app

Conflict of interest: EC could benefit from the commercialization of fit.healthy.me.

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Author contributions: Study conceptualization: HLT, EC, LL. Data collection: HLT, PM. Data analysis: HLT, EC, WT, YW, JCQ, LL. First draft: HLT, LL. All authors critically revised the manuscript and approved the final version.

Data availability statement: Summary data supporting the findings are available within the paper and its supplementary information files. The raw datasets are not publicly available due to ethical restrictions.

Ethics approval: Macquarie University's Human Research Ethics Committee for Medical Sciences (reference number: 5201600716)

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Chapter 5. Paper III—Using a mobile social networking app to promote physical activity: A qualitative study of users' perspectives

5.1 Chapter background

The article in this chapter forms the qualitative component of the mixed methods study. It builds on the previous chapter by examining participants' perspectives on the intervention, specifically, potential barriers and facilitators to user engagement, as well as the behavior change techniques and delivery features deemed important by users for physical activity promotion. The findings of this paper help to explain participant engagement and the System Usability Scale score observed in the previous chapter. This paper was published at Journal of Medical Internet Research on 21-12-2018.

5.2 Article content

This article was accepted for publication at Journal of Medical Internet Research on 9th Sep 2018 and published in 21st Dec 2018. The included article content is permitted under Journal Author Rights within the journal's publishing agreement. The appendices of this article can be found in Appendix 4 of the thesis.

Author contributions: HLT, EC and LL conceptualized the study. HLT developed and pilot tested the interview guide, conducted the interviews and focus groups, data analysis and wrote the first draft of the manuscript. LL pilot tested the interview guide, conducted some data collection and analysis, provided guidance on data analysis and critical feedback on the manuscript. EC critically revised the manuscript. All authors approved the final version.

Original Paper

Using a Mobile Social Networking App to Promote Physical Activity: A Qualitative Study of Users' Perspectives

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Abstract

Background: Despite many health benefits of physical activity, nearly a third of the world's adult population is insufficiently active. Technological interventions, such as mobile apps, wearable trackers, and Web-based social networks, offer great promise in promoting physical activity, but little is known about users' acceptability and long-term engagement with these interventions.

Objective: The aim of this study was to understand users' perspectives regarding a mobile social networking intervention to promote physical activity.

Methods: Participants, mostly university students and staff, were recruited using purposive sampling techniques. Participants were enrolled in a 6-month feasibility study where they were provided with a wearable physical activity tracker (Fitbit Flex 2) and a wireless scale (Fitbit Aria) integrated with a social networking mobile app (named "fit.healthy.me"). We conducted semistructured, in-depth qualitative interviews and focus groups pre- and postintervention, which were recorded and transcribed verbatim. The data were analyzed in Nvivo 11 using thematic analysis techniques.

Results: In this study, 55 participants were enrolled; 51% (28/55) were females, and the mean age was 23.6 (SD 4.6) years. The following 3 types of factors emerged from the data as influencing engagement with the intervention and physical activity: individual (self-monitoring of behavior, goal setting, and feedback on behavior), social (social comparison, similarity and familiarity between users, and participation from other users in the network), and technological. In addition, automation and personalization were observed as enhancing the delivery of both individual and social aspects. Technological limitations were mentioned as potential barriers to long-term usage.

Conclusions: Self-regulatory techniques and social factors are important to consider when designing a physical activity intervention, but a one-size-fits-all approach is unlikely to satisfy different users' preferences. Future research should adopt innovative research designs to test interventions that can adapt and respond to users' needs and preferences throughout time.

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KEYWORDS

exercise; fitness trackers; mobile apps; mobile phone; social networking

Introduction

Physical inactivity has been identified by the World Health Organization as a global public health problem, emerging as the fourth leading risk factor for global mortality [1]. Research has shown that physical inactivity increases the risk of many chronic diseases—most notably, type 2 diabetes, coronary heart disease, and colon cancer [2]. Nearly a third of adults worldwide are insufficiently active [3], highlighting the need for effective health interventions to change behavior and promote physical activity.

It is widely acknowledged that behavior change is a challenging process. The success of behavior change depends not only on an individual but also on social and environmental factors [4,5]. Behavior change interventions are usually complex (ie, involving several interacting components), which makes it hard to identify what is effective in changing a particular behavior, for whom, and in what context [6-8]. Several taxonomies for behavior change techniques (ie, the active components in health behavior change interventions) have been developed [9,10] in an attempt to isolate and identify the most effective components of interventions. For physical activity promotion, some behavior change techniques seem to be particularly relevant such as self-monitoring of behavior, goal setting, and social support [11,12]. In addition, the mode of delivery of the intervention is equally important, as it can influence its acceptance, dissemination, and long-term use [8,13].

The use of technology in the delivery of behavior change interventions has potential in promoting their success and diffusion. Notably, mobile health (mHealth) interventions, involving mobile apps and wearable devices, can reach individuals continuously, enabling the self-monitoring of health and physical activity data [14] and the tailoring of intervention components in real time [15]. In addition, Web-based social networks seem to hold great promise, as they can help address social processes related to behavior change such as social support and social comparison [16,17]. Given their potential, interventions combining mHealth technologies and Web-based social networks might be particularly effective in promoting physical activity.

To date, a few qualitative studies have sought users' attitudes and views on the use of mHealth technologies and Web-based social networks for physical activity promotion [18-22], with most focusing on just one of these technologies. This limits the ability of researchers and developers to assess whether these 2 technologies can work in synergy. In addition, it remains unclear which behavior change components are most effective and which are considered more engaging by consumers [23]. The aim of this study was to explore individuals' perspectives before and after using a mobile social networking app for physical activity promotion. Specifically, we were interested in exploring potential barriers and facilitators to engagement with the intervention, as well as the behavior change techniques and delivery features considered important by users to promote physical activity. This research will help guide the future development of interventions and public health initiatives that could be more effective in influencing physical activity.

Methods

Study Overview

This study is part of a larger mixed-methods feasibility study on the use of a social networking mobile app to promote physical activity and weight management [24]. Given the importance of physical activity and its impact on weight management [1-3], this paper focused specifically on factors influencing physical activity. This study adheres to the COnsolidated criteria for REporting Qualitative research checklist for reporting qualitative research (Multimedia Appendix 1) [25]. This study protocol was approved by the Macquarie University's Human Research Ethics Committee for Medical Sciences (reference number: 5201600716). The authors declare that the data supporting the findings of this study are available within the paper and its supplementary information files.

Study Setting and Participants

This study was conducted at Macquarie University (Sydney, Australia). We recruited 55 participants, mostly university staff and students, using purposive sampling techniques through several channels, including posters around campus, website information, social media, and an email newsletter. Eligible participants were healthy adults with sufficient English to understand and participate in the study; aged between 19 and 35 years; who planned to be living in Sydney for the duration of the study; and owned a mobile phone (iOS or Android) with internet access. The exclusion criteria included pregnancy; body mass index (BMI) <17; prior history of eating disorders; or having diabetes or other comorbid conditions that could impact the study participation (eg, severe mental illness and end-stage disease).

For a 6-month period, participants were asked to use an intervention bundle (detailed below). Interviews were conducted pre- and postintervention, with the aim of assessing participants' perspectives on the use of social networking and mHealth interventions to promote physical activity. Of 55 initial participants, 45 returned for the final interviews.

Intervention Description

The intervention bundle was composed of a mobile social networking app (named "fit.healthy.me"), a fitness tracker (Fitbit Flex 2), and short message service text messages and emails [24]. The mobile app "fit.healthy.me" consisted of several features—"My measures," "My team," "Social forum," and "Private message"—which directly supported different behavior changes techniques (self-monitoring, social support, and social comparison). Specifically, "My measures" provided a summary of the number of steps, weight, and BMI. "My team" was a platform for participants to visualize and compare their steps with others. "Social forum" and "Private message" were designed for individuals to network with other users and provide and receive social support.

To enable the automation of self-monitoring, the app was integrated with the Fitbit Flex 2 fitness tracker, through the Fitbit Application Programming Interface. Reminders to wear the trackers and check the app were sent to participants every 2 weeks in the form of short message service text messages and emails. Table 1 provides a detailed description of the modes of delivery and features of the intervention, and Multimedia Appendix 2 shows the screenshots of the "fit.healthy.me" app.

Table 1. Intervention description.

Modes of delivery	Features	Behavior change techniques[a]
fit.healthy.me app	My measures	Self-monitoring of behavior (ie, physical activity)
	My team	Social comparison
	Social forum	Social support Social comparison
	Private message	Social support Social comparison
	My journey	Instruction on how to perform the behavior
Fitbit Flex 2	Fitness tracker	Self-monitoring of behavior (ie, physical activity)
Texts and emails	Reminders	Prompts or cues

[a]Classified according to the behavior change technique taxonomy developed by Michie et al [26].

Interview Procedure

Prior to study commencement, an interview guide (Multimedia Appendix 3) was developed and pilot-tested. Participants were invited to attend the initial study session at the research center, where they received information about the purpose of the study, signed the consent form, and filled in a questionnaire about their demographic characteristics and smartphone usage (eg, the type of smartphone used and hours per day spent using the smartphone).

In the preintervention session, 55 participants attended a brief individual interview (10-15 minutes) in which they were asked about perceived facilitators and barriers to physical activity and their views on the potential advantages and disadvantages of the mobile app and wireless devices (fitness tracker and scale). The content of the preintervention interviews was summarized and used as prompts for discussion in the postintervention sessions.

In the postintervention session, we conducted 32 individual interviews and 5 focus groups with 13 participants (20-45 minutes); data saturation was reached. While the interviews allowed us to understand individual perspectives, the focus groups enabled us to explore group differences and similarities [27,28].

At the postintervention sessions, participants talked about their experiences regarding the use of the intervention and provided suggestions on the devices and the intervention. Furthermore, semistructured interviews were conducted by 2 researchers with expertise in qualitative methods. Field notes were taken throughout the interviews.

Data Management and Analysis

With participants' consent, the interviews were recorded and transcribed verbatim, and transcripts were analyzed in Nvivo 11 (QRS International Pty Ltd., Melbourne, Australia). The data were analyzed using thematic analysis techniques [29]. Specifically, the transcripts were explored using the inductive analysis to identify themes and patterns [29]. First, we open-coded the transcripts to identify all important aspects related to the research questions. Subsequently, by scrutinizing and comparing different data and codes (ie, constant comparison), we pinpointed concepts that seemed to cluster together [30]. Informed by engagement with the literature, we identified the similarities, differences, and general patterns in the open codes, to fill in underdeveloped categories, narrow excess ones, and organize them into major themes [30,31].

Results

Sample Characteristics

Table 2 summarizes participants' demographic characteristics. At baseline, 51% (28/55) participants were females; the mean age was 23.6 years. On average, participants spent 5.6 hours daily using smartphones, and 89% (49/55) participants stated that they frequently used social media. Of all, 76% (42/55) participants were university students.

Summary of Results

We found the following 3 types of factors emerging from the data as influencing user engagement with the intervention and physical activity levels: individual, social, and technological. At the individual level, participants mentioned that goal setting, self-monitoring, and feedback were important for their physical activity. At the social level, social comparison and the connection with other users in terms of familiarity and similarity were considered motivating. Finally, at the technological level, automation and personalization were considered to be facilitators, while technological limitations were observed as reducing user engagement. The following sections discuss each of these themes in detail, with illustrative quotations (Textboxes 1-3).

Table 2. Baseline sample characteristics (N=55).

Characteristics	Value
Age, mean (SD)	23.6 (4.6)
Female gender, n (%)	28 (51)
Weight, mean (SD)	78.1 (22.3)
BMI[a] (kg/m^2), mean (SD)	26.5 (6.8)
BMI categories[b], n (%)	
17-18.49	3 (6)
18.5-24.9	24 (44)
25-29.9	15 (27)
≥30	13 (24)
Steps/day, mean (SD)	9937 (3527)
Marital status, n (%)	
Single	27 (49)
In a relationship	22 (40)
Married or de facto	6 (11)
Daily smartphone use (hours), mean (SD)	5.6 (3.4)
Most used apps[c], n (%)	
Social media	49 (89)
Fitness apps	6 (10)
Occupation, n (%)	
Student	42 (76)
Other	13 (24)
Smartphone, n (%)	
iPhone	36 (66)
Samsung	6 (11)
Other	13 (24)

[a]BMI: body mass index.

[b]According to the World Health Organization, a BMI of <18.5 is classified as underweight, 18.5-24.9 as normal, 25-29.9 as preobese, and ≥30 as obese [32].

[c]Most used apps—options are not mutually exclusive.

Individual-Level Factors Influencing Physical Activity

Self-Monitoring

Self-monitoring was deemed important by many users, as it increased their awareness of activity levels and performance, as well as enabled them to review their progress over time and better plan their exercise (Textbox 1, quotes 1 and 2). Some users indicated that even though self-monitoring was important, knowing the daily number of steps was not sufficient, as they were doing other types of exercise. Thus, they would prefer to measure parameters that were relevant to the type of activity they did (Textbox 1, quotes 3 and 4).

Other than physical activity, users also expressed the desire to monitor a wide range of health-related information (eg, sleep). By having multiple types of information about themselves, users felt they could get an overall view of their daily patterns, and how external factors (eg, family, jobs, and study) affected their health and well-being (Textbox 1, quote 5).

Goal Setting

Many participants expressed that they benefited from goal setting. They believed that setting a goal (eg, 10,000 steps daily) kept them accountable for their physical activity performance and motivated them to reach that goal. Participants indicated that goal setting and self-monitoring complemented each other because, without self-monitoring, they would have no way of knowing whether their goals had been achieved (Textbox 1, quote 6). In addition, many participants expressed the desire to be able to personalize their goals to fit with their ability and daily routines, rather than having a standard goal (Textbox 1, quote 7).

Feedback on Behavior

For many users, the feedback on progress toward goals was particularly encouraging; knowing that they were close to reaching their goals would motivate users to do more physical activity, while being notified of goal achievement gave them positive emotions (Textbox 1, quotes 8 and 9). Nevertheless, some participants mentioned that knowing they had not achieved their goals also brought on some negative feelings such as disappointment or guilt (Textbox 1, quote 10).

Social-Level Factors Influencing Physical Activity

Social Comparison

Participants mentioned that comparing themselves with other users encouraged them to be more engaged with the intervention, as well as to be more physically active (Textbox 2, quotes 1 and 2). One interesting aspect was that comparisons with higher, lower, or similar standards of physical activity (upward, downward, and lateral comparisons in accordance to [33]) had different effects on performance, according to participants. Most users said that they preferred to compare themselves against higher performers because that motivated them to try to learn their strategies and be more physically active, to beat the top level (Textbox 2, quote 3). Other users mentioned that they would like to compare themselves to both similar and higher standards (Textbox 2, quotes 4 and 5). On the other hand, some participants mentioned that comparison to higher standards could be rather demotivating and confronting, especially when they failed to achieve as many steps as others. Instead, those users preferred comparing themselves with lower standards, which gave them a sense of confidence and assurance that they were on the right track (Textbox 2, quotes 6 and 7).

Familiarity With Other Users

For many participants, social comparison and providing social support did not hold much meaning if they did not personally know other users. Many suggested that they were more likely to be engaged if they were "familiar" with other users (eg, if other users were their real-life social connections; Textbox 2, quotes 8 and 9). On the other hand, some participants mentioned that they did not necessarily need to know other users in real life; however, they needed to have some information about other users such as their lifestyle, fitness goals, or the types of activity they did, which could form the basis for social comparison (Textbox 2, quotes 10 and 11).

Similarity With Other Users (Homophily)

Other users did not stress the importance of "familiarity"; instead, they described a preference to share data within a social network of people who shared *similar* attributes or goals to them (a phenomenon known as "homophily" [34]). Particularly, some participants preferred to connect with users who had similar BMI or were doing the same type of physical activities (Textbox 2, quotes 12 and 13). In addition, a lot of participants emphasized the importance of having a similar goal, as it might facilitate more meaningful comparison and discussion on PA strategies (Textbox 2, quotes 14 and 15).

Textbox 1. Illustrative quotations for individual-level factors that influence participant engagement and physical activity.

Self-monitoring of behavior

- Quote 1: The important part for me is [keeping track] – I know I'm going beyond the average, like the normal number of steps for a person […] - it makes me more motivated. (Female, 24)
- Quote 2: I could use the data, so I know how [many] steps for one run, or how long I take for one run. It helps me to evaluate how [many] runs I could actually do, or what should be my targets for next day. (Male, 24)
- Quote 3: I climb now […] I'm actually looking for a watch or something that can measure altitude, it will be more interesting because I'd get to see how far I've climbed. (Female, 20)
- Quote 4: [I do] martial arts, so it's not so much running and movement. I want to have heartrate, it'd probably be a bit more useful. (Male, 20)
- Quote 5: I realized because of work pressure, in fact, I'm doing two jobs right now […] my average sleep has gone down. (Male, 27)

Goal setting

- Quote 6: There was a goal to reach every day. It kept me motivated […]. I would feel bad if I'm not wearing the [Fitbit]. It was like an additional limb in my body sort of thing." (Male, 27)
- Quote 7: I want to set my own goals each day […]. Some days I'm more active than other days. On those days, I'll automatically reach 10,000 steps in […] one session alone. But if I changed [the goal] to 20,000 steps then […] it would not really [be] achievable on the days that I don't do that much physical activity. If you could tailor the steps per day, then the motivation would be continuous. Because the motivation only works if I get close up to the end. (Female, 20)

Feedback on behavior

- Quote 8: Because I work long hours, I would reach 10,000 steps at like 10am. It always made me feel good when it vibrated and all the colors everywhere. I was like, yes! (Female, 20)
- Quote 9: When I […] got 80% of my goal, [I would just] go aimlessly for a walk. So that was getting me to walk more. Solely because I was on 80% and I wanted that 100%. (Female, 20)
- Quote 10: It sorts of guilt-tripped a bit. When I'd see it and I was like oh, I'd only done so many steps today. (Female, 19)

Participation From Other Users

Participation from other users was important for people to engage with the social network component of the intervention. Many users described attrition as a "domino effect"—once a certain number of people stopped using the app or the wearable tracker, other users subsequently felt less motivated to use the technology (Textbox 2, quotes 16 and 17).

Textbox 2. Illustrative quotations for social-level factors that influence participant engagement and physical activity.

Social comparison

- Quote 1: It gives me positive reinforcement at the same time because…I'm at the top chart of the steps. It kind of motivates me to stay on that level of rank and in general it motivates me because I can see if I'm doing well or not. I compare myself with the others. (Male, 24)
- Quote 2: I find competition helps me to regularly exercise often by going for runs with friends or family or competing in team sports.…Other people can see [your effort] and keep you accountable to your fitness goals. There's also that element of showing off…and also being able to see how other people exercise and then try to match them. (Male, 23)
- Quote 3: I probably look up more.…A lot of my days, I get up to 17,000 steps. So, I don't look down, I'd look up and be like, "Oh, why are those people getting 21,000 steps? I need to get 21,000 steps." (Female, 24)
- Quote 4: I would obviously want my comparison to be done with somebody who is exactly like me, or similar in certain ways. It gives me some kind of happiness that I'm achieving my goals in comparison to this person. It's like a competition. It's like scoring 87 and the other person is scoring 84.…Then I would also want to know the person who has got a 96 and why did he get a 96?…If you want to achieve 100, you want to know where you went wrong and what did you do right. But I don't want to compare with a person who got a 40. (Male, 27)
- Quote 5: I was probably competing to the person closest in terms of kilometers that we were doing. It was interesting to see what they were doing and how they progress…. I tried to beat them every day. (Male, 21)
- Quote 6: Being compared to other people was a bit shocking—I was [at] the end of the group, so it was a bit demotivating. (Female, 20)
- Quote 7: If I'm having more steps than others, I feel motivated, and know that at least I keep myself healthy. (Female, 24)

Familiarity with other users

- Quote 8: It's like, I don't really know anyone [in the study] and then…the fad of comparing yourself against people wears off; I did try and use it a little bit more, but it was just like because you don't know anyone, you forget about it.…If it was in a group of my friends, we probably would've been checking it weekly. (Female, 24)
- Quote 9: I guess not knowing what they do…—whether they worked or whether they were students— not knowing that, it's a bit hard to…compare because there's all these variables. Also, because I really didn't know them, I didn't feel obliged to try to motivate them at all in any way. I guess with friends—and if I got to know them at all— yeah, I might have done that. (Male, 30)
- Quote 10: [I'd like to see] more information about the kind of fitness people are doing. For example, someone has done 20,000 steps in a day, which is a huge amount, then give me a basic idea of what that person has done to get to that goal. (Female, 19)
- Quote 11: If everybody [had a] profile, maybe it [would be easier] to make friends. At the beginning I thought "Maybe I can [make a] friend and we can train together to lose some weight." (Female, 34)

Similarity with other users

- Quote 12: I think it would help if you had people…with a similar body type doing similar things that would suit you more. (Female, 23)
- Quote 13: I like that you could go through and track people who were similar to you…. I went and found people with similar BMI. I'm happy to track myself against similar people and see how many steps [they've done]. (Female, 24)
- Quote 14: Everyone's goal might be different. So, you need to group people with similar goals together. …I would want to compare myself to somebody who [has similar goals] and is using it on a daily basis like me." (Male, 27)
- Quote 15: Having a goal section where people say whether they want to gain or lose weight would be good. Then all people who want to lose weight can get together and talk about it. (Male, 20)

Participation from other users

- Quote 16: It was a bit like a domino effect, so after about two months you could see that 20 to 30 per cent had zero [steps]. It felt like people weren't using the app, so there was no reason for me to use it as well. (Male, 22)
- Quote 17: There's no number of steps [from some people] sometimes. It can be a little demotivating when you see a lot of zeros…It's like are they taking this seriously? (Male, 24)

Technology-Level Factors Influencing Physical Activity

Technological Facilitators of Engagement and Behavior Change

Automation

Many participants found that using the wireless tracker and scale in combination with a mobile app offered many advantages. Specifically, wireless devices provided an automatic way for users to collect and self-monitor personal measurements, and their integration with the mobile app provided a user interface platform for participants to visualize those data and to review progress (Textbox 3, quotes 1 and 2).

Personalization

Many users mentioned that having personalized information and services would also support long-term engagement, as they could offer the advantage of providing relevant information tailored to each specific user, thus eliminating the cognitive burden of dealing with information overload. Many users described that personalization should go beyond the content generated by the system and extend to the provision of relevant services (eg, suggestion of exercise routines; Textbox 3, quotes 3-5).

Technological Barriers to Continued Usage

Additional Workload

As time went on, many users described the feeling that the novelty of the technology had worn off, and they started to think of it as a chore. Even apparently simple tasks like charging the devices were seen by participants as an extra burden in their already busy daily routines (Textbox 3, quotes 6 and 7).

Technical Problems and User Experience

Technical problems were often described as a common cause for attrition (Textbox 3, quote 8). In addition, user experience factors, such as the design aspects of the interface and its usability, were reported as important aspects of engagement and continued use (Textbox 3, quotes 9 and 10).

Textbox 3. Illustrative quotations for technological-level factors that influence participant engagement and physical activity.

Technological facilitators of engagement and behavior change

- Quote 1: I enjoyed how [the wearable tracker] linked with the app, and then on the app you could track how many steps you [did]. […] With the scale as well, the scale was able to track my weight and then it gives you a trend line to show how you're doing, so I enjoyed that as well. Having the combination of the tracker, the scale and the app was really good. (Male, 22)
- Quote 2: I like the [Fitbit] app. It integrates so well, so you wear your [tracker] and then [the app] tells you [how many] exercises you've done in a week, your steps, sleep. (Female, 31)
- Quote 3: [Having health information] would be good, but it has to be personalized or customized to me, (…) my body type, […] not like a general advice like [what is] BMI etc. […] A lot of people can read about general information; but if it's personalized to you or customized to your needs, it's going to be more interesting and more reliable […]. (Male, 24)
- Quote 4: I liked that at the end [of a fitness video], you can put a smiley face on how difficult it was. Based on my reaction, I want the app to give me recommendations on what types of exercises I should do. So, it was tailored to me, according on my reaction. (Female, 20)
- Quote 5:
  - Male: Whether to have one or multiple buddies, the choice depends on what works for the person. Maybe you can personalize it in some way. Maybe you can elect I want only one partner, or I want to be put in a group. (Male, 20)
  - Female: It is like gym training session, you can have private sessions, you can have small group sessions, or you can have a class session and you choose which one is best for you. The same with the app and your buddy. (Female, 20)

Technological barriers to continued usage

- Quote 6: The charge lasted three days, and because I had such a busy schedule, charging it again [was] such a big chore. So, it would then just sit for another week and I'd get a [reminder] email and then I would plug it in […]. I was doing so many things, so remembering to charge it became a challenge. (Male, 33)
- Quote 7: After a first couple of months, it started to feel more like a chore to do. I got into the thinking "I had to [check the app] everyday" as opposed to "I want to do this every day to keep track of my weight". Then university started, and things started getting busy. (Male, 22)
- Quote 8: The battery was discharging very quickly. In the morning it was telling me that I had achieved my goals when I just started the day. (Female, 20)
- Quote 9: I liked the social comparison feature in fit.healthy.me, but it's hidden in several menus. I liked the Fitbit app better—the design is certainly more elegant. (Female, 26)
- Quote 10: I checked the Fitbit app more than the fit.healthy.me app. I think the reason was because the Fitbit app was much sleeker, looks nicer and more inviting and easier to use. (Female, 20)

Discussion

Principal Findings

This study explored users' perspectives regarding facilitators and barriers in using mobile social networking interventions to promote physical activity. The following 3 categories of influencing factors emerged: individual, social, and technological. At the individual level, behavior change techniques, such as goal setting, self-monitoring, and feedback, were suggested as important for user engagement in physical activity. At the social level, social comparison, familiarity, and similarity with other users were mentioned as motivating aspects. Finally, automation and personalization were highlighted as technological facilitators, enhancing the delivery of both individual and social aspects of the intervention. However, some technological limitations were also found to be barriers to user engagement.

Comparison With Previous Literature

Our findings suggest that the success of a behavior change depends on a range of factors, including both individual and social aspects. These findings are in line with other behavior change theories, namely the social cognitive theory [4], and the Capability Opportunity Motivation—Behavior model [5]. Both theories suggest that even though several behavioral factors (eg, self-regulation [35], capability, and motivation [5]) are largely dependent on individuals, external factors (eg, peer modeling [4] and environmental structure [5]) can arise from the physical or social environments to prompt behavior. Hence, it seems sensible to integrate both individual and social aspects of behavior change in physical activity interventions to increase their long-term success.

In line with our results, behavioral informatics interventions (eg, a mobile social networking app, connected with a fitness tracker) can facilitate the delivery of both individual and social aspects in physical activity interventions [8]. Specifically, fitness trackers can automate the self-monitoring of behavior and connect to mobile apps with social features, allowing users to not only view their progress but also continuously benefit from social support [23,36]. To date, one qualitative study has examined how wearable trackers, mobile apps, and Web-based social networks may interact, finding that social support from Web-based networks can be effective in increasing users' adherence and engagement with the wearable trackers [37]. However, this study had a couple of limitations—it included a small number of users, as well as nonusers of wearable trackers; and it examined Web-based social networks as a stand-alone feature, not integrated with the trackers. In contrast, our study provided participants with an integrated intervention, including mHealth and social networking components, which allowed us to explore the informed perspectives of participants who used these technologies for 6 months.

Individual-Level Behavior Change Techniques

Our users indicated that goal setting, self-monitoring of behavior, and feedback on behavior could encourage them to engage in physical activity, which is in line with previous qualitative studies [18,19]. Indeed, these 3 self-regulatory techniques have demonstrated the effectiveness in physical activity interventions [11] and may work in synergy—to maximize the effects of goal setting, people may need to self-monitor and receive feedback, which allows them to see their progress in relation to their goals and change their strategies if necessary [38].

In addition, previous research has suggested the need to examine which type of goal is best for motivating individuals to be more active and how technologies can best support monitoring those goals and providing feedback. The literature seems to suggest that small goals (described as "graded tasks" in the Coventry, Aberdeen, and London—Refined taxonomy [10]) are more effective for long-term engagement compared with larger and harder to achieve goals [39]. For example, Fitbit provides users with small goals of taking 250 steps per hour, which then facilitates the achievement of the daily goal of 10,000 steps [23]. It is worth noting the importance of real-time self-monitoring and consistent feedback for the success of this "small goals" approach [23], underlining implications for the design of mobile apps and wearable trackers.

Social Networks and Social Features

This study emphasized the role of social comparison, familiarity, and similarity with other users in a social networking intervention. First, our participants revealed different preferences regarding social comparison. This finding is in line with previous research, where it has been demonstrated that individual preferences might depend on their tendency to make upward or downward comparisons [40]. Specifically, previous studies have illustrated that some people seek social comparison to self-improve [33], and thus, upward comparison may reinforce positive fitness behavior by making it seem normative or even rewarding [41,42]. For others, instead of seeking feedback about themselves, they want to create and maintain a positive self-image, and thus, prefer to make a downward comparison [33,42]. Taken as a whole, this finding suggests that a one-size-fits-all approach to social comparison is unlikely to suit all users, and thus, social comparison needs to be tailored to each individual.

Second, *familiarity* and *similarity* were found to be important factors in a social networking intervention for physical activity. The importance of familiarity seems to be in line with previous literature, where researchers have demonstrated that existing social networks can greatly influence individual health behaviors [43,44], leveraging social support and potentially increasing the intervention effectiveness [17,40,45-47]. Research has shown that strategies involving new networks might not be as effective as ones capitalizing on existing connections [46,47], which suggests that fitness technology may be most effective when groups of people who know one another have access to the same device or app [23]. Thus, allowing study participants to invite friends and family to join an app may increase the real-world effectiveness of these interventions [40], despite potential problems of contamination.

Furthermore, this study showed that similarity is important for motivation and engagement, highlighting the role of homophily (ie, the tendency of people to bond with alike individuals) [34]. Notably, previous research has indicated that social networks structured on the basis of homophily lead to higher adoption of healthy behaviors [48]. Moreover, it has been suggested that when people with similar interests interact to achieve a shared goal, they can provide each other with support and companionship in the activity, and thus, reduce the perceived costs of adopting a new exercise routine [46,49]. Taken together, these findings highlight the benefits of leveraging homophily to foster collective efficacy and improve physical activity.

Technology As a Platform to Bring Together Individual and Social Levels

Through automation and personalization, multiple modes and features of technology can work synergistically to deliver a physical activity intervention with both individual and social factors [37,50,51]. Thus, the integration of multiple mHealth technologies can automate several aspects of health management, reducing the burden on users. Furthermore, many users suggested the importance of personalized features within the intervention. Indeed, a one-size-fits-all approach is unlikely to satisfy many needs and wants of users [52], which emphasizes the need to consider individual lifestyles and preferences when designing interventions.

Strengths and Limitations

This study has several strengths. We interviewed users after 6 months of experiencing the intervention, ensuring that our sample had an informed perspective. The combination of individual interviews and focus groups enabled us to capture both individual perspectives and social dynamics in a group setting, which are essential aspects to understand in a social networking intervention. The findings of this paper must be interpreted in light of some limitations. First, study recruitment was limited to a university setting with a young age group. Though the main purpose of qualitative studies is not to make generalizable claims [53], future research with a diverse sample could explore other contextual factors related to behavioral informatics interventions (eg, an older age group might encounter different barriers and facilitators of a mobile social networking app). Second, as this was part of a feasibility study, the technology used was at a prototype stage and not yet extensively tested. Finally, despite our engagement efforts, we were not able to interview participants who dropped out of the study—they might have different perspectives on the facilitators and barriers of the intervention.

Implications for Future Research

This study highlights several important implications, including suggestions on the intervention design and new research avenues. Interventions for physical activity promotion should consider offering goal setting, self-monitoring, and feedback as a bundle, as these techniques have been shown to be both effective and acceptable to end users. Consequently, the design of mobile apps and wearable trackers need to effectively assist with real-time self-monitoring and provide consistent feedback to enable the achievement of goals [23]. In addition, the potential of social behavior change techniques (eg, social comparison) should be further explored, and aspects of leveraging existing social ties and homophily could be considered in constructing a social network intervention for physical activity. Questions remain about the cost-effectiveness of wearable trackers and mobile apps as a public health initiative, opening up new possibilities for future health economics research and public health programs [23,54].

Furthermore, this study highlights the importance of *personalization*. By identifying users' behavioral patterns and preferences, researchers can design and deliver interventions at the right time, using the right channel and tone, and the most relevant content or services [55,56]. Future studies should use innovative study designs to determine which intervention components are effective, what is the optimal sequence for delivering these components, and which tailoring variables should be used [23,57].

Conclusions

This study provides insights into the individual, social, and technological factors that influence user engagement with a mobile social networking app for physical activity promotion. Our findings reveal that self-regulatory behavior change techniques seem to be a necessary element in these interventions, and that aspects related to social comparison, existing social ties, and homophily should be considered in the development of the social network component. Future research should adopt innovative research designs to evaluate the effectiveness of these different components, as well as investigate the delivery of personalized interventions.

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Authors' Contributions

HLT, EC, and LL conceptualized the study. HLT developed and pilot-tested the interview guide, conducted the interviews and focus groups, performed data analysis, and wrote the first draft of the manuscript. LL pilot-tested the interview guide, conducted some data collection and analysis, and provided guidance on data analysis and critical feedback on the manuscript. EC critically revised the manuscript.

Conflicts of Interest

EC could benefit from commercialization of fit.healthy.me.

Multimedia Appendix 1

COnsolidated criteria for REporting Qualitative research checklist.

[PDF File (Adobe PDF File), 132KB - jmir_v20i12e11439_app1.pdf]

Multimedia Appendix 2

Screenshots of the fit.healthy.me mobile app.

[PDF File (Adobe PDF File), 177KB - jmir_v20i12e11439_app2.pdf]

Multimedia Appendix 3

Interview guides.

[PDF File (Adobe PDF File), 66KB - jmir_v20i12e11439_app3.pdf]

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Abbreviations

BMI: body mass index
mHealth: mobile health

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Chapter 6. Discussion and Conclusion

Chapter 6 provides a summary of the study results and integrates findings from the systematic review and the quantitative and qualitative components to address the overarching aim of the thesis—to evaluate the efficacy and acceptability of mHealth interventions with social features to promote physical activity. This is followed by a discussion of the original contribution of the research in light of the existing literature, examination of strengths and limitations of the study, and directions for future research. The conclusion section of this chapter provides an overall summary of the research.

6.1 Summary of results

Paper I: The use of social features in mobile health interventions to promote physical activity: a systematic review

This review showed that research surrounding mHealth interventions with social features for physical activity promotion appears to be in an early stage of development due to the recent timing of included studies (all published after 2010), and the predominance of quasi-experimental studies. In the interventions, social features were often examined as a stand-alone feature (e.g. delivered via an online social network like Facebook), and were used to provide social support or social comparison. Due to the multi-component nature of most interventions, it is difficult to assess the impact of social features on physical activity levels and retention. Users' perspectives on the use of social features were mixed: some users felt motivated because of social support and competition aspects, while others expressed concerns about social comparison.

Paper II: Efficacy of a mobile social networking intervention in promoting physical activity: Quasi-experimental study

This paper showed a non-significant increase of 1039 steps in average daily step count between baseline and six months. Post-hoc analysis comparing the high and low physical activity subgroups at baseline showed that the low physical activity group experienced a significant increase of 2677 steps in average daily step counts between baseline and six months (p-value= 0.002, *d*=0.37), suggesting that the app might be more beneficial for specific subgroups of the population (e.g. physically inactive individuals). At six months, the retention rate was 82%, with 42% of participants using the fit.healthy.me app at least once during the last month of the study. User engagement was higher for 'My team' and 'My measures' than 'Social forum' and 'Private messages' features of the app.

Paper III: Using a mobile social networking app to promote physical activity: A qualitative study of users' perspectives

Post-intervention interviews and focus groups identified three categories of facilitators and barriers to user engagement with the intervention and physical activity—individual, social and technological. At an individual level, behavior change techniques such as self-monitoring, goal setting, and feedback were seen as important to user engagement. At a social level, social comparison was suggested to be motivating, and users indicated that familiarity (i.e. having real-life social connections in the intervention) and similarity (i.e. homophily) with other users would help them engage more. Lastly, automation and personalization were highlighted as technological facilitators, enhancing the delivery of both individual and social aspects of the intervention.

6.2 Integration of findings and comparison with existing literature

To the best of my knowledge, this is the first study to evaluate the impact of a mobile social networking app, connected with a wearable tracker to promote physical activity. Previous research has examined interventions composed of either mHealth technologies [46-49] or online social networks [32, 50-52] in isolation. Some studies have incorporated social features into mHealth interventions [39, 53-57]; however, these features were often included as an additional component (e.g. Facebook group), rather than being fully integrated within the mobile app. This study examined whether different technologies can work in synergy to address different aspects of behavior change, as well as offered new evidence on the efficacy and feasibility of combining mHealth and online social networks to promote physical activity.

The integration of the study findings allowed me to draw important interpretations regarding the design and implementation of behavioral informatics interventions for physical activity promotion. Firstly, both the quantitative and qualitative components demonstrated the feasibility of an intervention combining a mobile app with social features, connected with a wearable tracker, for physical activity promotion. Our users found the Fitbit wearable tracker to be a portable means to facilitate self-monitoring, which is an important task in behavior change [13, 58]. The mobile app can then provide a platform to support other behavior change techniques such as goal setting, feedback on behavior, social comparison or social support. This finding is in line with several behavior change theories (e.g. Social Cognitive Theory, COM-B model, Theoretical Domains Framework) which have suggested that the success of behavior change depends not only on the individual, but also social and environmental factors [9, 10, 59], and thus, interventions need to effectively assist in these aspects. Thus, it seems logical to facilitate the delivery of both individual and social aspects in physical activity interventions.

Secondly, regarding the use of social features in mHealth interventions, users were more engaged with 'My team' features (which supported social comparison via displaying summary statistics and graphs) than 'Social forum' and 'Private messages' (which were more discussion-based). The qualitative component revealed more in-depth information regarding users' preferences of social features: while many users found social comparison to be motivating, they expressed different preferences regarding their tendency to make upward or downward comparisons. This is in line with previous research which has demonstrated that some people seek to self-improve and thus, benefit from upward comparison because it makes the positive fitness behavior more normative to them [60, 61]. For others, instead of seeking personal feedback, they want to create and maintain a positive self-image and therefore, prefer downward comparison [60, 62]. Taken as a whole, this finding suggests that while social comparison might be motivating, a one-size-fits-all approach is unlikely to suit all users and thus, social comparison needs to be tailored to each individual.

The qualitative component also explained why users were not as engaged in the 'Social forum' and 'Private messages' features. Specifically, users did not actively form discussion because they did not know other users in the app, which emphasized the importance of allowing for the support of existing social connections in a behavioral informatics intervention. Previous research has demonstrated the influential role of existing networks on individual health behaviors [15, 16] and suggested that interventions capitalizing on existing connections might be more effective [32, 50, 63, 64]. In addition to real-life connections, our users also mentioned the importance of sharing information and discussing with people who had *similar* attributes or goals (i.e. homophily). Several studies have suggested the importance of homophily [33, 65], showing that homophilous social networks can lead to higher adoption of healthy behaviors than other networks [66]. Taken together, these findings indicate the potential of leveraging existing social networks and homophily to build an effective and engaging behavior change intervention for physical activity promotion.

6.3 Strengths and limitations

This study has several strengths. Firstly, the use of a wearable tracker automated the monitoring of physical activity data, eliminating the need to rely on self-reported data. Secondly, the qualitative component was embedded into the intervention design in order to shed light on the quantitative results and to understand contextual factors that influenced the trial outcomes. This mixed-methods approach provided a more comprehensive understanding surrounding the efficacy and acceptability of mHealth interventions with social features for physical activity than either method in isolation could provide. Lastly, the combination of both interviews and focus groups enabled the capture of both individual perspectives and social dynamics, which are essential aspects of a social networking intervention.

The study findings must be interpreted in consideration of some limitations. Firstly, as this was a pilot study, the study was non-randomized with a small, self-selected sample of university staff and students. Hence, the study had low statistical power and limited generalizability. Secondly, the fit.healthy.me app was at a prototype stage and thus, lacked some advanced features and design aspects that can be available in commercial apps. Finally, the post-hoc subgroup analyses were exploratory in nature and might be subject to type I error.

6.4 Implications

The need for personalized interventions

There is convincing evidence that a one-size-fits-all approach to behavior change is insufficient—it seems important to personalize interventions based on individual characteristics, circumstances and preferences. Through personalization, behavior change interventions can be delivered at the right time, using the right channel and tone to provide the most relevant content or services [67, 68]. Adaptive study designs can be used to assess which intervention components are effective, which tailoring variables should be used, and the sequence in the delivery of intervention components [69]. Additionally, unlike traditional rigid trials, adaptive designs allow researchers to modify the interventions to include latest technology, which is highly important for a fast-moving field like mHealth [69, 70].

Suggestions for intervention design

Regarding the design of behavioral informatics interventions, two suggestions stand out. Firstly, future interventions should consider incorporating self-regulation behavior change techniques such as goal setting, self-monitoring and feedback on behavior as they seem particularly relevant for physical activity. Future studies should also explore other behavior change techniques (e.g. action planning, environmental restructuring), as they might be helpful for specific population subgroups (e.g. physically inactive people) [57, 63]. Secondly, to construct an engaging and effective social network, future research should consider leveraging existing social ties and homophily amongst users.

6.5 Conclusion

This study demonstrated the feasibility of using a mobile social networking intervention, connected with a wearable tracker to promote physical activity. The findings highlight the importance of developing personalized interventions that can take into account personal preferences and circumstances in order to tailor behavioral support. Self-regulatory behavior change techniques, existing social ties, and homophily may be leveraged to further improve intervention engagement and effectiveness.

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Appendix 1 of this thesis has been removed as it may contain sensitive/confidential content

Appendix 2: Appendices of Paper I

Supplementary Information File 1

List of articles excluded after full-text review, for not meeting inclusion criteria regarding the population, intervention, outcome or study design

Intervention:

1. Adams MA, Sallis JF, Norman GJ, *et al*. An adaptive physical activity intervention for overweight adults: A randomized controlled trial. *PLoS One* 2013;8(12): e82901
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13. McMahon SK, Lewis B, Oakes J, *et al*. Assessing the effects of interpersonal and intrapersonal behavior change strategies on physical activity in older adults: A factorial experiment. *Ann Behav Med* 2017;51(3):376-90
14. Plotnikoff RC, Wilczynska M, Cohen KE, *et al*. Integrating smartphone technology, social support and the outdoor physical environment to improve fitness among adults at risk of, or diagnosed with, Type 2 Diabetes: Findings from the 'eCoFit' randomized controlled trial. *Prev Med* 2017; 105:404-11

Study design:

15. Kernot J, Olds T, Lewis LK, *et al*. Effectiveness of a Facebook-delivered physical activity intervention for post-partum women: a randomized controlled trial protocol. *BMC Public Health* 2013; 13:518 doi: 10.1186/1471-2458-13-518.

Supplementary Information File 2

Conflict of interests and funding sources of included studies

Paper	Conflict of interest declaration	Funding
Ashton, 2017[20]	"The authors declare that they have no competing interests."	"HEYMAN was funded by a Hunter Medical Research Institute (HMRI) project grant. L.M. Ashton undertook this research as part of a requirement for the degree of PhD (Nutrition and Dietetics), The University of Newcastle, Australia. L.M. Ashton is supported by an International Postgraduate Award Scholarship and The Greaves Family Medical Research Scholarship through HMRI. CEC is supported by a National Health and Medical Research Council of Australia Senior Research Fellowship." "The research was funded by a project grant from the Hunter Medical Research Institute (HMRI) (14–30). HMRI did not have any influence on the performance of the trial, analysis of the data, writing, or the publication of the results. CEC is supported by an NHMRC Senior Research Fellowship."
Mendoza, 2017[21]	"The authors declare that there is no conflict of interest."	"This study was supported by a Supportive Care Research Grant from St. Baldrick's Foundation and matching internal funding from the Adolescent and Young Adult Cancer Program of Seattle Children's Hospital. The funders had no role in the design, collection, analysis, and interpretation of data or writing/submission of this report."
King, 2016[22]	"The authors have declared that no competing interests exist."	"This work was supported by US Public Health Service grant #RC1 HL099340 from the National Heart, Lung, & Blood Institute of the National Institutes of Health (NIH) awarded to Dr. King; US Public Health Service Grant 1U54EB020405 supporting The National Center for Mobility Data Integration and Insight; and US Public Health Service grant #5T32L007034 from the National Heart, Lung, & Blood Institute. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript."
Greene, 2012[23]	"The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article."	"The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Financial support for conducting the clinical trial was provided by SK Telecom Americas."
Muntaner-Mas, 2015[28]	NR	NR

Schoenfelder, 2017[24]	"None"	"Funding was provided by the Center for Child Health, Behavior and Development at Seattle Children's Research Institute, 2015."
Chung, 2016[25]	"The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article."	The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Funding for this project was received from the Academic Pediatric Association's Young Investigator Award and the NC Children's Promise Grant. Dr Chung receives funding support from the National Center for Advancing Translational Sciences, National Institutes of Health, through grant 1KL2TR001109."
Paul, 2016[26]	"The authors declare no conflicts of interest."	"This work was supported by Chest Heart & Stroke Scotland [CHSS Ref: Res146]."
Rosenberg, 2016[30]	NR	NR
Middleweerd, 2015[27]	"The authors declare that they have no competing interests."	"This research is supported by Philips and Technology Foundation STW, Nationaal Initiatief Hersenen en Cognitie NIHC under the Partnership program Healthy Lifestyle Solutions (grant no 12014)."
Pumper, 2015[29]	NR	NR
Kernot, 2014[31]	"The authors have declared that no competing interests exist."	"The software development for the Mums Step it Up Facebook app was funded by a research development grant from the Division of Health Sciences at the University of South Australia (http://www.unisa.edu.au). JK is supported by an Australian Postgraduate Award Scholarship. CM is supported by an Australian Research Council Australian Postdoctoral Fellowship. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript."
Al Ayubi, 2014[32]	"None declared"	"This work is partly funded by the following grants, Grant #R25 RR023274-03 from the National Center for Research Resources, National Institutes of Health, United States; Grant #1R21HD071810-01A1 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, National Institutes of Health, and Grant # SC090323 from the Department of Defense."
Khalil, 2013[33]	NR	"We would like to thank Emirates Foundation for their support to that research project."
Maher, 2017[40]	"The authors declare that they have no competing interests."	"The authors have no funding to declare."
Zhu, 2017[39]	NR	NR
Stragier, 2016[36]	NR	NR

Fritz, 2014[37]	NR	"This work was partially funded by the Natural Sciences and Engineering Research Council of Canada (NSERC)."
Bartlett, 2017[38]	"None declared"	"The work was funded by the EPSRC. The sponsors did not have a role in the preparation or publication of this manuscript. This research was supported by the NIHR Collaboration for Leadership in Applied Health Research and Care Yorkshire and Humber (NIHR CLAHRC YH). The views and opinions expressed are those of the authors and not necessarily those of the NHS, the NIHR, or the Department of Health."

Abbreviation: NR: not reported

Supplementary Information File 3

Additional information about experimental studies

First author, year	BCTs	Associated quotes	Other outcomes	Main results
Ashton, 2017[20]	Private Facebook discussion group *3.1 Social support (unspecified)* Website *4.1 Instruction on how to perform the behavior* *6.1 Demonstration of the behavior* Jawbone wearable tracker +app *1.1 Goal setting (behavior)* *2.3 Self-monitoring of behavior* One-hour weekly face-to-face sessions with researchers *1.1 Problem solving* *1.5 Review behavior goal(s)* *2.2 Feedback on behavior* *4.1 Instruction on how to perform the behavior* *8.1 Behavior practice/rehearsal* *8.3 Habit formation* *9.1 Credible source* Gymstick resistance band *12.5 Adding objects to the environment* TEMPlate Dinner disc *4.1 Instruction on how to perform the behavior*	3.1 "facilitate social support" 4.1 "a 'resource library' housing relevant information and resources, including fact sheets from best practice guidelines, […] and recommended mobile applications for improving eating habits, physical activity, reducing alcohol intake or coping with stress" 6.1 "support videos (e.g. short cooking videos and demonstration of Gymstick™ exercises)" 1.1 "goal setting" 2.3 "self-monitoring of key health behaviors" 1.4 "a mixture of practical (e.g., mindfulness-based stress reduction) and theoretical (e.g., problem solving strategies to address key issues apparent in young men, i.e., lack of money) components" 1.5, 2.2 "personalized feedback from a food and nutrient report (see below), and from the Jawbone physical activity data. From this, personal tailored goals were set." 4.1 "healthy eating education (e.g., meal planning and meal ideas for quick, cheap and healthy meals)" 8.1 "practical exercise activities focusing on aerobic (e.g., team based recreational games) and strength exercises (e.g., High Intensity Interval Training)" 8.3 "Group based sessions took place on Thursday evenings (18:00–19:00 pm)" 9.1. "Sessions were delivered by two male researchers from the same age demographic (one was a qualified P.E. teacher, undertaking a PhD in Education and the other was a PhD candidate in Nutrition and Dietetics)" 12.5 "A Gymstick™ resistance band, for home-based strength training with linked routines available on the website"	• Weight • Fat mass & skeletal muscle mass • BMI • Cholesterol (mmol/L) • Blood pressure (mmHg) • Resting heart rate • Diet quality (Australian Eating Survey) • Alcohol consumption (Alcohol Use Disorders Identification Test– consumption scale) • Subjective well-being (Satisfaction with Life Scale) • Self-reported measures of mental health and well-being (Kessler psychological distress scale, Depression Anxiety Stress Scale, Mental Health Continuum-Short Form, Quality of Life, Enjoyment & Satisfaction Questionnaire)	Participants reported frequent usage levels for most program components, other than Facebook discussion group and some of the materials on diet. They also gave a score of 3 – 4.6/5 for the program component acceptability. There was no significant change in steps/day, or total wellbeing score. Significant effects were found for daily vegetable servings, energy-dense, nutrient-poor food, MVPA< weight, BMI, fat mass, waist circumference and cholesterol.

		4.1 “guide main meal portion size for main meal components”		
Mendoza, 2017[21]	Facebook group *3.1 Social support (unspecified)* *10.3 Non-specific reward* Fitbit Flex tracker + app *2.2 Feedback on behavior* *2.3 Self-monitoring of behavior* SMS from researchers *1.7 Review behavior goal(s)* *7.1 Prompts/cues*	3.1 “a forum for participants to encourage and discuss their experiences using the Fitbit and their PA goals” 10.3 “The Facebook group was moderated by research staff, who provided intervention participants with badges for PA and participation achievements every week” 2.2 “displays progress towards a personalized goal” 2.3 “provide estimates of steps, very active minutes, energy expended (calorie burned) and distance travelled” 1.7 “Help set a daily step goal based on mean step counts for week 1”, “Gradually increase their step count goals to meet or maintain population recommendations for adolescents” 7.1 “sent affective text messages for PA every other day to encourage and remind intervention participants about their PA goals”	• Health-related quality of life (Pediatric Quality of Life Inventory 4.0 Generic Core and Cancer Module Scales)	There were no significant adjusted group differences for change in MVPA or sedentary time between intervention and control group. For PedsQL, social functioning scale of was the only one experienced significant adjusted difference i.e. intervention groups decreased from 86.1 to 83.9; while control group increased from 78.8 to 84.7. Intervention group also experienced increased introjected motivation (internalizing external pressure that leads to the desired behavior). 92.3% participants saw at least one post, 65.4% commented on at least one post. Liking posts was the lowest type of engagement (50%). Qualitative data revealed that participants found the Fitbit Flex and Facebook acceptable and helpful. Participants expressed the desire for more activity on the Facebook group; while many recommended the use of Snapchat and Instagram instead.
King, 2016[22]	Social app *3.1 Social support (unspecified)* *6.2 Social comparison* Analytic app *1.1 Goal setting (behavior)* *2.2 Feedback on behavior* *4.1 Instruction on how to perform a behavior* Affect app *2.2 Feedback on behavior* *10.3 Non-specific reward*	3.1 “social support”, “group-based collaboration”, “online message board” 6.2 “just-in-time social normative feedback”, “group-based […] competition” 1.1, 2.2 “personalized and quantified goal-setting and behavioral feedback” 4.1 “informational tips or advice for behavior change” 2.2 “The bird avatar, which was viewable on the phone’s glance-able display throughout the day, changed position, posture, and movement depending on how active or inactive the user was up to that time point.” 10.3 “rewards” (e.g., the bird avatar would unexpectedly appear in far-away cities) as a function of increased physical activity levels”	n/a	The social app users showed significantly greater increase in MVPA compared to the other arms, and significantly lowered sedentary behavior. For the Ecological Momentary Assessment of brisk walking variable, there were no significant effect for time or significant differences between study arms. For reported sitting time, the social and affect apps both reported significantly less sitting time than the Analytic app or control group.

Greene, 2012[23]	iWell OSN *3.1 Social support(unspecified)* *6.2 Social comparison* Wireless accelerometer + wireless scale *2.3 Self-monitoring of behavior* *2.4 Self-monitoring of the outcome of behavior* Paper-based materials *1.1 Goal setting (behavior)* *4.1 Instruction on how to perform the behavior* *5.1 Information about health consequences*	3.1 "participants could connect ("friend") others in the network, send individual messages to their friends, make public postings, view their contact's postings…"; 6.2 "view their physical activity or "steps," view their weight", "compete against others in the network on the number of "steps" walked or run" 2.3 "given an accelerometer that allowed them to capture their physical activity or steps" 2.4 "[…] a wireless weight scale for uploading weight data" 1.1, 4.1, 5.1 "All participants received printed lifestyle guidelines on diet and exercise (...); sample daily meal plan with recommended serving sizes, a handout about recommended daily levels of exercise, and a number of articles about the benefits of exercise and healthy eating."	• Weight • Triglycerides • Low-density & high-density lipoprotein	The intervention group was found to have significantly increased their weekly leisure walking from 129 to 341 minutes (164% increase) over six months, while the control group increased by 47%. The intervention group also lost more weight than the control group (5.2 vs 1.6 pounds). There was no significant difference between the two groups in changes in low-density and high-density lipoprotein. Amongst the intervention group, only the number of messages sent by participants was positively related to increased leisure walking ($p<0.05$), and negatively related to weight change ($p<0.01$).
Muntaner-Mas, 2015[28]	Mobile group: WhatsApp *3.1 Social support (unspecified)* *4.1 Instruction on how to perform the behavior* *7.1 Prompts/cues* Training group: In-person training sessions *4.1 Instruction on how to perform the behavior* *8.1 Behavior practice/rehearsal*	3.1 "a mobile phone app based on a social network", "all participants were added to a chat group" 4.1 "received 2 videos […] per week for 10 weeks", "the content of them were the exercise sessions", "the videos were attached to the group chat", "a member of the research group carrying out the prescribed exercises" 7.1 "the administrator sent out 2 messages in the group chat per week, which reinforced messages from the videos, and encouraged participants to perform physical exercise" 4.1 "training sessions on the sports ground (Mondays and Wednesdays)" 8.1 "involved participant exercising", "repetitions"	• Blood pressure • Waist circumference • Weight-to-height ratio • BMI • Fat-mass and fat-free mass index • Handgrip strength	The Mobile group increased handgrip strength, aerobic capacity and decreased systolic blood pressure and heart rate after exercise though there were no significant differences respect to Control group. The Training group decreased significantly blood pressure and heart rate after exercise, respect to Control group. Diastolic blood pressure decreased significantly more in Training group than Mobile group. There were no other significant differences between the intervention and control group, or between the Training and Mobile group.
Schoenfelder, 2017[24]	Facebook group *3.1 Social support (unspecified)* *10.3 Non-specific reward* Fitbit Flex + app *1.1 Goal setting (behavior)* *2.2 Feedback on behavior* *2.3 Self-monitoring of behavior* Emails from researchers *1.5 Review behavior goals*	3.1 "interact with other participants", "a study staff posted to the group, interacted with participants, and monitored posts daily" "participants were encouraged, but not required, to post in the group, encourage their fellow participants, and share their Fitbit data on Fb." 10.3 In the Facebook group, "participants earned digital badges for meeting weekly activity goals, as well as for social interactions (e.g., liking other's posts) or making improvement towards goals"	• ADHD symptoms (Vanderbilt ADHD Diagnostic Parent Rating Scale) • Mood valence (10-item Positive and Negative Affect Schedule for Children)	There was a significant increase in step counts (3218 in total, 95% CI: 931 to 5291, 107 steps/day). There was also a significant decrease in teen and parent-reported Inattentive and Hyperactive/Impulsive symptoms (-0.4 to -0.8). There was no significant change in mood valence. Total score for acceptability was 1.4 for both adolescents and parents (1=definitely, 4=not at all). In qualitative

		2.2 “feedback toward personalized goal attainment” 2.3 “collect data through its built-in accelerometer to provide proxy estimates of PA including steps, energy expended, and distant travelled”, “provide graphs of the data” 1.5 “an individualized goal based on their average week 1 steps plus 1% steps weekly”		interviews, participants reportedly said that they had positive experiences with the study, and increased awareness of their PA level and ADHD symptoms. The most common suggestions were increasing reminders, adding additional challenges/goals, and using other social media sites i.e. Instagram.
Chung, 2016[25]	Twitter *3.1 Social support (unspecified)* *2.2 Feedback on behavior* Fitbit app *6.2 Social comparison* Fitbit Zip tracker *2.3 Self-monitoring of behavior* Study team *10.1 Material incentive (behavior)* *10.2 Material reward (behavior)*	3.1 “post questions to the study team or to their Twitter group”, “received photo-based Twitter messages that were pictures of healthy food options, infographics, and website links related to healthy lifestyle tips” 2.2 “Personalized step challenges based on their physical activity patterns during the previous month” 6.2 “Fitbit accounts were set up to auto-tweet daily steps and distance travelled to the assigned private Twitter group so that individuals could see how others were doing, which was the basis of some of the competitions”, “individual vs group challenges” 2.3 “measure steps, physical activity intensity and duration, and caloric expenditure”, “displays the number of steps, miles travelled, and caloric expenditure on the small screen within the device so that users can view their data at any time” 10.1, 10.2 “Throughout the study period, the study team created individual vs. group challenges, including personalized step challenges, most steps/day or per week within groups, and so on, to determine whether participants could be incentivized to make behavioral changes using principles of gamification. We provided prizes that were $10 or less but provided regular challenges to facilitate ongoing engagement (i.e. water bottles, weights, etc.). We also periodically challenged participants to beat their own personal average steps/day.”	• Weight • Body fat percentage • Self-reported food intake and lifestyle changes	The participants were categorized as overweight/obese (BMI 25 – 34.9 kg/m^2) or healthy weight (BMI 22.5 – 24.9 kg/m^2). Overweight participants (OW) had 11,222 daily steps on average vs 11,686 steps for healthy weight (HW). Overall, there was an increase in PA during the challenges. 92% participants self-reported increased fruit intake; OW increased by 2.1 servings vs 1.8 servings (HW). 58% self-reported increased vegetable intake (2.5 servings for OW, 0.5 servings for HW). OW lost one to five pounds, and 3.9% to 10.6% body fat vs 0.2 to 7 pounds, and 0.5% to 13.5% for HW. 100% participants reported being very likely/likely to recommend the intervention to others. Compliance with daily Fitbit wear was 99% of all days for OW and 73% for HW.
Paul, 2016[26]	Starfish mobile app *1.1 Goal setting (behavior)* *1.5 Review behavior goals* *2.3 Self-monitoring of behavior*	1.1 “individualized step goals were set for each person” 1.5 “In week one, the daily step count target was the mean number of steps per day recorded on the phone during the baseline period (see below) plus 10%. At the end of each	• Weight • BMI • Resting heart rate • Blood pressure	The mean number of steps/day increased by 39.3% (1633 steps/day) in intervention group; while it decreased by 20.2% (747 steps/day) for the control group. Walking

	6.2 Social comparison *10.3 Non-specific reward*	week, if individuals achieved their step count target on five of seven days, their target for the following week was increased by 5%. This update was indicated to the user by an exclamation mark attached to their fish. If the target was not reached, it remained unchanged for the following week." 2.3 "When the participant is active their fish swims and blows bubbles which they, and other participants, can see" 6.2 "When the participant is active their fish swims and blows bubbles which they, and other participants, can see" 10.3 "Individual and group "rewards" for achieving goals were provided. As the participant reached their target number of steps, their fish's fins and tail grew. If all four members reached their step count target on at least five days of the week then the group was rewarded by another sea creature being added to their fish tank e.g. sea horse or crab."	• Impact of fatigue (Fatigue Severity Scale) • Complex activities of daily living necessary for functioning in community settings (Instrumental Activities of Daily Living Scale) • Quality of life (Stroke Specific Quality of Life Scale) • Subjective well-being (Psychological General Well-Being Index)	time also increased by 20 mins/day for the intervention group and reduced by 14 mins/day for the control group. There was a significant group/time interaction effect. Average daily sedentary time reduced in both groups (I: 4.8%, 55 mins; C: 2.9%, 34 mins) but there was no significant group/time interaction. Fatigue also reduced in the intervention group and increased in the control group, with a significant group/time interaction effect. Systolic blood pressure, gait speed, quality of life had significant time effect, but no group or interaction effect. There were no significant results from other outcomes.
Rosenberg, 2016[30]	Wearable activity trackers i.e. Fitbit Zip *3.1 Social support (unspecified)* *1.1 Goal setting (behavior)* *2.3 Self-monitoring of behavior*	3.1 "Posting to social media sites", "creating networks with friends and family" 1.1 "setting goals" 2.3 "track step count, distance walked, and calories burned", "display visual presentations of data"	n/a	Thematic analysis revealed that most participants found the device comfortable and easy to wear; however, a barrier is technical problems i.e. perceived inaccuracy and sync problems. Participants were happy to share their PA data with HCPs, and they expressed a desire to go through their data with HCPs and get feedback. Step count and distance walked were reportedly the most common feature used. Some participants used social features with family members. Very few participants reported using other Fitbit features (e.g. challenges, minutes active).
Middleweerd, 2015[27]	Nexercise app *3.1 Social support (unspecified)* *6.2 Social comparison* *2.3 Self-monitoring of behavior* *10.3 Non-specific award*	3.2 "chat features", "linking with social media" 6.2 "a competition feature" 2.3 "GPS tracking, activity log book" 10.3 "earning points"	n/a	Participants reportedly became more aware of their PA level through the app; however, they tended to stop using the app once the novelty disappeared and they encountered a technical problem. The preferred features included (1) goal setting, (2) self-monitoring

				and (3) a virtual coach that can motivate and provided tailored feedback towards personally set goals. Chat features were seen as redundant. The students also liked apps that enabled competition with friends or earning rewards. They would only share their PA data through social media only when the accomplishments were exceptionally positive. There were some differences between people with high PA level and low PA level. Those with low PA level acknowledged that they liked getting Facebook likes for their achievements, and that it could make a difference to their behavior.
Pumper, 2015[29]	Facebook group *3.1 Social support (unspecified)* *10.6 Non-specific reward* Fitbit Flex *2.3 Self-monitoring of behavior*	3.1 "This group was a place where participants could ask questions, interact with both the moderator and the other participants" 10.6 "This group was a place where participants could […] receive weekly badges (i.e. virtual acknowledgements public to the group) for their fitness accomplishments" 2.3 "an activity tracker that can measure amounts of steps taking among other fitness measures"	n/a	Over the four-week intervention, on average, participants have 4.9 interactions in the form of likes (1.6 times), comments (0.6 times), and wall posts (0.3 times). Qualitative interviews revealed that the participants like being a part of the Facebook group as they perceived a sense of social support and membership, and the group also offered a comparison to their peers. Participants specifically liked the badge feature. They also reportedly tended to view the posts, but not contributed. They expressed the desire for more contribution to the group from both the other members and the moderator. They suggested that the moderator could give group members some ideas of what to post or included a motivational quote of the day.
Kernot, 2014[31]	Team-based Facebook group *1.1 Goal setting (behavior)* *2.2 Feedback on behavior* *3.1 Social support (unspecified)*	1.1 "used the app for 28 days with the cumulative goal being 280,000 steps"	n/a	Total activity time increased significantly by an average of 177 minutes/week. 68.4% of women accepted the invitation to join the

	4.1 Instruction on how to perform the behavior *5.1 Information about health consequences* *5.3 Information about social and environmental consequences* *7.1 Prompts/cues* *10.6 Non-specific reward* Pedometer (NL-1000) *2.3 Self-monitoring of behavior*	2.2 "Additional feedback is provided regarding step count achievements via a team tally board, graphs", "Receive weekly emails detailing their progress" 3.1 "participated in teams of four to eight friends", "teammates can also send each other virtual gifts for encouragement" 4.1 "daily tips for increasing physical activity" 5.1, 5.3 "statistics on hours of life gained, fat burned, carbon emissions and transport costs saved" 7.1 "Receive weekly emails […] reminding them to log their steps" 10.6 "awards which participants can unlock based upon step count, login and team achievements" 2.3 "measured their daily step count with a pedometer"		Facebook team. Teams took a median of 13 days to form. Facebook app was found to be easy to use, though participants reported difficulty finding the app on Apple devices and seeing all the features due to small screen size. The average number of logins was 13.5 times throughout the 28-day intervention. There was a decline in log in rates towards the end of the study.
Al Ayubi, 2014[32]	Persuasive Social Network for Physical Activity (PersonA) mobile app *1.1 Goal setting (behavior)* *2.2 Feedback on behavior* *2.3 Self-monitoring of behavior* *3.1 Social support (unspecified)* *6.2 Social comparison*	1.1 "allows users to define a target that they want to reach" 2.2 "Once the data is stored on the smartphone, it can be displayed as immediate and persuasive feedback", "visual feedback", "aural feedback" 2.3 "PA data to be captured automatically using sensor devices and then transferred to a smartphone", "self-monitoring chart […] shows how users can easily check the actual value for each activity item while they are performing a physical task. They can also monitor the progress they make by looking at the progress bar for each item and its percentage count, all of which is displayed on the same screen" 3.1 "Third, the peer-support feature that allows individuals to support each other with one peer in a closed interaction where the individual and her/his peer only can see and communicate using this channel. Fourth, the group-support feature that allows users to support each other in open interaction where every member of the group can see and interact."	n/a	During the first week (app without social features), the step number/day increased by 4,202 on average. During the last three weeks (app with social feature), the mean step number/day increased by 6,352. Distance travelled increased by 1.15 miles per day in the first week, and by 1.74 miles per day in the last three weeks. No trends were apparent in the relationship between step number/day and social interaction. Overall, participants gave a score of 4.52 out of 5 for usability factors. Some participants said that they were not interested in social comparison as they had their own plan and schedule, while others found social comparison to be motivating and encouraging them to do more PA.

		6.2 “First, the peer-comparison feature allows an individual to compare his/her performance with that of one person in the app. This allows a more personal comparison, especially with a peer who is personally known, such as a close friend or spouse. Second, the group-comparison feature, which allows an individual to compare his/her current PA performance and target with the group average, the larger community average, or the normal standard set by health practitioners.”		
Khalil, 2013[33]	Step Up mobile app *2.3 Self-monitoring of behavior* *6.2 Social comparison*	2.3 “view number of steps walked, distance travelled, and calories burned”, “view walking history”, “view progress during the current week” 6.2 “view one’s team’s progress during the week”, “share step counts with their friends”	n/a	For the experimental study, during the second week, step counts increased for five out of seven participants. (Due to technical errors, data from one participant were removed.) The user survey indicated that the application was easy and fun to use. Six out of seven participants said using the app as a group motivated them to walk more. All seven participants said they liked to see friends’ steps, and that it motivated them to walk more. No one expressed concern about their friends’ ability to see their steps. Six participants reportedly tried to communicate with their friends when they noticed that one of their friends was not asking as much.

Abbreviation: BCTs: behavior change techniques; app: application; BMI: Body Mass Index (kg/m^2); n/a: not applicable; MVPA: moderate to vigorous physical activity; NR: not reported; SMS: short message services; PA: physical activity; OSN: online social network; ADHD: Attention deficit hyperactivity disorder; HCPs: health care providers; GPS: Global positioning system

Supplementary Information File 4

Behavior Change Techniques (BCTs) classification for non-experimental studies

First author, year	BCTs	Associated quotes
Stragier, 2016[36]	3.1 Social support (unspecified) 6.2 Social comparison 2.3 Self-monitoring of behavior	3.1 “users can interact with others[…]”, “give kudos, […] equivalent of a Facebook like to activities posted by a Strava user, as a means of endorsing each other’s achievement.”, “comment on the activity” 6.1 “view other athletes’ activities and can allow others to view theirs.” 2.3 “manually add activities to their profile or to upload sessions logged through wearable devices or dedicated smartphone applications which use the sensors and GPS of the smartphone to automatically log a user’s activities once a session is started.”
Barlett, 2017[38]	**Virtual coach system** 3.1 Social support (unspecified) 1.1 Goal setting (behavior) 1.4 Action planning 2.2 Feedback on behavior 4.1 Instruction on how to perform the behavior 7.1 Prompts/cues **Music and maps system** 1.1 Goal setting (behavior) 2.2 Feedback on behavior 2.3 Self-monitoring of behavior 7.1 Prompts/cues **Online community system** 3.1 Social support (unspecified) 6.2 Social comparison 2.3 Self-monitoring of behavior 10.2 Material reward 10.3 Non-specific reward	3.1 “praise and encouragement from the virtual coach” 1.1, 1.4 “a suggested exercise plan with daily walking goals that increased to reach an overall goal (walking for 30 minutes)” 2.2 “recorded messages telling the user how many minutes they have been walking, or when they are halfway to their goal” 4.1 “Tips and advice on performing activity” 7.1 “choose to receive reminders to complete the activity” 1.1 “Set goals” 2.2 “feedback would be offered on a satellite map, as a summary table, or on a calendar (with activity levels shown for each day)” 2.3 “Track their activity using their mobile phone” 7.1 “local exercise facilities would be highlighted on the map” 3.1 “encourage interaction through […] collaborations” 6.1 “encourage interaction through competitions” 2.3 “track their activity using a mobile phone” 10.2 “real-world rewards (either through vouchers or donating money to charity)” 10.3 “points would be given when users achieved their goals (the details of the goal completed would not be shared”, “earn virtual (stars or trophies on their profile) rewards”

Supplementary Information File 5

Risk of bias assessment for included randomized controlled trials[1]

Author, year	Random sequence allocation	Allocation concealment	Blinding of participants and personnel	Blinding of outcome assessment	Incomplete outcome data	Selective reporting
Ashton, 2017[20]	+	+	-	+	+	+
Mendoza, 2017[21]	+	?	-	?	+	?
King, 2016[22]	+	+	-	?	+	+
Greene, 2012[23]	+	?	-	-	-	?

+: Low risk of bias; -: High risk of bias; ?: Unclear risk of bias

[1] Assessment based on Cochrane's risk of bias tool

Supplementary Information File 6

Predefined search strategy

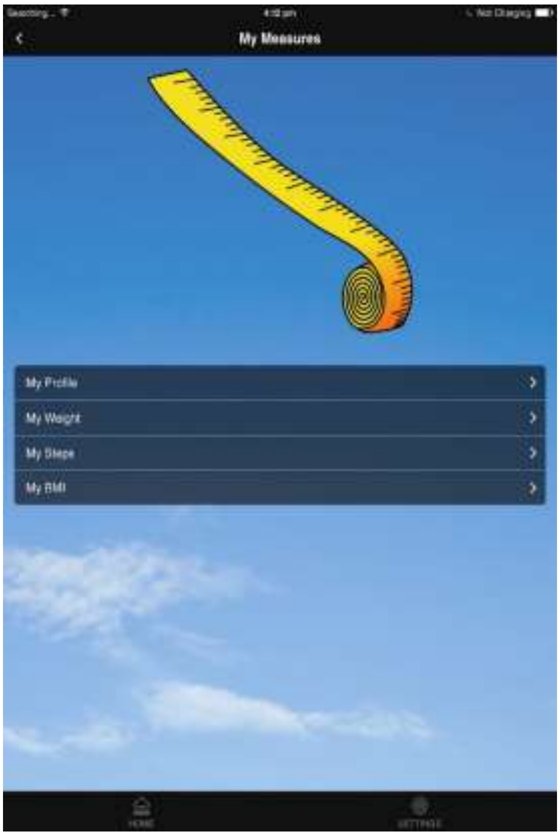
1.1 Search strategy for MEDLINE (via PubMed interface)
(https://www.ncbi.nlm.nih.gov/pubmed/)
Filters: none
Conducted in January 2018 and continuously updated until April 2018
#1 (((((("Mobile applications"[MeSH] OR "Smartphone"[MeSH] OR tablet computer*[tiab] OR wearable device*[tiab] OR acceleromet*[tiab] OR activity monitor*[tiab] OR "Fitness trackers"[MeSH] OR fitbit*[tiab] OR armband*[tiab] OR arm band*[tiab] OR fitness watch*[tiab] OR pedomet*[tiab] OR wearable technolog*[tiab] OR wearable system*[tiab] OR wearable sensor*[tiab] OR fitness monitor*[tiab] OR garmin[tiab] OR bodymedia[tiab] OR nike fuelband[tiab] OR jawbone[tiab] OR step count[tiab] OR smartwatch*[tiab] OR smart watch*[tiab] OR sports watch*[tiab] OR wristband*[tiab] OR wrist band*[tiab] OR MyFitnessPal [tiab]))))
AND
#2 ((("Social Support"[Mesh] OR "Social Networking"[Mesh] OR "Reinforcement, Social"[Mesh] OR "Social media"[Mesh]) OR "social comparison" OR "social reward" OR "social network" OR "social influence" OR "social media" OR "social feature")))))

1.2 Search strategy for Embase
URL: Macquarie University Library (via OVID Interface)
Limits: none
Conducted in January 2018 and continuously updated until April 2018
#1 Mobile Application/ or Smartphone/ or pedometer/ or ("tablet computer" or "wearable device*" or "activity track*" or fitbit* or "fitness track*" or "fitness watch*" or "wearable system*" or "fitness monitor*" or garmin or bodymedia or "nike fuelband" or jawbone or "step count*" or smartwatch or "smart watch*" or "sports watch*" or wristband* or "wrist band*").mp
AND
#2 social support/ or social network/ or reinforcement/ or social media/ or ("social comparison" or "social reward" or "social network*" or "social influence" or "social media" or "social feature*").mp.

1.3 **Search strategy for PsycInfo**
URL: Macquarie University Library (via OVID Interface)
Limits: none
Conducted in January 2018 and continuously updated until April 2018
#1 Mobile Application/ or Smartphone/ or pedometer/ or ("tablet computer" or "wearable device*" or "activity track*" or fitbit* or "fitness track*" or "fitness watch*" or "wearable system*" or "fitness monitor*" or garmin or bodymedia or "nike fuelband" or jawbone or "step count*" or smartwatch or "smart watch*" or "sports watch*" or wristband* or "wrist band*").mp
AND
#2 social support/ or social network/ or reinforcement/ or social media/ or ("social comparison" or "social reward" or "social network*" or "social influence" or "social media" or "social feature*").mp.

Appendix 3: Appendices of Paper II

Appendix 1: Screenshots of fit.healthy.me app



Chapter 2. Homepage

b) My measures

c) Social comparison features

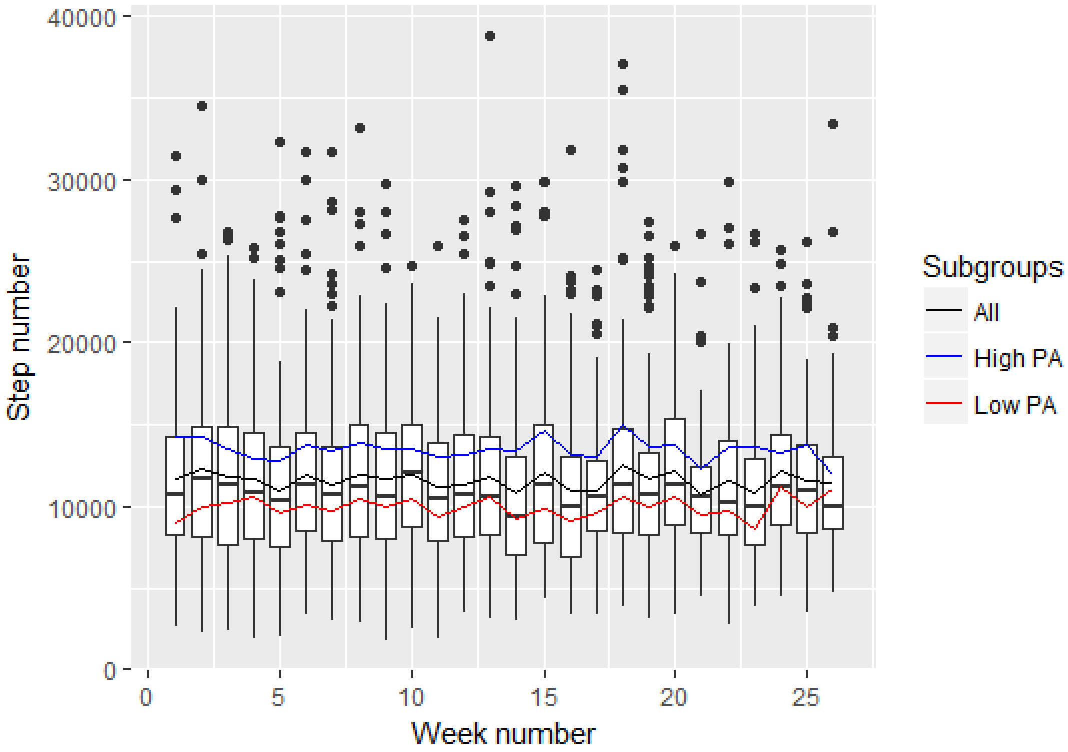
Appendix 2. Responses to individual system usability scale statements

Statement	Raw Mean	Raw SD
1. I think that I would like to use this application frequently	2.5	1.1
2. I found the application unnecessarily complex	2.7	1.2
3. I thought the application was easy to use	3.6	1.2
4. I think that I would need the support of a technical person to be able to use this application	1.9	1.1
5. I found the various functions in this application were well integrated	3.1	1.0
6. I thought there was too much inconsistency in this application	2.8	1.1
7. I would imagine that most people would learn to use this application very quickly	3.9	0.9
8. I found the application very cumbersome to use	3	1.1
9. I felt very confident using the application	3.5	1.0
10. I needed to learn a lot of things before I could get going with this application	2.1	1.1

Abbreviation: SD: standard deviation

Note: Response categories vary from 1 (strongly disagree) to 5 (strongly agree). To calculate the total system usability score, first the score contributions from each item are summed. For items 1, 3, 5, 7, 9, the score contribution is the scale contribution minus 1. For items 2, 4, 6, 8, 10, the contribution is 5 minus the scale position. Then, the sum of the scores are multiplied by 2.5 to obtain the overall value of system usability. System usability score ranges from 0 to 100.

Appendix 3: Boxplots of the 55 participants' daily step count over 26 study weeks



Abbreviations: PA: physical activity**. Notes:** A 'high' physical activity level was defined as having at least 10,000 steps per day on average for the first week, while a 'low' physical activity level was defined as having less than 10,000 steps per day on average during the first week.

Appendix 4: Differences in characteristics between frequent app users and non-frequent app users[a]

	Frequent users (N=28) mean (SD)	Non-frequent users (N=27) mean (SD)	*P* (95% CI)
Baseline weight (kg)	76.3 (19.3)	79.9 (25.3)	0.79[b] (-13.3, 9.7)
Baseline BMI (kg/m^2)	26.4 (6.1)	26.7 (7.5)	0.86[b] (-3.0, 3.2)
Baseline steps/day	11534 (3317.5)	10379 (4424.5)	0.60[c] (-1111.5, 2384.2)
Pre-post intervention step difference	-117.4 (4472.9)	168.4 (3533.3)	0.42[c] (-2264.1, 1126.1)
SUS score[d]	65.6 (13.4)	52.6 (23.5)	0.04[b] (0.6, 25.3)

Abbreviation: N: frequency count, SD: standard deviation, *P*: p-value, CI: confidence interval, kg: kilogram, m: metre, SUS: system usability scale; Notes: [a]The median of frequency (i.e. 1328 times) of app usage is used as a cut-off point to define frequent and non-frequent users, [b]Assessed using two-sample t-test, [c]Assessed using Wilcoxon rank sum test, [d]Only study completers (i.e. participants who returned to the final session) completed the SUS (n=45; 26 frequent users, 19 non-frequent users).

Appendix 5. Differences in characteristics between frequent users and non-frequent users[a] of the social features in the fit.healthy.me app

	Frequent users (N=28) mean (SD)	Non-frequent users (N=27) mean (SD)	*P* 95% CI
Baseline weight (kg)	72.4 (17.4)	75.6 (25.5)	0.06[b] (-23.3, 0.3)
Baseline BMI (kg/m²)	24.9 (5.2)	28.2 (7.9)	0.07[b] (-6.9, 0.3)
Baseline steps/day	11021 (3932.4)	10911 (3955.4)	0.77[c] (-1866.0, 1592.2)
Pre-post intervention step difference	-702.8 (4520.4)	851.3 (3266.6)	0.25[c] (-3041.0, 851.5)

Abbreviation: N: frequency count, SD: standard deviation, *P*: p-value, CI: confidence interval, kg: kilogram, m: metre; **Note**: [a]The median of frequency (i.e. 112 times) of social features usage is used as a cut-off point to define frequent and non-frequent users, [b]Assessed using two-sample t-test, [c]Assessed using Wilcoxon rank sum test

Appendix 4: Appendices of Paper III

Appendix 1: Consolidated criteria for reporting qualitative studies (COREQ): 32-item checklist

Developed from:

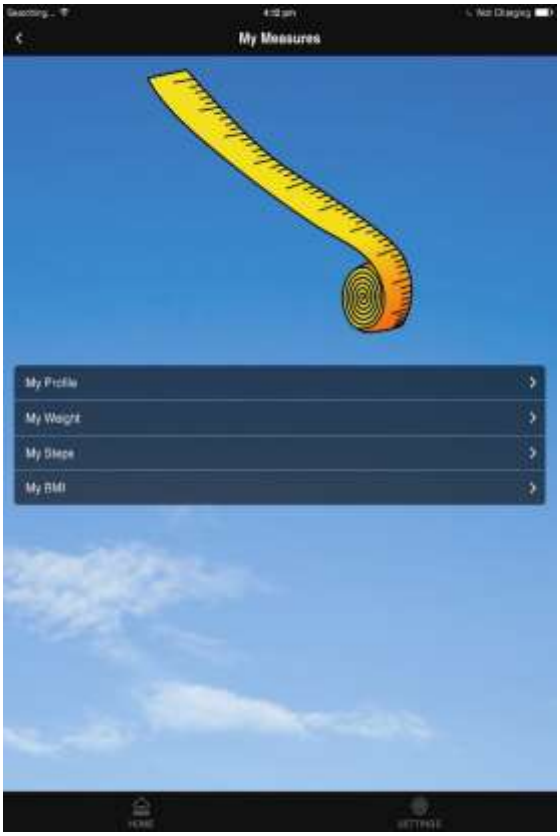
Tong A, Sainsbury P, Craig J. Consolidated criteria for reporting qualitative research (COREQ): a 32-item checklist for interviews and focus groups. *International Journal for Quality in Health Care*. 2007. Volume 19, Number 6: pp. 349 – 357

No. Item	Guide questions/description	Reported on Page #
Domain 1: Research team and reflexivity		
Personal Characteristics		
1. Interviewer/facilitator	Which author/s conducted the interview or focus group?	Page 23
2. Credentials	What were the researcher's credentials? E.g. PhD, MD	Page 1
3. Occupation	What was their occupation at the time of the study?	Page 1
4. Gender	Was the researcher male or female?	Page 1
5. Experience and training	What experience or training did the researcher have?	Page 1&5
Relationship with participants		
6. Relationship established	Was a relationship established prior to study commencement?	No
7. Participant knowledge of the interviewer	What did the participants know about the researcher? e.g. personal goals, reasons for doing the research	Yes- page 6
8. Interviewer characteristics	What characteristics were reported about the interviewer/facilitator? e.g. Bias, assumptions, reasons and interests in the research topic	All the authors had a positive attitude towards mobile health technologies and online social networks, but the authors strived to remain neutral in the conversations with participants.

Domain 2: study design		
Theoretical framework		
9. Methodological orientation and Theory	What methodological orientation was stated to underpin the study? e.g. grounded theory, discourse analysis, ethnography, phenomenology, content analysis	Page 7
Participant selection		
10. Sampling	How were participants selected? e.g. purposive, convenience, consecutive, snowball	Page 5
11. Method of approach	How were participants approached? e.g. face-to-face, telephone, mail, email	Page 5
12. Sample size	How many participants were in the study?	Page 5
13. Non-participation	How many people refused to participate or dropped out? Reasons?	Page 5
Setting		
14. Setting of data collection	Where was the data collected? e.g. home, clinic, workplace	Page 6
15. Presence of non-participants	Was anyone else present besides the participants and researchers?	No
16. Description of sample	What are the important characteristics of the sample? e.g. demographic data, date	Page 8
Data collection		
17. Interview guide	Were questions, prompts, guides provided by the authors? Was it pilot tested?	Page 6
18. Repeat interviews	Were repeat interviews carried out? If yes, how many?	Page 6
19. Audio/visual recording	Did the research use audio or visual recording to collect the data?	Audio
20. Field notes	Were field notes made during and/or after the interview or focus group?	Page 6
21. Duration	What was the duration of the interviews or focus group?	Page 6
22. Data saturation	Was data saturation discussed?	Page 6

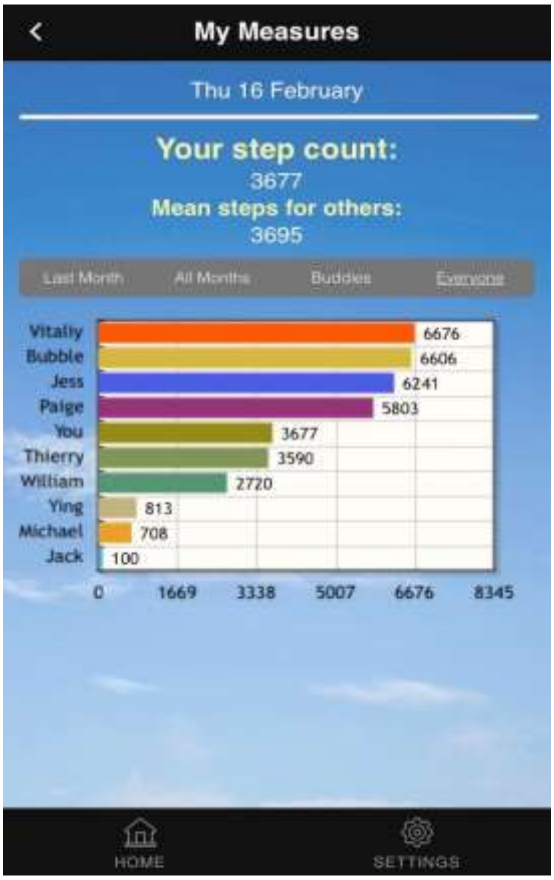
23. Transcripts returned	Were transcripts returned to participants for comment and/or correction?	No
Domain 3: analysis and findings		
Data analysis		
24. Number of data coders	How many data coders coded the data?	Page 7
25. Description of the coding tree	Did authors provide a description of the coding tree?	N/A
26. Derivation of themes	Were themes identified in advance or derived from the data?	Page 7
27. Software	What software, if applicable, was used to manage the data?	Page 7
28. Participant checking	Did participants provide feedback on the findings?	No
Reporting		
29. Quotations presented	Were participant quotations presented to illustrate the themes/findings? Was each quotation identified? e.g. participant number	Page 11, 13-14, 15-16
30. Data and findings consistent	Was there consistency between the data presented and the findings?	Yes, there was. From page 9 to 21
31. Clarity of major themes	Were major themes clearly presented in the findings?	Yes. they were. From page 9 to 21
32. Clarity of minor themes	Is there a description of diverse cases or discussion of minor themes?	Discussion of major and minor themes From page 9 to 21

Appendix 2: Screenshots of the fit.healthy.me app



a) Homepage

b) My measures



d) Social comparison features

Appendix 3. Interview guides at pre-intervention sessions and post-intervention sessions

Pre-intervention sessions

1. **Physical activity**
   a. What helps you to exercise regularly?
   b. What prevents you from exercising regularly?
2. **Weight management**
   a. What helps you to maintain a healthy weight?
   b. What prevents you from maintaining a healthy weight?
3. **Wearable devices**
   a. What do you think are possible advantages of monitoring physical activity and weight? What are the disadvantages?
   b. Are you using, or have you used in the past, any wearable/tracking devices to monitor your physical activity and weight? If yes, which ones?
   c. What do you think are possible advantages of using wearable/tracking devices to monitor your health? And disadvantages?
4. **Mobile apps**
   a. Do you use, or have you used in the past, any mobile apps to monitor your health or to track lifestyle/fitness activities? If yes, which ones?
   b. What do you think are possible advantages of using a mobile app to monitor your health? And disadvantages?
5. **Social features**
   a. Do you use any social networking sites? Have you ever used social networking sites for health purposes? (e.g. search health information, participate in fitness or health-related groups)
   b. What do you think are possible advantages of using social network features to facilitate weight management and physical activity? And disadvantages?
6. Is there any comment you want to make?

Post-intervention sessions

1. How did you find the experience of participating in the study?
2. **Wearable devices**
   a. What were the benefits of using the wearable device to monitor your activity and weight?
   b. What were the disadvantages of using the wearable device to monitor your physical activity and weight? Prompts: ease-of-use; convenience; integration in daily routine
   c. In your previous interview, you mentioned that … Has your opinion about the wearable device changed after using it?
   d. What device (Fitbit tracker/scale) do you choose to keep? Why?

3. **Health apps**

a. What were the benefits of using the fit.healthy.me app to monitor your physical activity and weight?
b. What were the disadvantages of using the fit.Healthy.me app?
c. In your previous interview, you mentioned that … Has your opinion about using the app changed after using it?

4. **Social features**
   a. What were the benefits of the social components in this intervention? (Prompts: tables, graphs to compare yourself, the social forum)
   b. What were the disadvantages of the social components?
   c. In your previous interview, you mentioned that … Has your opinion about using social media to help physical activity and weight management changed after using it?
   d. Did you have any social connections with other people who are in the study? (Did you know them before or after the study?)
5. **Suggestion:**
   a. **Keep using**: We noticed that you were really engaged with the study (using the app, scale and tracker). What helped you to be so engaged?

   OR

   b. **Stop using**: We noticed that you stopped using the app/tracker after [X months]. Why did you stop? What could we have done to help you stay engaged?
   c. Do you have **any suggestions** about additional aspects of the app or the devices that could be helpful in terms of monitoring activity and weight?