

# From Personalized Medicine to Population Health: A Survey of mHealth Sensing Techniques

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**Abstract**—Mobile sensing systems have been widely used as a practical approach to collect behavioral and health-related information from individuals and to provide timely intervention to promote health and well being, such as mental health and chronic care. As the objectives of mobile sensing could be either *personalized medicine for individuals* or *public health for populations*, in this work, we review the design of these mobile sensing systems, and propose to categorize the design of these systems in two paradigms—1) *personal sensing* and 2) *crowdsensing* paradigms. While both sensing paradigms might incorporate common ubiquitous sensing technologies, such as *wearable sensors, mobility monitoring, mobile data offloading, and cloud-based data analytics* to collect and process sensing data from individuals, we present two novel taxonomy systems based on the: 1) *sensing objectives* (e.g., goals of mobile health (mHealth) sensing systems and how technologies achieve the goals) and 2) *the sensing systems design and implementation (D&I)* (e.g., designs of mHealth sensing systems and how technologies are implemented). With respect to the two paradigms and two taxonomy systems, this work systematically reviews this field. Specifically, we first present technical reviews on the mHealth sensing systems in eight common/popular healthcare issues, ranging from depression and anxiety to COVID-19. By summarizing the mHealth sensing systems, we comprehensively survey the research works using the two taxonomy systems, where we systematically review the *sensing objectives* and *sensing systems D&I* while mapping the related research works onto the life-cycles of mHealth Sensing, i.e.: 1) *sensing task creation and participation*; 2) *(health surveillance and data collection*; and 3) *data analysis and knowledge discovery*. In addition to summarization, the proposed taxonomy systems also help the potential directions of mobile sensing for health from both personalized medicine and population health perspectives. Finally, we attempt to test and discuss the validity of our scientific approaches to the survey.

**Index Terms**—Mobile crowdsensing (MCS), mobile health (mHealth), mobile sensing, personal sensing (PS).

## I. INTRODUCTION

MOBILE sensing [1] refers to a sensing paradigm that leverages the ubiquitous sensors embedded in mobile devices (e.g., mobile phones and smartwatches) to monitor human behavior, physiology, environment, and interactions between them in a human-centric manner [2], [3]. Lots of work studied the adoption of mobile sensing techniques in health domains [4]–[6], such as mental health [7] and chronic care [8]. Early visionary works [9], [10] proposed the basic framework of the mobile health (mHealth) sensing techniques that leverage “noninvasive” mobile sensing schemes [11] to collect data for human activities recognition and infer the individual’s health status using machine learning algorithms with longitude and real-time sensory data accordingly [7], [12]–[14].

Compared to traditional medical sensors that are frequently operated by health professionals to collect data from patients in a clinical context, mHealth sensing relies on participation of voluntary users to obtain information for health-related well-beings in their daily life [15]–[17]. Furthermore, the goal of mHealth sensing research is to study the innovative applications of mobile sensing techniques to collect behavioral and physiological data related to health and well being, while medical sensing aims at designing new measurement and instrument techniques for medical purposes [18]. More comparison between mHealth sensing and medical sensing could be found in Appendix A. In this work, given the rapid development in such areas, we propose to review and survey the recent progress in mHealth sensing techniques.

### A. Health Outcomes in mHealth Sensing Systems

There are several works reviewing and surveying the research problems [19]–[23], emerging techniques [24], [25], system design [26]–[28], and prototyping tools [14], [29], [30] for mHealth sensing systems. In this work, we propose to first categorize the research works on mHealth sensing systems with respect to the major health issues they are addressing (e.g., depression and anxiety). Furthermore, for every major health issue reviewed here, we also discuss mHealth sensing research from the perspectives of *personalized medicine*

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and *population health*—two major health outcomes of modern healthcare [31]–[34], which are defined as follows.

- 1) *Personalized Medicine*: Personalized medicine focuses on individual patients—with *medical decisions, practices, interventions, and/or products being tailored to the individual patient based on their predicted response or risk of disease* [35]. Thus, the goal of personalized medicine is to improve and optimize the individual treatment effects through sensing, monitoring, and predicting their health status [36].
- 2) *Population Health*: Population health is defined as *the health outcomes [37] of a group of individuals, including the distribution of such outcomes within the group* [38]. The goal of population health is to promote the health of a target population [39], where the approaches include discovering health outcomes, understanding patterns of health determinants, and policy making for interventions.

Though the outcomes of *personalized medicine* and *population health* promote the well being of individuals and communities in diversified directions, they often incorporate some ubiquitous sensing technologies, such as personal health surveillance with wearable sensors [40], mobility monitoring [41], [42], mobile data offloading, and cloud-based data analytics [43] to collect and process sensing data from individuals. In practice, *personalized medicine* mainly aims to continuously monitor the health conditions and medical progressions of individual users with fine-grained data collection, while *population health* is focused broadly and comprehensively on studying the health issues and their determinants in a community with a considerable scale. Thus, there is a significant need to survey mHealth sensing systems and techniques designed and implemented from the perspectives of personalized medicine and population health.

### B. Challenges of Design and Implementation (D&I) in mHealth Sensing Systems

For the two health outcomes of mHealth Sensing, we plan to generalize and categorize existing works into two design paradigms—1) personal sensing (PS) and 2) crowdsensing (CS) paradigms, according to the significant differences in app design, such as user engagement strategies [44], [45] and data analysis approaches [46], [47]. Moreover, as shown in Fig. 1, we follow the common frameworks of mobile sensing systems [1], [48] and propose to modularize the design of mHealth sensing systems [49] for both PS and CS into a three-stage pipeline as follows.

- 1) *Sensing Task Creation and Participation*: With a pool of potential mobile users, the mHealth Sensing researchers create tasks for specific health issues via deployed systems [4], [50], [51], then prompt users' participation [10], [52], [53] and the engagement with incentives [54], [55].
- 2) *Health Surveillance and Data Collection*: With actively engaged participants, the mHealth sensing systems collect health-related data from participants in their daily life scenarios [11], [56], and then store and

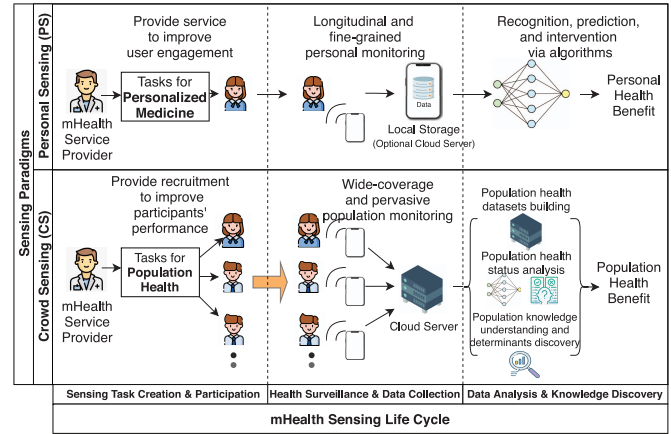


Fig. 1. Three-stage pipeline of mHealth sensing systems.

offload the sensing data often with security and privacy protection [57]–[60].

- 3) *Data Analysis and Knowledge Discovery*: With health-related data collected, the mHealth sensing systems carry out data processing and analysis under ethical certification [61]–[63] to predict health-related events for individuals [64], [65] and discover determinants of health [38], i.e., knowledge about population health and well being [10], [66].

Based on the above two mHealth sensing design paradigms and the pipeline of three stages, it is reasonable to assume the way that existing works designed and implemented mHealth sensing systems, kept participants engaged, and discovered knowledge might be significantly different from the perspectives of personalized medicine and population health. In this article, we provide two taxonomy systems that cover the major technical challenges and methodologies in this area. Specifically, we focus on the *sensing objectives* (e.g., data privacy, data quality, energy efficiency, and other goals targeted at enabling practical mHealth Sensing systems) and *sensing systems design and implementation (D&I)* (e.g., designs of mHealth Sensing systems and implementations of technologies), respectively. Furthermore, we review and categorize the sensing objectives and systems D&I issues by the combination of two mHealth Sensing design paradigms and three stages in detail.

### C. Organization of the Survey

The remainder of this manuscript is organized as follows.

- 1) In Section II, we review and summarize mHealth sensing systems for eight common/popular health issues. Specifically, we discuss how mHealth sensing techniques study the health issues for personalized medicine and population health purposes with case studies. We report the procedure to select the health issues for the review in Appendix B.
- 2) In Section III, we introduce the taxonomy system classifying mHealth sensing systems from the *sensing objectives* perspective. Specifically, we identify and discuss the detailed objectives considered to achieve personalized medicine and population health goals, as well as their differences and connections, in each step of the mHealth sensing life cycle.

- 3) In Section IV, we present the taxonomy system from the perspective of *sensing systems D&I*, where we discuss, with respect to identified objectives, how mHealth sensing systems are designed and how technologies are implemented to handle the PS for personalized medicine or CS for population health.
- 4) In Sections V and VI, we discuss the future directions in mHealth sensing area and conclude the article. Specifically, we discuss the limitations of this survey, including the use of scientific approaches and the coverage of topics. In Appendix C, we review and discuss the scientific approaches to this survey in detail.

## II. REVIEWING MHEALTH SENSING SYSTEMS FOR COMMON HEALTH ISSUES

In this section, we first list the definitions of health-related terms in Table I. With respect to the eight most commonly researched health issues (i.e., depression and anxiety, sleep quality and insomnia, diabetes, heart diseases, elder care, diet management, tinnitus, and COVID-19) in reviewed papers, we summarize typical mHealth sensing apps for *personalized medicine* and *population health*.

In general, as shown in Table II, to promote *personalized medicine*, mHealth sensing systems leverage PS paradigm and focus on an individual's health outcomes with systems D&I of health status monitoring, recognition, and intervention; while for *population health*, the CS paradigm mainly aims to measure/understand population health status and discover knowledge for public health benefit. Here, we discuss three typical health issues among the eight with respect to the outcomes of mHealth Sensing.

### A. Depression and Anxiety

Depression and anxiety are mental health disorders broadly experienced by 548 million people worldwide [136]. mHealth sensing gives ubiquitous solutions to these issues, both on monitoring and intervention at the personal level [51], [83], [85] and surveying and understanding at the population level [88].

1) *Personal Depression and Anxiety Monitoring and Intervention*: Mobile devices are providing broad services for individual patients with mental disorders, as they can continuously collect behavior and physiology data, as well as deliver timely interventions without scarce clinical resources [25]. Typically, Mobilyze! [84], a mobile mental intervention application with a two-step framework—context sensing and ecological momentary intervention—collects contextual data and feeds them into a medical diagnosis model, then it infers the user's mental health status and provides interventions to overcome psychological dilemmas (e.g., lack of social interaction). Furthermore, in the mental health domain, advances in artificial intelligence are promoting decision making of just-in-time adaptive intervention (JITAI) by learning from individual longitudinal behaviors [137], [138].

2) *Population Depression and Anxiety Survey*: Mobile sensing techniques are increasingly being adopted for population depression and anxiety surveys, as they provide a

TABLE I  
TERMS AND DEFINITIONS

Terms	Definitions
Mobile Health	Namely <i>mHealth</i> , a term used for the practice of medicine and public health supported by mobile devices [22].
mHealth Provider	People (e.g., researchers, business companies) who organize healthcare services by designing and deploying mHealth techniques and applications [67].
Ubiquitous Sensing	A paradigm using networked sensors pervasively exist in daily-life scenarios to capture information about humans, environments, and their interactions [68].
Personal Sensing	A technique collecting and analyzing data from sensors embedded in the context of an individual's life with the aim of identifying his/her behaviors, thoughts, feelings, and traits [3].
Crowd Sensing	A technique where a large group of individuals having mobile devices capable of sensing and computing collectively share data and extract information to measure, map, analyze, estimate, or predict any processes of common interest [69].
Passive Sensing	Sensing via devices that detect and respond to some type of input from the physical environment [70].
Health Status	One's medical conditions (both physical and mental), claims experience, receipt of health care, medical history, genetic information, evidence of insurability, and disability [71].
Health Outcomes	Health events occurring as a result of interventions [72]; in our work, an intervention could be the consequence of mHealth sensing.
Health Determinants	Conditions which contribute to a wide range of health and quality of life, risks and outcomes [73].
Mental Health	A state of well-being in which the individual realizes his/her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his/her community [74].
Treatment Effects	Causal effect of a given treatment or intervention on an outcome variable of health interests [75].
Health Benefit	Positive phenomena that a medicine treatment, substance or activity is improving health [76].
Health Intervention	A treatment, procedure, or other action taken to prevent or treat disease, or improve health in other ways [77].
Digital Biomarkers	Objective, quantifiable physiological and behavioral data that are collected and measured by means of digital devices [78].

low cost and off-the-shelf, cheap, and online data collection manner versus laborious and high-cost clinical testing and questionnaires. For example, by studying the correlation between anxiety and behavioral indicators (e.g., activity locations, text messages, and calls) of 54 students over two weeks, Boukhechba *et al.* [87] proposed to pervasively monitor college students' mental status by tracking their GPS trajectories.

3) *Population Mental Health Determinants Understanding*: New findings for population mental health determinants can be gained by widely collecting and comparatively analyzing data among populations [89], [139]. For example, a mobile CS (MCS) platform—Sensus [4] was leveraged by Chow *et al.* [86] to verify clinical models of depression and

TABLE II  
SUMMARY TABLE OF THE mHEALTH APPS ON EIGHT COMMON HEALTH ISSUES CREATED FOR THE MOTIVATIONS IN: 1) PERSONALIZED MEDICINE AND 2) POPULATION HEALTH, RESPECTIVELY

Health Issues	Personalized Medicine		Population Health	
	Motivations	Examples	Motivations	Examples
<b>Depression and Anxiety</b>	Identification and interventions for depression and anxiety	[51], [52] [79]–[85]	Population mental health screening and determinants inferring	[56], [86]–[90]
<b>Sleep Quality and Insomnia</b>	Sleep quality monitoring and sleep stage recognition	[12], [50], [91]–[93]	Population sleep statistics for understanding sleep science issues	[94], [95]
<b>Diabetes (type 2)</b>	Glucose monitoring for diabetes management	[8], [96]–[98]	Understanding the social determinants contributing to diabetes	[16] [99], [100]
<b>Heart Diseases</b>	Heart health monitoring and heart failure prevention	[15] [101]–[103]	Studying the impact of determinants on heart diseases	[104], [105]
<b>Elder-care</b>	In-home healthcare and assistance	[106], [107]	Understanding the health status and lifestyle of the elderly population	[108]
	Outdoor monitoring and notification	[109], [110]		
<b>Diet and Weight Management</b>	Diet self-monitoring and exercise management	[64], [65]	Understanding population eating habits, episodes, and disorders	[111], [112]
<b>Tinnitus</b>	Tinnitus self measurement and retraining therapy	[113], [114]	Studying symptoms, causes, and treatments of tinnitus population	[115]–[117]
<b>COVID-19</b>	Remote self-diagnosis	[118]–[121]	Epidemiological analysis	[42], [122]–[124]
	Contact tracing	[125]–[128]	Public health policy making and evaluation	[129]–[135]

anxiety. Taking the levels of depression and social anxiety as moderators, researchers tested the relations between state effect and time spent at home of 72 recruited students, and finally, they gain an understanding of the significant correlations between depression and anxiety and home-stay behaviors in the target population.

### B. Sleep Quality and Insomnia

mHealth Sensing applications are widely applied to monitor sleep quality and identify sleep stage, as well help with understanding sleep problems in populations.

1) *Personalized Sleep Monitoring and Insomnia Assistance:* Mobile and pervasive sensing devices are providing more personalized sleep quality monitoring and sleep-aid service [12], [92], [140]. Sorts of sleep monitoring systems are embedded in wearable devices, but they are not widely used and uncomfortable to wear [141], [142]. mHealth sensing solutions are to use off-the-shelf sensors built in mobile phones, such as microphones, to detect sleep stage and infer sleep quality. For example, Hao *et al.* [50] proposed a model leveraging audio to detect sleep events such as body movement for sleep quality estimation [92]. Furthermore, with off-the-shelf smartphones and commodity WiFi devices, Yu *et al.* [93] designed a low-cost sleep stage monitoring system by extracting respiratory rate and body movement from channel state information from WiFi antennas.

2) *Population Sleep Science Research:* CS methods are widely used to create population sleep status data sets for sleep research, such as understanding psychological and physiological causes of insomnia. In practice, to understand the relationship between phone usage and sleep quality, Sharmila *et al.* [94] collected a large-scale phone usage data set and sleep questionnaires from 743 participants in a CS manner and evaluate the effect of mobile phone usage patterns on sleep with statistical methods. During the pandemic, Tahara *et al.* [95] studied the changes of mHealth app

users' sleep phase and revealed the impact of the pandemic on delayed sleep onset and offset with increased sleep duration and decreased social jetlag, especially for young populations in Japan.

### C. Mobile Sensing in the COVID-19 Era

Mobile devices that people carry around are like the “witnesses” to the spread of the pandemic, continuously and passively collecting human mobility and social interactions [143].

1) *Personal Remote Detection:* Mobile microphones collect audio data, including sigh, breath, and voice, which are indicators to diagnose lung diseases [144], giving great potential of automatic COVID-19 remote detection [118]. For example, Brown *et al.* [119] proposed methodologies to detect diagnostic signs of COVID-19 from voice and coughs, which well differentiated COVID-19 from other viral infections. Han *et al.* proposed to diagnose COVID-19 infections by learning from the cough, breathing, and voice data collected by COVID-19 Sounds App leveraging a three-channel neural network. In addition to audio-based methods, novel wearable sensors also provided long-term monitoring for vital but tiny signs that may indicate infections to assist diagnosis [121].

2) *Personal Contact Tracing:* The most common way of transmission of the COVID-19 virus is through contact between people [145], which causes finding the contacts of positive patients an essential task for epidemic control. Many mobile apps were developed and deployed for the privacy-preserving contact tracing during the pandemic, automatically and securely recording and communicating the contact history, where the most crucial technology is the Bluetooth proximity network [125], [126], [128], [146]. For example, Carli *et al.* [127] developed WeTrace, a mobile virus tracing app that detects one's contact history with others by identifying Bluetooth signal interactions; and proposed a trusted information transmission framework for the tradeoff between public health benefits and privacy leakage.

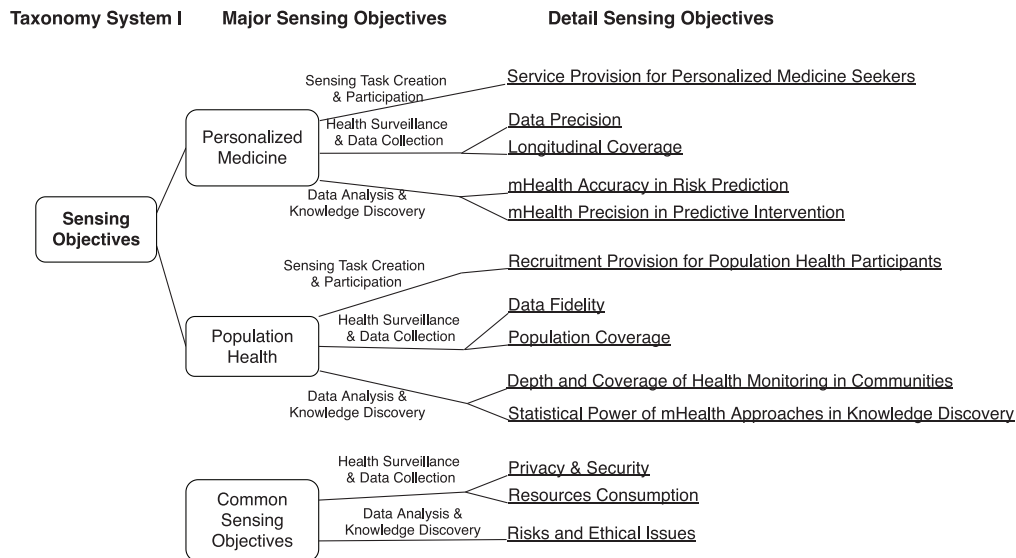


Fig. 2. Taxonomy system I—sensing objectives.

3) *Population Epidemiological Analysis*: The recently revealed significant correlations between regional human mobility and COVID-19 infections provide guidance on investigating and understanding the pandemic spread with multiscale mobile data [123], [124]. Human mobility data (e.g., cell tower records, GPS location, Bluetooth proximity, and opt-in application data) on multiple scales are guiding the COVID-19 epidemiological studies [122]. To be specific, from the perspective of human movement, cell tower records and GPS location data of mobile phones help describe the human flow from origins to destinations of multilevel spatial scales (e.g., city, state, and country) [42], [147]; in terms of human interaction, GPS location data and Bluetooth proximity data could measure population density to estimate the exposure risk [148].

4) *Public Policy Making and Evaluation*: Public policies (e.g., travel restriction, quarantine, and social distancing) were commonly proposed by governments around the world to limit the fast spread of COVID-19. mHealth sensing data among populations were effectively applied in policy making and evaluation processes [149], [150]. For instance, mobile data broadly sensed from a large group, such as app usage logs and Bluetooth encounters, helped estimate the public response to specific events (e.g., social distance ban published) and evaluate the efficiency of social distancing [129], [151]. Furthermore, with the mobile sensing data gathered publicly, statistical and machine learning methods can be used to estimate, simulate, and predict the policy effects on spread control in a data-driven manner [131], [132], [152].

#### D. Discussion

Note that in this work, we review and summarize the works on mHealth sensing systems deployed over smartphones and commodity devices, such as tablets, smartwatches, and other wearable consumer electronics in noninvasive sensing manners. Many other works intending to monitor the physiological status of patients for medical purposes or professional

devices/systems for critical cares/assisted living, such as dedicated medical sensors [153]–[156], Internet of Medical Things (Medical IoTs) and Medical Cyber–Physical Systems (Medical CPSs) [157]–[174], and medical robots [175]–[178], are not included here. Of course, many behavior-related health issues are not well covered in this work, such as drug/alcohol abuse or addiction [179], [180].

What is more, there are also sort of pervasive IoT devices (e.g., WiFi, LoRa, and RFID) studied to serve as mHealth sensing tools, typically applied in motion tracking [181]–[183], activity/gesture recognition [184]–[186], and respiration monitoring [187]–[190] tasks. The basic idea of these ubiquitous sensing practices is to mine the wireless signals of IoT devices (such as the channel state information of WiFi) for information that expresses physiology and behavior [191]. For instance, the Fresnel diffraction model was leveraged by Zhang *et al.* [192] to reveal the quantified relationship between channel state diffraction gain and human subtle displacement/movement.

### III. TAXONOMY SYSTEM I (CLASSIFICATION OF MHEALTH SENSING BY SENSING OBJECTIVES)

In taxonomy system I, for each step of mHealth sensing life cycles, we identify and discuss the mHealth sensing systems on: 1) *personalized medicine* and 2) *population health*, as shown in Fig. 2.

#### A. Objectives in Sensing Task Creation and Participation

In order to attract enough participants in mHealth Sensing practices, the main objective in this step is to provide proper health service and/or recruitment to collect sufficient data.

1) *Service Provision for Personalized Medicine Seekers*: mHealth sensing systems for *personalized medicine* usually provide helpful *healthcare services* [17], [193], [194] such as health status monitoring and personalized interventions or treatments.

In most cases of the *personalized medicine* systems, participants actively engage in the sensing task for personalized medicine outcomes [195]. Thus, the detail objective of personalized medicine systems in this step is to provide exact healthcare services (e.g., exercise reminders and user-friendly interface) and keep improving service quality (e.g., optimizing intervention accuracy and timing via advanced algorithms) to scale up the participation [196].

- 2) *Recruitment Provision for Population Health Participants: Population health* systems are mostly for studying population health issues leveraging massive collected data from groups with less straightforward personal health benefit for participants to compensate for their concerns on cost and privacy (e.g., time consumption, privacy exposure risk [197], and battery usage [198]). For example, in a COVID-19 infectious population screening [199] or a rare clinical disease causes understanding program [200], the results are valuable for public health researchers but relatively useless for participants. The above reasons lead to a unique detail objective of population health systems in attracting participation—providing recruitment to gather participants and motivating their performance with incentives [55], [201].

### B. Objectives in Health Surveillance and Data Collection

With exact sensing tasks and a pool of participants, the objectives in *Health Surveillance and Data Collection* are collecting and gathering sufficient trustworthy data for further analysis. As show in Fig. 3, we summarize that the *data trustworthiness* lies in *data quality* and *data quantity*; further, the *data quality* could be further indicated as *data precision* and *data fidelity*, and the *data quantity* could be measured by *longitudinal coverage* and *population coverage*. Also, some objectives (i.e., *privacy and security* and *resources consumption*) are commonly expected by the two kinds of mHealth sensing systems.

1) *Personal Sensing for Personalized Medicine: In personalized medicine* systems, the detail objectives in data collection are *data precision* and *longitudinal coverage*.

- 1) *Data Precision: The data precision* is the most straightforward objective for personalized medicine goals, which determines the quality of personal healthcare services. Here, we take the mobile medical devices in the intensive care unit (ICU) as examples of the data precision objective in personalized medicine [202], [203]. Wearable devices with incentive monitoring sensors collecting patients' physiology and behavior in ICU are typical schemes for personalized medicine outcomes with high sampling rate and precision. They finely capture patients' physical and behavioral biomarkers, such as facial expressions, functional status entailing extremity movements, and severe progression indicators [204].
- 2) *Longitudinal Coverage: The coverage of longitudinal data* (in observations and objects) helps not only

accurately capture complex dynamics of individual indicators in the long term [14], [205]–[207] but also comprehensively analyze the nontrivial casual relationships between multiple pathogenic determinants and health outcomes [208]–[210]. In addition, the interactions between mHealth Sensing systems are also beneficial to enlarge the longitudinal coverage of sensing in individuals, which share and gather multiple observations. For instance, Google Health and HealthVault are cross-platform health record systems storing and sharing information between mHealth systems in a secure manner, which enlarge the personalized medicine power of single systems [211].

2) *Crowdsensing for Population Health: To achieve population health* goals, the task of Health Surveillance and Data Collection is to build a large-scale and error-free data pool correlated to the health issues to be analyzed, with detail objectives of ensuring *data fidelity* and enlarging *population coverage* in the sensing process.

- 1) *Data Fidelity: Versus data precision*, data fidelity in the mHealth sensing systems refers to there is no human error (e.g., intentional cheating) in gathered data [40], [212]. Especially, different from the collection of some simple data (e.g., traffic speed data or urban temperature data), collecting daily/clinical health-related data requires enormous manpower, incentive cost, and devices resources for a long time [213], [214]. Also, once human errors are introduced into the gathered data, it leads to inaccurate health modeling, inaccurate progression measurement, and wrong medical conclusions, which are harmful to the population health goals [215].
- 2) *Population Coverage: Enlarging the population coverage* of health surveillance and data collection is beneficial to obtain comprehensive and effective data analysis and knowledge discovery [216]. For varied research purposes, the expectations of population coverage vary [41]. For example, data for population mental health research should cover balanced genders and diversified ages for comparative analysis and knowledge discovery with no/limited prior knowledge leveraging machine learning [217] or statistical inference [218] approaches; data for sleep science research should cover kinds of patient groups, such as sleep apnea, insomnia, Parkinson's disease, and periodic limb movement disorder (PLMD), as well as healthy people as the control group.

Though the detail sensing objectives of personalized medicine and population health practices in data collection processes are specified as the above perspectives, they are usually overlapped. For example, *data precision* and *longitudinal coverage* are also desirable in *CS for population health* systems. However, *data fidelity* and *population coverage* are more in need of dedicated systems D&I issues for specific problems in population health practices.

3) *Commonly Existing Objectives—Concerns and Costs: Beyond the technical objectives in trustworthiness of data*, issues about users' practical concerns and costs are the commonly existing objectives for mHealth sensing systems.

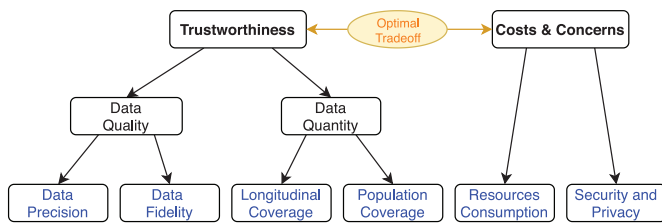


Fig. 3. Detail sensing objectives in health surveillance and data collection.

- 1) **Security and Privacy:** Issues in security and privacy are great concerns in health-related domains [57], [146]. As for personalized medicine systems, the security/privacy issues include identity privacy [219] (participants do not want to expose personal information), data privacy [220] (health-related data is sensitive), and attribute privacy [221] (for attributes, such as locations and trajectories). Besides, the risk of privacy leakage in population health systems is greater [222], [223], as it requires regular sensitive health-related data uploading and offloading between mobile devices and cloud servers via networks [224]. To be specific, additional privacy concerns in population health data collecting and uploading processes are task privacy [225] (the sensing tasks may correlate to participants' illnesses) and decentralized privacy [226] (frequent communication with a central server could be more easily hacked).
- 2) **Resources Consumption:** Keeping mobile sensing data sampling consumes considerable battery, hardware, and software resources. From the *personalized medicine* perspective, the resource consumption is more intense, as the data collection actions are generally continuous and intensive [227]. Against this background, the type and combination of sensors working and their sampling rate, data accuracy, and sampling abundance are under consideration [228], [229]. In terms of *population health*, when the hardware consumption of each individual's perception is already economical, the decrease in resources consumption is mainly achieved by optimizing the task allocation in spatial, temporal, participants, and content to achieve cost-effective global sensing [66], [230]–[233].

Worth mentioning, to obtain fine-grained sensing data with wide coverage (in terms of either surveillance time or the number of human subjects), it is frequently needed to intensively and continuously collect data from wide range of participating individuals, thus violating participants' privacy controls or data/battery plans. Hence, mHealth sensing systems need to grant every individual participant the right to make trade-off between *data trustworthiness* and *costs and concerns* as shown in Fig. 3. Ideally, the mHealth sensing systems need to prove themselves have already minimized data access privileges subject to the actual needs, to persuade and encourage participants to involve in the CS for public health.

### C. Objectives in Data Analysis and Knowledge Discovery

After gathering expected data, the main objective in data analysis and knowledge discovery is to discover health-related

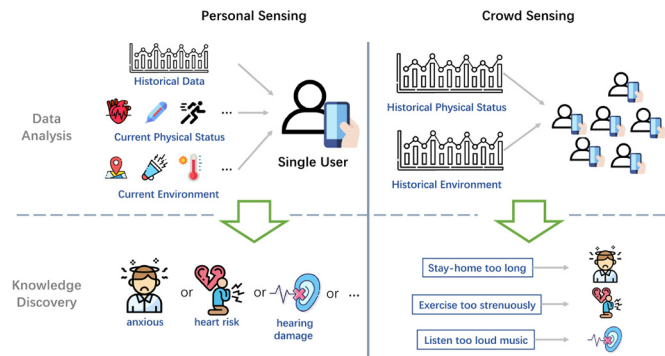


Fig. 4. Comparison of main objectives of data analysis and knowledge discovery in the systems for personalized medicine and population health.

knowledge about individuals and populations from data, and proper healthcare actions [234], [235].

Systems for personalized medicine usually recognize [236] or predict [237], [238] the individual user's health status by integrating his/her historical, as well as physical and environmental data surrounding a specific health issue to accurately recognize/predict health risks and provide precise healthcare interventions at the right time, as shown in Fig. 4.

- 1) **mHealth Accuracy in Risk Prediction:** Effective personalized healthcare services rely on the accuracy of health status modeling and progression prediction. Sufficient multimodal data collected in user daily, such as medicine history, physical biomarkers (e.g., heart rate), and environmental biomarkers (e.g., locations), provides great information for accurately modeling and predicting one's health outcomes and progressions via machine learning approaches [239]–[241]. For example, by passively monitoring schizophrenia patients' psychiatric symptoms represented by surveys and behavioral/contextual characteristics (e.g., physical activity, conversation, mobility) over months, Wang *et al.* [242] proposed a prediction system which predicts psychiatric symptoms' dynamics and progression merely based on mHealth Sensing data without traditional self-reported ecological momentary assessment (EMA).
- 2) **mHealth Precision in Predictive Intervention:** A typical detail objective in this step for the personalized medicine systems is to provide predictive interventions with high mHealth precision responding to recognized/predicted health outcomes and progressions (e.g., increasing depression and anxiety and exposed to high heart risk). Specifically, the precision above lies on precise intervention timing, measures, and intensity, which leads to just-in-time and adaptive mHealth supports [17], [243]. For example, Costa *et al.* [244] proposed to improve one's cognitive performance by unobtrusively regulating emotions with smartwatch notifications in varying detected heart rates. Lei *et al.* [245], by formulating the intervention tasks in real-time as a contextual bandit problem, provided an online actor-critic algorithm to guide JITAI practices.

1) *Crowdsensing for Population Health*: CS practices investigate population health issues by comprehensively mining massive health-related data among researched groups, such as monitoring and screening the population health status in a region in both depth and coverage [241], [246], and verifying and inferring [94] the determinants of specific diseases via powerful statistics-based approaches.

1) *Depth and Coverage of Population Health Monitoring in Communities*: For population health systems (especially for population health monitoring, screening, and surveying), in terms of data analysis, it is meaningful to deeply mine and widely enlarge the information of targeting communities leveraging collected CS data. For example, in many mHealth CS practices, some specific characteristics of health problems (e.g., the contact infection of infectious diseases [247], familial heredity phenomenon of genetic diseases [248], and regional relevance of conventional health habits [249]) give great possibility to finish a mobile population health screening of the whole community by only investigating a subset of this group, which is a manner with accuracy guarantee and lower cost.

2) *Statistical Power of mHealth Approaches in Knowledge Discovery*: The statistical power of the mHealth approaches is a key pursuit for knowledge discovery in large-scale population data. Specifically, in mHealth field, CS is being used as a useful tool to collect and analyze massive population health-related data to obtain medical knowledge, where new knowledge can be summarized or inferred by statistical methods for a better understanding of health determinants [73], such as staying home too long causes mental health problems [87], and lacking exercise would increase the risk of heart attack [102]. For example, Zhang *et al.* [41] revealed how large-scale human mobility affects one's health conditions leveraging the statistical approach (i.e., additive explanation value analysis), which shed light on understanding population health from the perspective of human mobility.

2) *Commonly Existing Objectives—Risks and Ethical Issues*: In both mHealth-based *personalized medicine* and *population health* knowledge discovery practices, some risks and ethical issues cannot be ignored in sensing objectives.

1) *Risks and Ethical Issues*: Risks and ethical issues are crucial in human-subject mHealth research, since personally identifiable health-related data of users would be collected, uploaded, and analyzed, as well as sensitive scientific study results would be made public to varying degrees, even if some certifications are issued by the developers [250], [251]. For instance, funded by advertisers, such as insurance companies, the developer may exposure information to them; some patients and victims may be forced to pay more or even fail to apply, which goes against ethics [252]. Besides revealing private health information, common risks and ethical issues in mHealth sensing systems include data loss, theft and hack [253], excessive or unauthorized collection of data [254], loose medical conclusions,

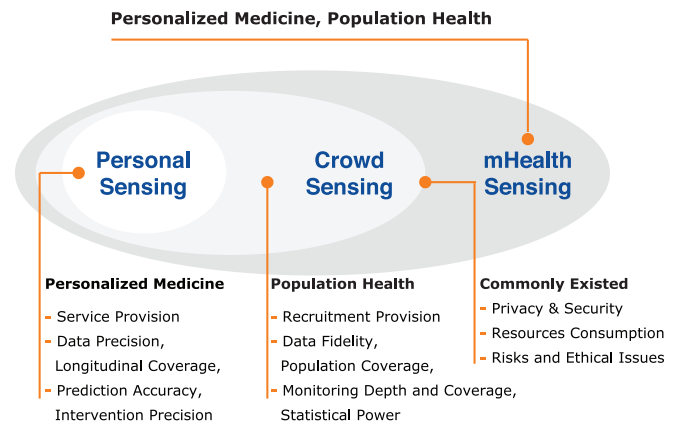


Fig. 5. Relationship between the objectives of PS and CS paradigms.

and negative impact [255], [256]. Besides, the scientific studies carried out with mHealth Sensing systems may be not statistically solid enough, since most of the obtained conclusions are based on limited observation samples and periods; for example, few studies have conducted follow-up studies on large-scale populations for more than a few months, and exact long-term impact of mHealth Sensing systems on personal and population health is still not scientifically clarified [257]. Against this background, appropriate analysis of potential risks [256], ethical issues [258], [259], as well as previously mentioned security and privacy issues should be done ahead of issuing certifications of mHealth systems being used in daily life and even medical scenarios.

It is worth mentioning that deploying CS systems can be regarded as the accumulation of deploying PS systems in a community, sometimes leveraging the same sensor technologies, collecting the same kinds of data, but varying in specific individual-level or population-level purposes. Thus, most of the objectives in PS are also what the CS paradigm pursues in practice by-the-way. In summary, here we present a Venn diagram to conclude the objectives of PS, CS, and mHealth sensing specified above, as shown in Fig. 5. For example, in CS for population health practices, improvements in service provided and data precision also certainly increase the performance of the systems.

#### IV. TAXONOMY SYSTEM II (CLASSIFICATION OF MHEALTH SENSING BY SENSING SYSTEMS D&I)

In this section, as shown in Fig. 6, for each step of the mHealth sensing life cycle, we present and discuss the sensing systems D&I issues on *PS for personalized medicine* and *CS for population health*.

##### A. Design and Implementation Issues in Sensing Task Creation & Participation

To clarify how to promote users' participation and engagement leveraging *services* and *recruitment*, respectively, in *PS for personalized medicine* and *CS for population health*



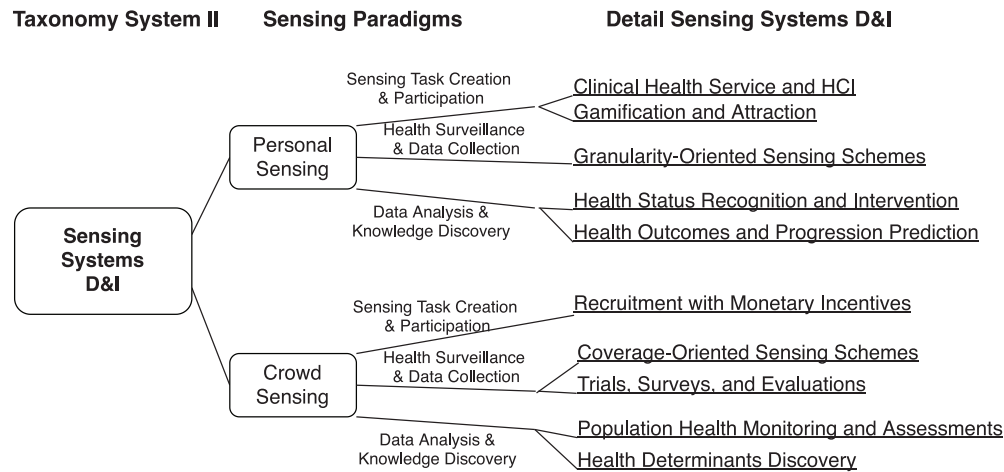


Fig. 6. Taxonomy system II—sensing systems design and implementation (D&I).

systems, in this section, we intend to specify the detail D&I issues of the two paradigms as follows.

1) *Personal Sensing for Personalized Medicine*: The promotion of user engagement in personalized medicine systems is by providing *services*. Here, we discuss two typical forms of user engagement services—1) *clinical health service and human–computer interaction (HCI)* and 2) *gamification and attraction*.

1) *Health Service and HCI*: Providing straightforward and effective clinical health service with good HCI design for user experience is the most intuitive way to increase users' active engagement, since the essential motivation of the users downloading the app is to obtain personal health benefit [260], [261]. In practice, user engagement strategies can be organized as setting sensing health-related targets around users' personalized objectives, delivering adaptive therapeutic feedback, including positive reinforcement, reflection reminders, and challenging negative thoughts [262], and designing easy-to-use platforms [198]. For instance, Cai *et al.* [263], [264] proposed to prompt an adaptive and passive personal mobile sensing framework to provide EMA and intervention services based on reinforcement learning techniques, which significantly increased user engagement in healthcare systems.

2) *Gamification and Attraction*: Gamifying the mHealth sensing systems for providing entertainment would promote user engagement, as not only mobile sensing data can be used as input for gamification [265] but also mobile apps are excellent and prevailing mobile carriers for pervasive entertainment [266]. In practice, gamification strategies are widely applied in *personalized medicine* systems to promote participation, such as self-report data collection [267], [268] (e.g., setting the goals of the game as the indices to be sensed), data preanalysis on client [269] (e.g., pop-up windows asking the user about the activity and status when the app detects a sequence of abnormal indices), and health intervention wrapping [270] (e.g., relaxing users via games). Typically, Rabbi *et al.* [268] designed an app named

SARA, which integrates gamified engagement strategies, including contingent rewards, badges for completing active health tasks, funny memes/gifs and life insights, and health-related reminders or notifications.

2) *Crowdsensing for Population Health*: While gamification could attract participants to engage PS and enable personalized medicine for every participating individual, to scale-up the coverage of health status monitoring for public health purposes, *participant recruitment with monetary incentives* has been frequently used [271] as the compensation to participants' concerns on costs and privacy.

1) *Recruitment With Monetary Incentives*: Monetary incentivization is an intuitive way to quantify and equalize participants' efforts and benefits, though some voluntary CS activities also do exist. In practice, for research or business purposes, mHealth professionals and insurance companies may consider mHealth systems as tools for groups of interests [272]. The monetary incentives strategies can be further divided into categories as platform-centric and user-centric methods [55]. The platform-centric methods refer to that the allocation and adjustment of incentives are charged by the organizers. For example, based on game theory [273], the organizers can lead the task and adjust the strategies by measuring the individual/overall performance of the participants [274]. The user-centric methods are mostly conducted in an auction manner, where participants bid for the tasks published, and the participants with the lowest bids are dynamically paid to complete the sensing tasks [275].

In addition to the above incentive models, there are some works focusing on the participant selection and incentive allocation problems [54], [58], [59], [231], [232], [276]–[278] under certain budgets and data collection objectives/constraints, since sometimes too straightforward incentive allocation may lead to biased selection and low retention rate in recruited populations [279]. Specifically, Xiong *et al.* [59], [276]–[278] proposed several participant recruitment strategies for MCS in either online or offline manners. Wang *et al.* [231], [232] studied the problem of

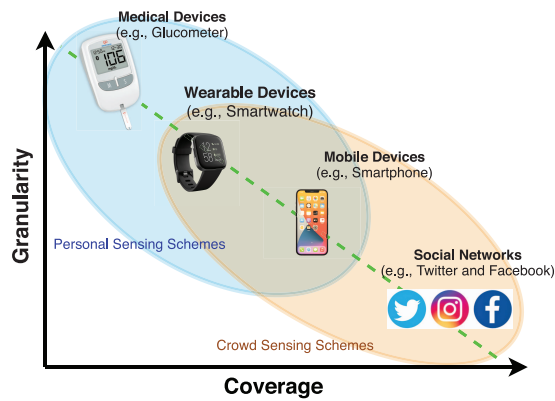


Fig. 7. Comparison of sensing schemes from granularity and coverage perspectives.

participant recruitment and task/incentive allocation in the context of multitasking, where incentives are allocated to the same pool of potential participants for multiple tasks with shared budgets, via hierarchical data collection objectives. The same group of researchers also studied to collect population health-related data from large crowds with nonmonetary incentives in practice [66], [280].

### B. Design and Implementation Issues in Health Surveillance and Data Collection

In health surveillance and data collection, for *data quality*, sensing schemes and data gathering approaches are the main D&I issues. As shown in Fig. 7, in mHealth Sensing data collection, either it requires widespread hardware/media (e.g., social network) with pervasive coverage for population health, or more dedicated devices (e.g., portable medical devices) for granularity and professionalism in personalized medicine, though in most cases they share some pervasive sensing technologies (e.g., smartphone and wearable sensing). Also, besides varying sensing schemes, several specific trails, surveys, and evaluation approaches mostly considered in the CS paradigm are discussed in this phase.

1) *Personal Sensing for Personalized Medicine*: Though the two paradigms sometimes adopt common sensing schemes (e.g., wearable devices and mobile devices shown in Fig. 7) under some circumstances, for the objectives on numerical accuracy and longitudinal coverage, the sensing schemes in PS practices are more granularity oriented.

1) *Granularity-Oriented Sensing Schemes*: To accurately monitor user physical/environmental dynamics in a timely manner, some dedicated and intensive sensors deployed in medical devices are commonly used in PS practices, such as mobile fall detection devices for elderly care in living scenarios [281]–[283] and intensive location/maneuvers monitoring devices in hospital scenarios [284], [285], which are equipped with radar. For example, Fang *et al.* [286], [287] purposely embedded the radio sensor into wearable devices as a powerful sensing modality to provide whole-body activity and vital sign monitoring in a clinical context, which serves

as an example that specialized sensing schemes provide richer function in PS scenarios.

2) *Crowdsensing for Population Health*: To broadly collect health-related data with guarantees of population coverage and data fidelity, in CS practice, the specific sensing systems D&I issues lie in *coverage-oriented sensing schemes* (for population coverage), *trials, surveys, and evaluations* (for data collection efficiency and fidelity).

1) *Coverage-Oriented Sensing Schemes*: In CS practices, though many sensing schemes are the same as those used in the PS systems as shown in Fig. 7, in order to enable the system to be used in a larger population coverage, ubiquitous sensing schemes are prevailing in CS practices, such as social media (e.g., Facebook and Twitter) [288] and large-scale human mobility data, which is not gathered dedicatedly for health-related purposes [87], [289]. For instance, De Choudhury *et al.* [290], [291] used passive sensed data from social medias to measure and predict depression in populations, even further to discover shifts to suicidal tendency from content in Reddit [292].

2) *Trials, Surveys, and Evaluations*: In the CS data collection process, it is essential to motivate participants to keep uploading sensing data with efficiency and fidelity. Typically, trail and survey schemes are for efficiency, and data evaluation schemes are for fidelity. As for *trials and surveys*, microrandomized trials (MRTs) are tools for maintaining and improving participants' efficiency by optimizing the combinations of incentives (e.g., varying levels of monetary incentives, and virtual rewards) [293]–[295]. As for *evaluation schemes*, they are for enforcing data fidelity [296]. In specific, once a new round of data is *collected*, but before accepting the data as convincing, the data fidelity is estimated and only convincing data is *gathered*; according to the estimation, positive or negative feedback is given to participants to reward/punish them in the following rounds. An intuitive scheme, named truth discovery [297], is to let multiple participants finish a same task to find the wrong-data providers [298]. However, this repeated validation manner cannot be adopted for health-related data collection, since sensitive personal data can only be sensed by the individual himself/herself. The trust framework [299] is an alternative means to solve this. Some measurement methods can be used to establish a credit rating measurement system for participants, and implement different acceptance of data contributed by users with different credits, and varied tasks and incentives are dynamically allocated to enforce participants' performance in the following sensing rounds [300], [301].

### C. Design and Implementation Issues in Data Analysis and Knowledge Discovery

With respect to detailed sensing objectives listed in Section III-C, we one-by-one discuss the detail systems D&I issues in this section. Generally, data analysis in personalized medicine practices mostly classify and predict the health status

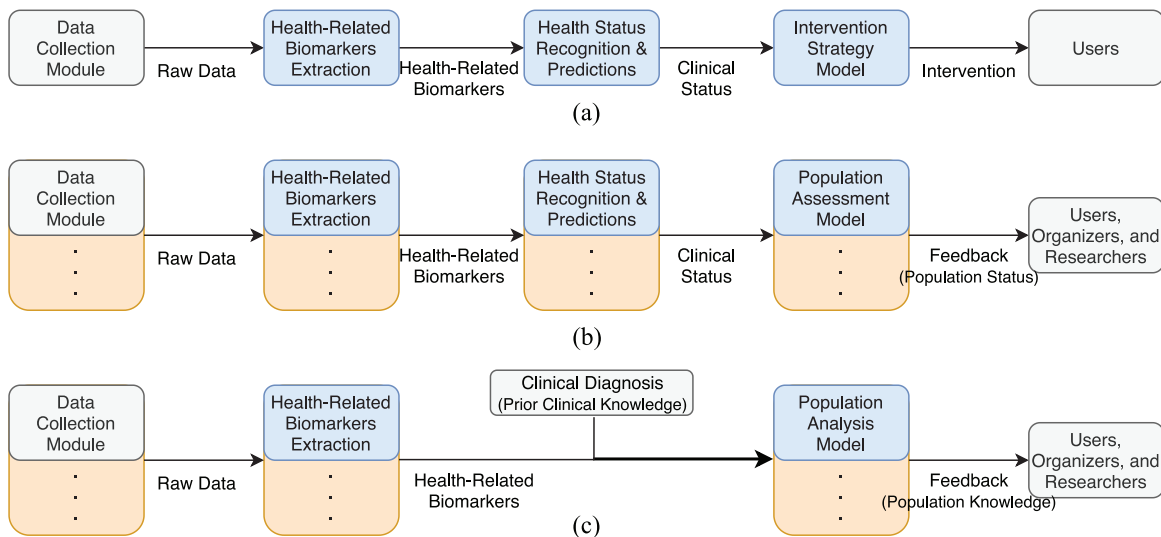


Fig. 8. Data analysis and knowledge discovery workflows in three typical PS and CS systems. (a) Personal sensing for personalized medicine—both for health status recognition and prediction. (b) Crowdsensing for population health monitoring and assessments. (c) Crowdsensing for population health determinants discovery.

and progression via longitudinal data precisely collected from individuals; while, for the population health objective, data analysis is mainly to regress and discover the health determinants leveraging data ubiquitously collected among large groups.

1) *Personal Sensing for Personalized Medicine*: In PS, Data Analysis & Knowledge Discovery serves to mine collected raw data to realize health status *recognition* or health progression *predictions*.

1) *Health Status Recognition and Interventions*: As shown in Fig. 8(a), according to different health status, the PS systems could deliver varying interventions as health-care services for users. What is more, the systems can further recognize users' following status for measurement of the interventions' effectiveness to refine the strategies and suit the users [302], [303]. As for implementations, activity recognition approaches are helpful for health status modeling and recognition [304]–[306]. Okeye *et al.* [307], [308] proposed multiple-sensors-based activity recognition schemes by extracting knowledge from smart ambiances; and Triboan *et al.* [309]–[311] improved the activity recognition methods to be applied in complex environments in a more real-time and fine-grained manner. Besides, MRTs [312] are ideal tools to deliver JITAI for patients. As stated in Section IV-B, the analogous to the designs of MRTs in improving the effectiveness of interventions.

2) *Health Outcomes and Progression Predictions*: Due to the fact that most health problems are determined by multiple pathogenic factors and sometimes progress slowly, it is not trivial for conventional clinical methods to effectively predict health outcomes and progressions via sparse clinical records [313]. PS data provide rich personalized information to model the health status of the user and predict his/her future health outcomes and progressions. As shown in Fig. 8(a), after collecting *raw data* (e.g., GPS location, microphone signal,

and screen status), digital physical and environmental biomarkers (e.g., places, ambient noises, and app usages) can be extracted [314], [315]. Then, personal health status modeling and prediction models analyze individuals' *clinical status* and predict health outcomes and progressions with consideration of longitudinal data, both current and historical. For instance, in the machine learning era, feature embedding and deep learning techniques are good tools to solve the challenges in multidimensional pathogenic factors and long-term disease progression; specifically, feature embedding techniques (e.g., graph embedding) automatically learn and extract influential features [316], and deep learning models (e.g., RNNs and GNNs) could serve as predictors with great performance in dynamically capturing patterns in temporal and other dimensions [237], [238], [317].

2) *Crowdsensing for Population Health*: We discuss two typical applications (i.e., *population health status measurement* and *health determinants discovery*) to conclude D&I in CS applications.

1) *Population Health Monitoring and Assessments*: Intuitively, as shown in Fig. 8(b), once sensing tasks among a group of users are adopted, organizers can scan the clinical status among populations and achieve assessment of population status. Furthermore, in the population assessment models, some techniques (i.e., transfer learning [318]) inspired by some characteristics of population health problems, such as spatial correlation, help achieve low-error surveys of the entire target group by only monitoring a subset of users. For example, to investigate a large group of people, such as the citizens of a country, Chen *et al.* [66] studied and indicated spatiotemporal correlation of neighboring regions and proposed to do data inference for the whole map with limited region samples, which gives insights in operating population health monitoring in a CS manner.

TABLE III  
SUMMARY OF TWO TAXONOMY SYSTEMS FOR mHEALTH PS AND CS

	Sensing Objectives (System I)		Sensing Paradigms and D&Is (System II)	
	Personalized Medicine	Population Health	Personal Sensing	Crowd Sensing
<b>Sensing Task Creation &amp; Participation</b>	Service provision for personalized medicine seekers	Recruitment provision for population health participants	Improving user engagement via clinical health services, gamification and attractions	Extra motivating participants' performance via recruitment with monetary incentives
<b>Health Surveillance &amp; Data Collection</b>	More focusing on data precision and longitudinal coverage	More focusing on data fidelity and population coverage	Using granularity-oriented sensing schemes	Using coverage-oriented sensing schemes with trails, surveys, and evaluations
	Privacy & Security and Resources Consumption			
<b>Data Analysis &amp; Knowledge Discovery</b>	Improving mHealth accuracy in risk prediction and precision in predictive interventions	Pursuing depth and coverage of health monitoring in communities and statistical power of mHealth approaches	Leveraging health outcomes and progressions predictions, and health status recognition and interventions	Leveraging population health assessment and health determinants discovery
	Risks and Ethical Issues			

2) *Health Determinants Discovery*: As shown in Fig. 8(c), the sensing systems D&I issues on mHealth sensing systems for *population health determinants discovery* may differ. Specifically, in clinical practices, especially for mental health and chronic illness, with prior knowledge, such as clinical diagnosis and EMA, organizers massively collecting multimodal data from participants and analyze population patterns among participants' biomarkers and clinical diagnosis to understand health determinants; finally, population knowledge serves as feedback, which benefits to the participants themselves (for health-related interests), organizers, and researchers (for knowledge about the health issues). From the implementation perspective, large-scale data analysis methods give insights on population health knowledge discovery (e.g., inference and understanding) from CS data. For instance, machine learning methods such as clustering algorithms are widely used to classify individuals into groups according to common health-related patterns [319]. Statistical methods, such as statistical inference, are also promising confirmatory tools for understanding and inference on clinical conclusion, which, compared to machine learning, is commonly leveraged by medical scientists since it is a hypothesis-driven and more interpretable method [320]. For example, Boukhechba *et al.* [87] used social interaction anxiety scale (SIAS) correlation analysis to understand how social anxiety symptoms manifest in the daily lives of college students. Huang *et al.* [7] operated a least absolute shrinkage and selection operator (LASSO) linear regression model to infer the causal relationship between mental health disorders and location semantics. In addition to the above issues, the sparsity, bias, and insufficient coverage of collected data, in terms of either surveillance time or the number of human subjects, due to the privacy controls and other concerns, requires more efforts in sensing systems design and implementation [25], [321], [322].

## V. FUTURE DIRECTIONS

In this work, we reviewed the applications and systems of PS and CS for personalized medicine and population health,

respectively, and proposed two taxonomy systems for mHealth Sensing systems from the perspectives of "sensing objectives" and "sensing systems D&I". Here, we summarize the two taxonomy systems in Table III. In future work, we would be looking forward to research in the following directions.

### A. Sensors and Sensing Platforms

Innovations in sensors and sensing platforms have driven the advances of mHealth Sensing. For example, over the past decade, GPS embedded in cell phones has enabled pervasive location-based services and related platforms, which provided new insights on understanding health issues by monitoring human mobility and behavior [41]. Similarly, we see tremendous potential for leveraging recent advancements in recent smartphone-embedded sensors (e.g., TrueDepth sensor<sup>1</sup> deployed in the iPhone, Radar sensor embedded in the Google's Pixel,<sup>2</sup> and mobile biosensors for blood oxygen, skin, etc.) to design the next generation of mHealth sensing. A promising direction would be related to the design of novel sensors and related sensing platforms to enable better health management systems. For example, mobile radar can be creatively used to improve the precision of body vibration recognition, which has good application prospects, especially in at-home elderly care scenarios.

### B. Data Limitation and Data Fidelity

In terms of the data collected in mHealth practices, data limitation and data fidelity are still problems hindering research progress. To be specific, from the perspective of *participation*, mHealth studies are usually small and adherence is a consistent challenge that can cause the collected data to be not sufficient enough to verify the conclusions. As for the *data collection* process, imperfect data collection caused by different user habits, and sensors' manufacturer, model, version, and sampling rate commonly exists [323], [324], causing discontinuous collected data. Furthermore, participants'

<sup>1</sup>About Face ID advanced technology, <https://support.apple.com/en-us/HT208108>.

<sup>2</sup>Google's Pixel 4 will include a radar sensor—here is why that could matter for health, <https://www.mobihealthnews.com/news/north-america/googles-pixel-4-will-include-radar-sensor-heres-why-could-matter-health>.

misoperation or nonadherence would lead to biased/error data gathering and false health conclusions [325]. In terms of *data analysis*, inevitable missing data problem causes difficulties in data analysis. Due to the limitation of the model, many missing data fragments can only be cut off. Thus, works focused at investigating novel mechanisms for improving participants' engagement are still needed. We believe that research in enhancing user-experience design and improving incentive strategies are crucial. Furthermore, advances in data imputation and embedding methods tailored to mHealth studies are needed to mitigate the impact of heterogeneous mHealth data.

### C. Privacy and Security Preserving for mHealth

Note that privacy and security have been widely studied in medical IoTs or medical CPSs [162], [163], [167]–[169], [326], [327]. Compared to medical IoTs or medical CPSs deployed at homes or professional clinics, the mHealth sensing systems leveraging the sensors embedded in ubiquitous mobile devices make the privacy and security issues even more complicated. Moreover, the lack of privacy and security protection is still a challenging obstacle that affects users' willingness of participation and engagement in mHealth sensing. To secure the personal health data from potential leakages, encryption techniques [328] could be used and optimized for mHealth data management. Additionally, privacy protection that controls the access of mobile apps to some critical information [329], [330] is also required to scale-up mHealth in societies. In this way, mobile developers should frequently develop and update the applications with user verification as needed to minimize data access. Thus, a unified and integrated approach, combining the data security and privacy controls subject to the *principle of least privilege* [331], [332] for mHealth sensing, might be a promising direction for future research.

### D. Risks and Ethical Issues in Human-Subject Studies

mHealth research is heavily based on human-subject studies where human are actively being involved in the data collection, data analysis, and information disclosures, causing potential risks and ethical issues. Though some works have been done in software development and data science domains [333], [334], this topic is still understudied. While clinical medical practices pay significant attention to risk analysis and ethical principles [335], the risk analysis and ethical issues in mHealth area are not properly studied and addressed [258], [259]. For example, while medical records and conclusions are drawn under highly professional processes and stored separately by hospitals' databases with strict rules for sharing, the measurements and decisions in mHealth practices may not be as strictly conducted [257]. Truly, some mHealth sensing systems, such as *sensus* [4], already include protocol certification and ethical review components in the system to monitor the whole life cycles of mHealth CS. In the future, scientific study, protocol management, risk analysis, ethical review, and even prescription management [336] criteria and techniques should be further studied, especially for commercially used mHealth sensing systems.

## VI. LIMITATIONS AND CONCLUSION

The mHealth sensing is a practical approach in the modern healthcare domain, which is being widely used for the objectives on either: 1) *personalized medicine for individuals* or 2) *public health for populations*. In this work, we reviewed and summarized mHealth sensing systems deployed over smartphones and commodity ubiquitous devices. Though there are many methods for reporting systematic reviews (e.g., PRISMA [337]), in this article, our review method is mainly intuition driven and vision based. We have covered more than 300 papers, and have proposed new taxonomy systems that summarize and categorize existing works in two sensing paradigms (i.e., Personal and CS) and three stages of the mHealth sensing life cycles in detail.

Also, though we have tried our best to cover the important works in this area and related fields, this survey is still with several limitations. For example, this work did not include professional medical systems for medicare/rehabilitation/assisted living purposes, such as medical sensors [153]–[156], Internet of Medical Things (Medical IoTs) and Medical Cyber-Physical Systems (Medical CPSs) [157]–[174], and medical robots [175]–[178]. Furthermore, there have been a number of great works surveying or reviewing this area and related fields [1], [44], [107], [140], [216], [222], [224], [225], [234], [259], [273], [285], [296], [338]–[342], while we have not compared our taxonomy systems with these works.

To systematically summarize the existing studies and identify the potential directions in this emerging research domain, this work actually presents two novel taxonomy systems from two major perspectives [i.e., *sensing objectives* and *sensing paradigms and Designs and Implementations (D&Is)*] that can specify and classify apps/systems from steps in the life cycles of mHealth sensing: 1) *sensing task creation and participation*; 2) *health surveillance and data collection*; and 3) *data analysis and knowledge discovery*. By discussing the real-world mHealth sensing apps/systems within the proposed taxonomy systems, most of the research problems in mHealth sensing can be formally classified, and several future research directions are pointed out, targeting to provide structural knowledge and insightful ideas and guidance for researchers in the related field.

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