

# Mobile Health

James M. Rehg • Susan A. Murphy • Santosh Kumar  
Editors

# Mobile Health

Sensors, Analytic Methods, and Applications

Foreword by Deborah Estrin, Ph.D



*Editors*

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*For Jim and Marci—J.M.R.*

*For Terry—S.A.M.*

*For Smriti—S.K.*

# Foreword

The confluence of advances in mobile computing, wireless sensors, and digitization of healthcare has led to the emergence of mobile health (mHealth) during the past decade. mHealth broadly refers to the use of mobile technologies for managing health and wellness in the natural environment. Wearable fitness trackers and smartwatches are increasingly popular mHealth accessories and have contributed to enthusiastic interest on the part of the public in self-monitoring devices and practices.

Concurrent with growing interest and activity from the technology industry, there is growing interest in the computing research community in mHealth. mHealth represents a promising research area in computing that can make important contributions to society by advancing scientific understanding, driving technology advances, and improving health and wellness.

mHealth is unusually broad in its need for and relevance to computing research—cutting across many subdisciplines within computing; they include sensor design, mobile computing, networking, signal processing, data modeling, bioinformatics, machine learning, visualization, privacy and security, and human–computer interaction. Numerous workshops and conferences have also emerged in the area of mHealth, including National Institutes of Health (NIH) and National Science Foundation (NSF) backed summer institutes that provide immersive multidisciplinary training to faculty, postdoctoral fellows, and predoctoral candidates.

Both undergraduate and graduate level courses have also begun to address mHealth as an important component or as the primary focus, but in both cases there has not existed a high-quality reference book that provides a comprehensive introduction to mHealth for the computing community, especially for those just beginning to work in this area. This book fills this important gap by focusing on the sensing and modeling aspects of mHealth, while showcasing compelling and motivating applications, design and evaluation of sensors, markers derived from mobile sensors, and interventions designed to be triggered by sensor-derived markers.

I expect this book to become an indispensable resource for community members as they address new research problems, prepare publications and grant applications, plan courses, and act as consultants to other practitioners or researchers. The online lectures to accompany each chapter will make it particularly valued by students, faculty, and practitioners.

The authors of this book, led by the editors James Rehg, Susan Murphy, and Santosh Kumar, represent many of the most respected and accomplished leaders in this rapidly growing field. They together represent the diversity of disciplines that make up mHealth.

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# Preface

The field of mobile health (mHealth) is focused on the use of mobile technologies to improve health outcomes through sensing of behavioral and physiological states and interaction with individuals to facilitate health-related behavior change. Its promise is the ability to automatically identify and characterize the behaviors and decisions of everyday life that play a critical role in an individual's health and well-being, and provide personalized assistance and interventions under real-life field conditions to enable an individual to control their health, manage existing health conditions, and prevent future health problems from emerging. Examples of mHealth applications include physical activity tracking and encouragement, stress management, and preventing relapse to addictive behaviors, among many others.

The mHealth field is currently experiencing rapid growth, driven by advances in on-body sensor technology and its adoption by users, big data analytics, cloud computing, and the increasingly large-scale use of data in medicine. As a consequence of these diverse influences, the mHealth literature is scattered across a variety of conference proceedings and journals, making it challenging for researchers to obtain a holistic view of this emerging technology. This volume provides a solution in the form of a comprehensive introduction to the current state of the art in mHealth technology, with the agenda of advancing a systematic approach to mobile data analysis and exploitation.

This book is designed to be accessible to technology-oriented researchers and practitioners with backgrounds in computer science, engineering, statistics, and applied mathematics. The chapters provide a comprehensive overview of the major topics in sensing, analytics, and mobile computing which are critical to the design and deployment of mHealth systems. As a result, the book enables researchers and practitioners who are entering the mHealth field to obtain a complete introduction to current research and practice. Our contributing authors include many of the leading researchers and practitioners in the mHealth field.

## Introduction to the Book

Chronic health conditions are a major burden of disease in the United States and the world, and they are increasing in prevalence due to improvements in critical care, longer life, and changing lifestyles. Chronic diseases such as cardiovascular disease, cancer, diabetes, obesity, hypertension, and asthma need to be managed throughout the entire life of the patient with an appropriate medication regimen and lifestyle modifications. Mobile health (mHealth) can help both in assisting with the management of chronic diseases for those who have already become patients and in helping to prevent their occurrence in at-risk individuals. Chronic conditions such as smoking and other forms of dependence, along with developmental conditions such as autism and mental health conditions such as depression, also persist over time and can benefit from the use of mobile health technologies to support more effective, individualized approaches to behavior change and management.

Chronic diseases are usually complex in their etiology as they are caused by multiple risk factors that interact in complex patterns and include genetic, behavioral, social, and environmental components. The modifiable risk factors are the behavioral, social, and environmental components that can be monitored with mHealth in the user's natural environment. A key promise of mobile health technology is to provide, for the first time, the ability to not only monitor risk factors but also monitor the health states of individuals in their natural environment and quantify the interactions between the risk factors, their temporal dynamics, and outcomes, in order to gain a deeper insight into the factors that contribute to health and disease risk. Such activities would yield new levels of biomedical understanding and significantly improve clinicians' ability to identify person-specific disease risk and treatment response. For example, such ubiquitous monitoring with mHealth can help discover early indicators, antecedents, and precipitants, which can then be used in preventive interventions to reduce incidence rates of chronic diseases. Moreover, the availability of mobile computing platforms (in the form of smartphones) provides new opportunities to develop personalized prevention and treatment programs that can complement existing clinical mechanisms of care. By measuring the changes in health states, risk factors, daily behaviors, and medication adherence, mHealth can also help in detecting trends and adapting treatment and interventions so as to better manage the health and wellness of chronic disease patients, with a resulting reduction in adverse health events that require hospital readmission.

Advances in sensing and analytic methods, along with the proliferation of mobile platforms, have laid the groundwork for the collection of mobile sensor data, the quantification of risk factors, the measurement of changes in health status, and the delivery of treatment in the natural environment. However, substantial research is needed in order to realize the potential of this technology to improve health outcomes. The chapters in this volume provide a description of the challenges that must be overcome, along with some promising solution approaches. The chapters are organized into four parts: I. mHealth Applications and Tools; II. Sensors to mHealth Markers; III. Markers to mHealth Predictors; and IV. Predictors to mHealth



Interventions. This organization provides a useful conceptualization of the process of going from on-body sensor data to mobile interventions.

The first part on “mHealth Applications and Tools” provides a series of examples of health conditions and biomedical research questions that can be addressed using mHealth technology and methods. A range of study designs are represented. One category focuses on a particular mHealth technology and assesses its utility in the context of a specific health concern or population. A second category focuses on a specific health condition and prospectively explores the value of mHealth technologies in characterizing and quantifying trajectories of risk. A third category offers lessons learned in the design and implementation of mHealth studies or the use of particular sensing technologies. The populations addressed in these papers range from college students to older adults. A variety of intervention targets are described, ranging from the maintenance of circadian rhythms to the reduction in caloric consumption and the increase of physical activity. These papers collectively provide a useful introduction to the breadth of mHealth technologies and the current state of the art in their application.

While the increased availability of affordable sensors with improving battery life has driven the commercial growth of the mHealth market, the process of converting noisy on-body sensor data into valid and accurate measurements of behavioral, physiological, and environmental risk factors remains challenging. The chapters in Part II, “Sensors to mHealth Markers,” outline these challenges in detail and describe a variety of solution approaches. The chapters in this part cover a wide range of sensing technologies, including motion and activity sensing, acoustic analysis, optical sensing, and radar-based imaging. The central concern of this part is the development of computational models. Models must be informed by the physiological mechanisms and behavioral theory that guide our understanding of mobile health applications. At the same time, models must be able to address the challenges of streaming sensor data, namely its high volume, velocity, variety, variability, versatility, and the semantic gap between the data and underlying mHealth constructs of interest. A variety of modeling tools are used by the chapters in this part, including both probabilistic data models and classifier-based approaches. The validation of markers derived from on-body sensors against existing gold standard measures is another important topic. Validation can be done under laboratory conditions by collecting reference data from gold standard clinical instruments simultaneously with mHealth sensors. Validation in the field is much more challenging and typically involves a combination of self-report and human annotation to establish a reference. The techniques and approaches described in these chapters will provide a valuable resource for researchers and practitioners who are interested in developing novel mHealth markers or in using such markers in applications.

Given the ability to convert raw on-body sensor streams into mHealth markers, the next step in the processing pipeline is to convert multiple time series of marker values into predictions of risk for future adverse outcomes. Predictions of future risk are vital to the delivery of mobile interventions, as they can be used to pinpoint

windows of opportunity in which to act, before an undesired outcome occurs. Part III, “Markers to mHealth Predictors,” presents an introduction to the prediction task. Prediction is challenging because it requires the ability to make statements about future events for which no measurements are currently available. Moreover, the targets for prediction tend to be complex constructs which necessarily draw upon multiple streams of markers. The prediction of lapse in smoking cessation, for example, might utilize information about stress, craving, negative affect, and the presence or absence of social supports. The chapters in Part III cover a range of topics, from visualization techniques for uncovering patterns in marker streams to machine learning methods for capturing the temporal dynamics of multimodal patterns of markers, and finally ending with a case study on stress prediction in the context of a stress management intervention. While the prediction task has its own unique challenges, it shares with the task of marker generation the need to build effective computational models that capture the complex dynamics of noisy signals. The inherent complexity of the mHealth domain, in which both sensor signals and their derived markers exhibit tremendous variability in their properties and dynamics over time, creates a number of exciting research opportunities in machine learning and stochastic modeling. The chapters in this part provide an introduction to this exciting research area and will hopefully serve as inspiration for future research activities.

The final set of chapters addresses the use of predictions of future risk to develop and deliver mobile interventions. While the widespread adoption of smartphones has made it feasible to deploy mobile interventions on a large scale, many challenges remain in bringing about effective behavior change and an improvement in health outcomes. These challenges, along with a variety of solution approaches, are presented in Part IV, “Predictors to mHealth Interventions.” A key challenge is to optimize interventions so that they are tailored to the needs and context of the participants, and optimize a cost or provide a benefit to the participants. One approach is to use reinforcement learning algorithms to optimize both the content of an intervention and the timing of its delivery. Another approach is to formulate intervention design as a control systems problem, in which a dynamical model is used to describe the evolution of a participant’s state over time and the intervention takes the form of a feedback law which maintains the homeostasis of the closed loop system. In addition to these diverse methodological approaches, Part IV also provides examples of specific intervention designs for a gamut of behavioral health applications, including smoking cessation, increased physical activity, and chronic pain management.

Collectively, these four parts comprise a comprehensive and in-depth treatment of mobile health technologies, methodologies, and applications. We believe these chapters provide a useful characterization of the current state of mHealth research and practice. It is clear that we are at the cusp of a dramatic increase in the development and adoption of mHealth technologies. Substantial work remains to be done, however, in order to realize the potential of this new field and bring about meaningful improvements in health on a large scale. Achieving this goal will require a transdisciplinary approach and a strong partnership between experts in sensor

design, mobile systems, machine learning, pattern mining, big data computing, health informatics, behavioral medicine, experiment design, clinical research, and health research. This collective effort will be a critical factor in achieving the broadly held societal goals of reducing healthcare costs and improving individual and population health outcomes.

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