Feasibility of Obtaining Measures of Lifestyle From a Smartphone App
The MyHeart Counts Cardiovascular Health Study

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IMPORTANCE Studies have established the importance of physical activity and fitness, yet limited data exist on the associations between objective, real-world physical activity patterns, fitness, sleep, and cardiovascular health.

OBJECTIVES To assess the feasibility of obtaining measures of physical activity, fitness, and sleep from smartphones and to gain insights into activity patterns associated with life satisfaction and self-reported disease.

DESIGN, SETTING, AND PARTICIPANTS The MyHeart Counts smartphone app was made available in March 2015, and prospective participants downloaded the free app between March and October 2015. In this smartphone-based study of cardiovascular health, participants recorded physical activity, filled out health questionnaires, and completed a 6-minute walk test. The app was available to download within the United States.

MAIN OUTCOMES AND MEASURES The feasibility of consent and data collection entirely on a smartphone, the use of machine learning to cluster participants, and the associations between activity patterns, life satisfaction, and self-reported disease.

RESULTS From the launch to the time of the data freeze for this study (March to October 2015), the number of individuals (self-selected) who consented to participate was 48,968, representing all 50 states and the District of Columbia. Their median age was 36 years (interquartile range, 27-50 years), and 82.2% (30,338 male, 6,556 female, 10 other, and 3115 unknown) were male. In total, 40,017 (81.7% of those who consented) uploaded data. Among those who consented, 20,345 individuals (41.5%) completed 4 of the 7 days of motion data collection, and 4,552 individuals (9.3%) completed all 7 days. Among those who consented, 40,017 (81.7%) filled out some portion of the questionnaires, and 4,990 (10.2%) completed the 6-minute walk test, made available only at the end of 7 days. The Heart Age Questionnaire, also available after 7 days, required entering lipid values and age 40 to 79 years (among 17,245 individuals, 43.1% of participants). Consequently, 1,334 (2.7%) of those who consented completed all fields needed to compute heart age and a 10-year risk score. Physical activity was detected for a mean (SD) of 14.5% (8.0%) of individuals' total recorded time. Physical activity patterns were identified by cluster analysis. A pattern of lower overall activity but more frequent transitions between active and inactive states was associated with equivalent self-reported cardiovascular disease as a pattern of higher overall activity with fewer transitions. Individuals' perception of their activity and risk bore little relation to sensor-estimated activity or calculated cardiovascular risk.

CONCLUSIONS AND RELEVANCE A smartphone-based study of cardiovascular health is feasible, and improvements in participant diversity and engagement will maximize yield from consented participants. Large-scale, real-world assessment of physical activity, fitness, and sleep using mobile devices may be a useful addition to future population health studies.
Investigators have established the importance of physical activity, fitness, sleep, and diet in the maintenance of cardiovascular health. Low fitness is a key risk factor, while insufficient physical activity accounts for 5.3 million deaths per year and approximately 6% of the burden of coronary heart disease. Decrement in sleep quality through sleep fragmentation and obstructive sleep apnea also affect overall mortality.

Most of these observations, particularly with respect to activity, have been achieved through individual efforts of research coordinators and have required in-person consent, interviews, exercise or sleep studies, and follow-up. Such methods rely on accurate post-hoc participant recall. Survey-based physical activity estimation has been shown to systematically overestimate measured activity.

Mobile technology, in particular advances in smartphone sensors, offers a new approach to the study of cardiovascular health and fitness. Direct measurement of activity through always-on, low-power motion chips provides a promising alternative to questionnaire-based approaches, as recognized by large-scale projects, such as the United Kingdom Biobank and the US Precision Medicine Initiative. Widespread ownership of smartphones worldwide could thus transform global clinical research.

In 2015, Apple Inc (Cupertino, California) introduced an open-source framework (ResearchKit) to facilitate clinical research and standardization of data collection. Herein, we report the first findings from MyHeart Counts, one of the launch smartphone apps for the framework. MyHeart Counts is a cardiovascular health study administered entirely via smartphone, incorporating direct sensor-based measurements of physical activity and fitness, as well as questionnaire assessment of sleep, lifestyle factors, risk perception, and overall well-being.

Our objectives in this study were 2-fold. The first objective was to establish the feasibility of mobile consent and real-time gathering of sensor and survey data from a large ambulatory population. The second objective was to investigate the associations between patterns of physical activity, fitness, and self-reported well-being or medical history.

Methods

Data Acquisition

This study was approved by the Stanford University Institutional Review Board. The MyHeart Counts smartphone app was made available in March 2015, and prospective participants downloaded the free app from the Apple Inc app store between March and October 2015. Consent process was developed specifically for the smartphone platform and incorporates unambiguous language in a “card” format optimized for reading and understanding on a telephone. After consent, a secondary screen seeks specific permission for sharing of each category of telephone data with researchers. At any time, the participant can withdraw a specific category of data or his or her entire participation directly from the telephone.

Consented participants were able to contribute data to a range of study components, including health surveys on diet, well-being, risk perception, work-related and leisure-time physical activity, sleep, and cardiovascular health. Participants also self-reported demographic information, such as age, sex, and race/ethnicity. For reporting of race/ethnicity, they were given the opportunity to select multiple options (defined by the investigators) or none at all. During the initial 7-day monitoring period, the participant’s motion was recorded through the motion coprocessor chip of the telephone. The low-power motion chip integrates signals, including triaxial accelerometer, gyroscope, compass, and barometer, to estimate distance, as well as the presence and modality of movement, such as stationary, walking, running, cycling, or driving. On day 7, participants were requested to complete a self-administered 6-minute walk test that uses global positioning system-calibrated pedometer functionality built into the motion coprocessor chip. Reminders to complete surveys occur on a daily basis during the initial 7-day monitoring period.

Statistical Analysis

K-means and hierarchical clustering were applied to define groups with cohesive patterns of physical activity from the motion tracking data. Features for clustering included percentage of time spent stationary, percentage of time spent active, number of state changes between active and stationary, and the fraction of time spent on each activity (stationary, walking, running, cycling, driving, or unknown). Categorical comparison among groups was performed using the χ2 test. We tested for associations with life satisfaction using linear regression models with age and sex included as covariates. For the self-reported presence of disease, we tested the association using logistic models with age and sex as covariates. For both outcomes, stepwise selection of significant univariate associations was performed to build a multivariable model. When analyzing geographic differences in life satisfaction and activity, we developed a mixed-effects model with 3-digit zip code prefix modeled as a random effect and US census region modeled as a fixed effect. Detailed information on the statistical analysis and study findings is available in the eMethods and eResults in the Supplement.
Results

Participation and Demographics

From the launch to the time of the data freeze for this study (March to October 2015), the number of individuals who consented to participate was 48,968 (Figure 1 and eTable 1 in the Supplement). Participants were predominantly male (82.2% [30,338 male, 6,556 female, 10 other, and 315 unknown]), with a median age of 36 years (interquartile range, 27-50 years). Participants were from all 50 states and the District of Columbia, with the most participants from California (n = 4,423) and the fewest participants from North Dakota (n = 35). Of 23,351 respondents, 6,987 reported having a disease, while 3,185...
Figure 2. Patterns of Physical Activity and Model of Life Satisfaction

A, Based on proportion of time participants’ smartphones indicated they were stationary during 2 weekdays and 2 weekend days. Two dimensions of clustering are illustrated for clarity from the original 4. In total, 20 345 individuals were included in the analysis. B, Chest pain ($P < .001$, n = 17 062, $\chi^2 = 23.07$, and Cramer $\nu$ = 0.0121), type 2 diabetes ($P < .001$, n = 17 062, $\chi^2 = 22.68$, and Cramer $\nu$ = 0.0122), heart disease ($P < .001$, n = 17 062, $\chi^2 = 23.07$, and Cramer $\nu$ = 0.0122), joint pain ($P < .001$, n = 17 062, $\chi^2 = 23.07$, and Cramer $\nu$ = 0.0122), type 2 diabetes, heart disease, and joint pain (Figure 2B and Table 2 in the Supplement). Clusters of recorded physical activity are illustrated for clarity from the original 4. In total, 20 345 individuals (9.3%) completed all 7 days. Of the 20 345 individuals whose devices recorded physical activity, 13 896 (68.3%) were estimated by their smartphones to be stationary for more than 50% of the time for which data were recorded, spending a mean (SD) of 14.5% (8.0%) of their time active (10.9% of time walking and 3.5% of time on vigorous activity, such as running) (Table 2). On average, smartphones of male participants reported 3.8% more time active than smartphones of female participants ($P < .001$). A linear regression of sensor-measured active time onto age yields $P = .58$ (adjusted $R^2 < .001$). The linear regression of self-reported active time onto age yields $P < .001$, with a coefficient of interaction between age and activity equal to −0.49 (30 seconds). This result indicates no strong associations between active time and age. Weekend warriors, inactive, or drivers). Each white circle in C indicates the mean of the corresponding box plot. Analysis of variance tests were performed to check for significant associations of cluster membership with likelihood of having a particular health condition. Footnotes a, b, and c over a pair of bars indicate a significant difference between that pair of clusters and likelihood of the measured health condition.

Patterns of Physical Activity

Among those who consented, 20 345 individuals (41.5%) completed 4 of the 7 days of motion data collection, and 4552 individuals (9.3%) completed all 7 days. Of the 20 345 individuals whose devices recorded physical activity, 13 896 (68.3%) were estimated by their smartphones to be stationary for more than 50% of the time for which data were recorded, spending a mean (SD) of 14.5% (8.0%) of their time active (10.9% of time walking and 3.5% of time on vigorous activity, such as running) (Table 2). On average, smartphones of male participants reported 3.8% more time active than smartphones of female participants ($P < .001$). A linear regression of sensor-measured active time onto age yields $P = .58$ (adjusted $R^2 < .001$). The linear regression of self-reported active time onto age yields $P < .001$, with a coefficient of interaction between age and activity equal to −0.49 (30 seconds). This result indicates no strong associations between active time and age.

Patterns of Physical Activity

K-means clusters of physical activity data are shown in Figure 2A. Clusters of activity levels were significantly correlated with self-reported cardiovascular health status, as determined by a $\chi^2$ test for the presence or absence of chest pain, type 2 diabetes, heart disease, and joint pain (Figure 2B and Table 2 in the Supplement). Individuals in the least active cluster were found to have an elevated risk for all conditions listed above, with $\chi^2$ standardized residuals ranging from 2.5 for hypertension to 6.3 for heart disease. Conversely, individuals in the “weekend warriors” cluster were at a significantly lower risk (standardized residuals below −2) for chest pain, diabetes, heart disease, and joint pain (Figure 2B and Table 2 in the Supplement). Weekend warriors were defined as individuals who were more active during the weekend than during the weekdays. These individuals (Figure 2A) spent approximately 25% more time in the “active” state during the weekend.

The second analysis focused on the number of state changes from stationary to active and vice versa (eFigure 7 in the Supplement). Cluster analysis suggested that, although state changers were less active overall than weekend warriors, they experienced similarly better cardiovascular health status compared with those in inactive clusters.

Fitness

In total, 4990 individuals (10.2% of consented participants) completed the 6-minute walk test, made available only at the end of 7 days, with a mean (SD) step count of 693 (127) steps and a mean (SD) distance walked of 455 (520) m (Table I). Participants who completed the 6-minute walk test were slightly older than the general study population (median age, 42 years and mean age, 43.2 years) and had a higher ratio of men to...
women (5.6 vs 4.6 for the entire cohort). Sensor recordings indicated that the 6-minute walk test cohort was active during a mean (SD) of 15.1% (7.1%) of their total recorded time compared with a mean (SD) of 14.5% (8.0%) for the full cohort.

Sleep
Each participant self-reported the number of hours slept each night (Table 2). Overall, 34,048 participants (69.5% of those consented) reported a mean of 7.8 hours of sleep per night. Female respondents to the sleep survey (n = 5827) reported a mean of 0.3 hours more sleep than male respondents (n = 25,871) (P < .001).

We derived daily bedtimes for each participant based on the last time of movement recorded by the motion chip. We then compared the distributions of self-reported life satisfaction ratings (on a scale of 1-10) for participants with the earliest bedtimes (earliest tertile) with those for participants with the latest bedtimes (latest tertile) using the median bedtimes for each participant (among 14,895 patients, 30.4% of those consented). Individuals with 2 or fewer bedtimes recorded or outliers (bedtimes before 7:30 PM or after 3:30 AM) were excluded. Participants who retired the earliest in the evening reported an overall higher life satisfaction rating (mean, 7.48) than participants who stayed awake the latest (mean, 6.80) (P < .001) (Figure 3B). Individuals who retired the earliest tended to be older (median, 44 years) than those who retired the latest (median, 33 years old). A linear model adjusted for age and sex (n = 14,179) found the median bedtime in hours to be a significant univariate predictor of life satisfaction (β = −0.16; 95% CI, −0.18 to −0.14; P < .001).

Models of Life Satisfaction and Self-reported Disease
In addition to associations with health conditions, activity levels were also found to correlate with participants’ life satisfaction (P < .001) (Figure 2C). Individuals in the inactive cluster reported the lowest life satisfaction (mean, 6.82), while
individuals in the most active cluster reported the highest life satisfaction (mean, 7.48). Drivers and weekend warriors reported mean life satisfaction values of 7.14 and 7.36, respectively.

We tested the association of life satisfaction and self-reported disease status in our population with dietary, lifestyle, and other factors. Overall life satisfaction scores clustered around a mean of 7.12. Because many lifestyle predictors are correlated, we derived a multivariable linear model using stepwise selection on all significant univariate predictors, including age and sex as covariates. We found that fruit consumption, sugary drink intake, recorded activity, and minutes of self-reported vigorous activity remained significant predictors of life satisfaction (eTable 3 in the Supplement). Perceived Activity and Actual Activity
At baseline, participants were asked to rate how active they were on a scale of 1 to 6 on the Leisure-Time Activity Survey (eFigure 4A in the Supplement). On the Moderate or Vigorous Physical Activity Questionnaire, participants were also asked to report the number of minutes of moderate and vigorous physical activity that they performed in a week. These values were compared with the total time participants spent in the walking, running, and cycling states, as determined by the motion tracker data. Despite the large number of participants in the study, we observed a significant association between the perceived and reported activity levels (P < .001), but the correlation between the perceived and reported levels was negligibly small (R² < .001).

Perceived Risk and Actual Risk
A participant’s 10-year risk and lifetime risk of stroke and myocardial infarction19 were calculated according to the 2013 American College of Cardiology and American Heart Association atherosclerotic cardiovascular disease guidelines.20 Predicted risk calculations were compared with individuals’ self-reported perceptions of risk (eFigure 4B and eFigure 8 in the Supplement).21 A Pearson product moment correlation (R²) of 0.18 was observed between individuals’ perceived 10-year risk and the calculated 10-year
risk (Figure 3C). The Heart Age Questionnaire, available only after 7 days, required entering lipid values and age 40 to 79 years (among 17,245 individuals, 43.1% of participants). Of the 1334 participants who completed all questions on the Heart Age Questionnaire, necessary to compute heart age and a 10-year risk score, 512 underestimated their 10-year risk (mean difference, 6.0%), while 817 overestimated their 10-year risk (mean difference, 1.2%). The remaining 5 individuals had predictions close to the actual value. Similarly, participants did poorly at predicting their lifetime risk: a Pearson product moment correlation of 0.09 was observed between individuals’ perceived and calculated risk (Figure 3D). In total, 457 participants overestimated their lifetime risk by a mean of 12.7%, while 501 participants underestimated their lifetime risk by a mean of 12.0%, indicating that individuals predicted their personal risk with low accuracy.

Discussion

Seminal investigations established the importance of physical activity, fitness, sleep, and diet for cardiovascular health. Such studies were completed with time-consuming, in-person measurements with substantial reliance on participant recall. Mobile technology allows an alternative approach to such studies, with major challenges and opportunities.

Large-scale data afford approaches to analysis and insights that are not available from smaller-scale data. Herein, we used an unsupervised clustering approach to define categories of individuals by their physical activity patterns. Such approaches allow the data, rather than prior assumptions about the structure, to drive categorization. Despite decades of research, there is little certainty as to the optimal pattern...
Feasibility of a Smartphone App to Measure Cardiovascular Health

Research Original Investigation

We found a significant disconnect between an individual’s perceived cardiovascular risk and his or her actual risk derived from the 2013 atherosclerotic cardiovascular disease pooled cohort equations. These findings are in line with those reported by Mazalin Protulipac et al., who concluded that the actual presence of cardiovascular disease risk factors in participants did not appear to alter their perception of risk compared with participants without cardiovascular disease risk factors. Similarly, Ko and Boo found that, among cardiovascular risk factors, dyslipidemia, obesity, smoking, and family history of cardiovascular disease did not affect self-perceived health. Imes and Lewis observed that, even when individual

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Yeung, Ashley. Waggot, Cho, Haskell, Myers, Mignot, Landray, McConnell, Shcherbina, Homburger, Goldfeder, Acquitect, analysis, or interpretation of data: Waggot, Rosenberger, Myers, Champagne, Harrington, Yeung, Ashley; Division of Cardiovascular Medicine, Department of Medicine, Stanford University, Stanford, California (McConnell, Shcherbina, Pavlovic, Goldfeder, Waggot, Cho, Myers, Champagne, Harrington, Yeung, Ashley); Verly Life Sciences LLC, South San Francisco, California (McConnell); Department of Genetics, Stanford University, Stanford, California (Homburger, Ashley); Stanford Center for Cardiovascular Innovation, Stanford University, Stanford, California (Waggot, Yeung); Stanford Center for Biomedical Ethics, Stanford University, Stanford, California (Cho); Stanford Prevention Research Center, Stanford University, Stanford, California (Rosenberger, Haskell); Stanford Sleep Center, Stanford University, Palo Alto, California (Mignon); Big Data Institute, Nuffield Department of Population Health, University of Oxford, Oxford, England (Landray); Oxford Institute of Biomedical Engineering, Oxford, England (Tarassenko).

Author Contributions: Ms Shcherbina and Dr Ashley had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Dr McConnell and Ms Shcherbina contributed equally to this work.

Study concept and design: McConnell, Pavlovic, Waggot, Rosenberger, Myers, Champagne, Landray, Yeung, Ashley. Acquisition, analysis, or interpretation of data: McConnell, Shcherbina, Homburger, Goldfeder, Waggot, Cho, Haskell, Myers, Mignon, Landray, Tarassenko, Harrington. Drafting of the manuscript: McConnell, Shcherbina, Homburger, Goldfeder, Waggot, Myers, Ashley. Critical revision of the manuscript for important intellectual content: McConnell, Pavlovic, Homburger, Goldfeder, Waggot, Cho, Rosenberger, Haskell, Myers, Champagne, Mignon, Landray, Tarassenko, Harrington, Yeung, Ashley. Statistical analysis: Shcherbina, Homburger, Goldfeder, Waggot, Myers. Administrative, technical, or material support: McConnell, Pavlovic, Myers, Harrington, Yeung, Ashley. Study supervision: McConnell, Waggot, Myers, Yeung, Ashley.

Conflict of Interest Disclosures: All authors have completed and submitted the ICMJE Form for Disclosure of Potential Conflicts of Interest. Dr McConnell reported that he is on partial leave of absence from Stanford University and is an employee of Verly Life Sciences LLC. Dr Harrington reported being on the board of directors for Scanadu Inc (which is privately held) but reported receiving no consulting fees and reported having stock options with no current value. Dr Ashley reported that Samsung and Intel have provided small numbers of wearable devices for testing that were used for demonstration. No other disclosures were reported.

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REFERENCES


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**First Steps Into the Brave New Transdiscipline of Mobile Health**

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Given substantial evidence that healthy lifestyle behaviors lessen the odds of cardiovascular disease, a guideline from the American Heart Association and American College of Cardiology advises physicians to foster patients’ physical activity. But how is the clinician to evaluate a patient’s healthy lifestyle behaviors, let alone enhance them? Traditionally, patient self-reports supplied almost all behavioral data available to health professionals. However, whether given by free recall, structured questionnaire, or written logs, post hoc surveys inherently manifest forms of error well known to behavioral scientists. People forget. Many have no idea what moderate to vigorous activity feels like. Individuals also experience demands and motivations that distort what they report.

For a long while, not much could be done to increase confidence in the validity of behavioral assessments. Although one could observe peoples’ behavior objectively in controlled laboratory conditions or experimental tasks, legitimate questions arose about whether individuals would behave the same way in real life as they had in the laboratory. This state of affairs began to change in the 1980s, when acceleration signals from a worn sensor were first used to measure physical activity.

Fast forward to the present, and sensors are everywhere, including the tiny accelerometer, gyroscope, ambient light detector, compass, and barometer inside smartphones. In this issue of *JAMA Cardiology*, McConnell and colleagues are to be congratulated for pioneering efforts to examine the physical activity, sleep, and fitness data from MyHeart Counts, a launch smartphone app developed by Apple Inc’s ResearchKit. The team’s first aim was to evaluate the feasibility of using a smartphone to consent a large representative sample of ambulatory adults and to gather real-time sensor and survey data from them. Their second aim was to analyze those data to gain insights about associations among physical activity, well-being, and physical health.

MyHeart Counts succeeded as a proof of concept, demonstrating the potential for personally owned mobile devices to accomplish real-world ambulatory assessment. McConnell and