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SURVEY

A Study on Mobile Crowd Sensing Systems for Healthcare Scenarios

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ABSTRACT Due to the growing capabilities of mobile phones and devices, mobile crowd sensing (MCS) is rapidly gaining popularity among researchers in different fields, given its ability to collect data at scale and low cost. MCS is particularly important in the healthcare domain since it provides opportunities to collect health, wellness, and Quality of Life information from a large and diverse population. For example, MCS can be used to detect early signs of emerging health conditions, track the spread of infectious diseases, and assess the effectiveness of interventions without the need for frequent clinical visits. Consequently, MCS can also reduce healthcare costs and help overcome barriers to healthcare access. This article takes a closer look at MCS systems that have been used to collect data for research in the medical and healthcare domains. We provide a thorough analysis of selected systems based on their different health-related objectives, such as monitoring physical activity, detecting and preventing disorders, and providing medical treatment. We also adopt a three-layered architecture to structure health-centric MCS frameworks, consisting of application, data, and sensing layers. In the application layer, we analyze participant recruitment, incentive mechanisms, and task allocation strategies. In the data layer, we analyze the types of data collected and how they are stored and processed for future use. The sensing layer specifies the sensing methods and explains the fundamental requirements at a lower level. Additionally, we explore the significant challenges faced by existing MCS systems and domains that offer promising avenues for future research, which are user privacy, resource utilization, data quality, and user compliance. This work provides insights into some practical applications of MCS, highlights challenges faced by existing MCS solutions, and how they can be addressed, all of which can help catalyze future research in MCS development.

INDEX TERMS Mobile health, mobile crowd sensing, opportunistic sensing, participatory sensing.

I. INTRODUCTION

Mobile Crowd Sensing (MCS) is a powerful strategy that leverages both mobile computing and human intelligence to solve complex problems. The concept of MCS was first introduced by Ganti et al. [1]. *Mobility* is fundamental to this concept, enabled by the portability of mobile and wearable devices, and therefore, the ability to collect data from a user at all times and at all locations [2]. *Crowd* means that participation is based on a group of users rather than a single individual, e.g., leveraging the rapidly growing mobile and wearable user population [3], [4]. In contrast to personal sensing tasks, MCS focuses on multiple participants simultaneously, because it requires a greater amount of information to accurately measure and predict shared patterns, which cannot be achieved with limited data. Finally, *sensing* refers to the data collection tasks participants perform via their mobile and wearable devices and their rapidly growing input and sensor capabilities. The goal of MCS is to leverage these three characteristics to measure and map shared interests by collecting data and extracting information from them [5]. Figure 1 serves as a visual guide that illustrates the different components and processes involved in MCS, providing a comprehensive overview of the MCS

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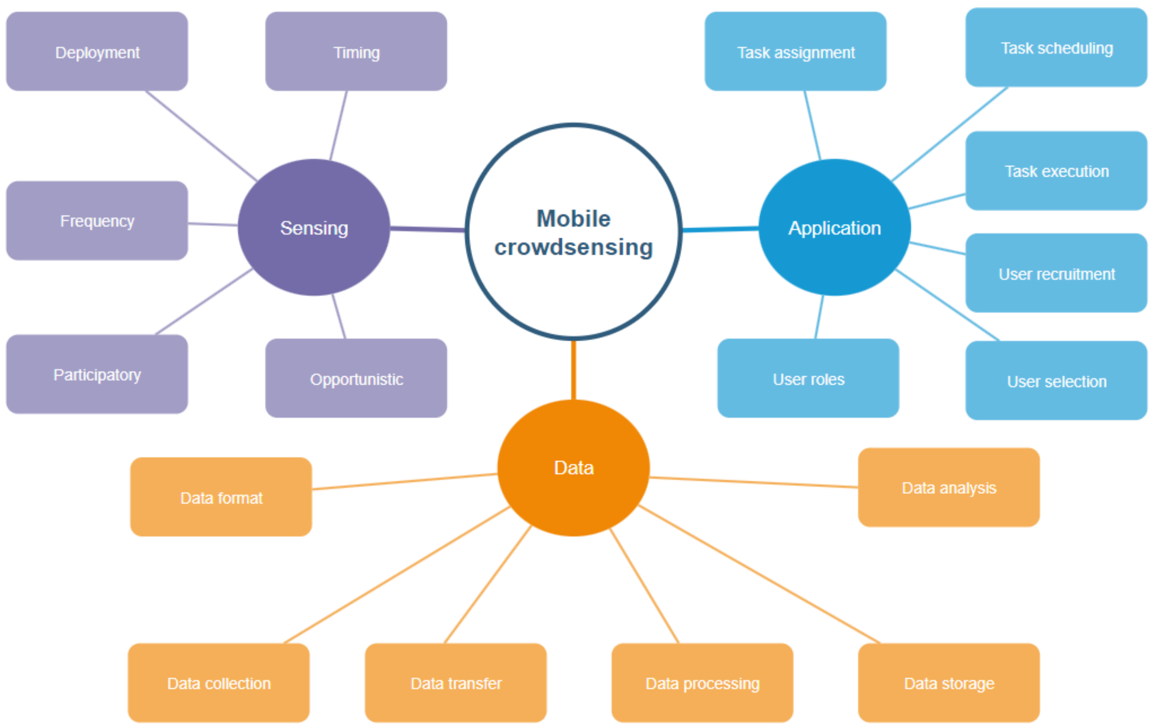

FIGURE 1. A visualization of key features of mobile crowd sensing systems.

system and its various design considerations and interaction points.

The rapidly growing number of smartphones and wearable devices on the market facilitates the growing reliance on the MCS paradigm. For example, in [6], location and phone data were used to detect behavioral changes among study participants to predict factors that might affect their physical and mental well-being. The work in [7] presents a similar study that explores findings on behavioral trends based on the correlation between data collected from smartphones and the academic performance of college students. The study goes further by collecting data from accelerometers, microphones, light sensors, and self-reported surveys to classify participants' activities and emotional states. Conversations and physiological activities were also recorded and analyzed. Today's mobile devices have a wide range of sensors, including GPS, accelerometer, gyroscope, camera, and microphone, but also a growing number of physiological and health sensors. With access to such rich data resources, MCS applications are increasingly being used in application domains such as emergency management [6], [8], [9], [10], public safety [11], [12], urban planning [13], [14], [15], [16], [17], environmental monitoring [18], [19], [20], [21], [22], localization and tracking [23], [24], [25], [26], and social network activities [27], [28], [29], [30], [31].

The growing interest in MCS has also led to various systems specifically designed for healthcare research, with goals such as disease detection and prevention [32], monitoring and detection of activities of daily living (ADLs), assessing behavioral change strategies, and measuring the effectiveness of medical treatment options [33]. The capabilities of smartphone sensors have contributed significantly to research efforts in areas such as activity recognition [7], [34], [35], [36], [37] and emotion recognition [4], [38], [39], [40], which has also enabled the development of comprehensive patient-centric applications and tools such as discussed in [33]. For patients with chronic diseases and their need to closely track their symptoms, it can be beneficial to continuously monitor their health status, allowing them, or their physicians, to make necessary changes based on the collected information [41]. Such data can help detect subtle changes in dietary habits, activity level, and the ability to effectively perform essential ADLs, all of which can be early signs of a variety of health conditions and diseases. While these personal sensing activities provide insights into an individual's health, the collective information from many individuals, often over extensive geographic regions, can also provide insights into disease patterns, environmental factors that contribute to a disease, or the impact of modifiable risk factors on disease outcomes.

This study provides a detailed analysis of existing MCS systems in the healthcare sector that have been used and evaluated in real-world scenarios. Our work demonstrates the importance of a unified architectural framework for MCS systems. The main contributions of this paper are as follows:

- We examine representative healthcare-centric MCS systems and propose a three-layer architecture to analyze their frameworks and functionalities in detail.
- We highlight the benefits and challenges derived from the functionalities chosen by researchers and provide potential solutions to open challenges.
- We present future research directions for MCS systems in healthcare based on today's advanced technologies and techniques.

II. METHODS

The section describes the databases and methods used to choose the most relevant projects. Table 1 shows the complete list of mobile crowd sensing systems covered in this work.

A. DEFINITION AND DATA SOURCES

In this study, we adopted the approach of 'Preferred Reporting Items for Systematic reviews and Meta-Analyses' (PRISMA) [42] for finding related studies. We reviewed and selected relevant papers from various databases such as IEEE Xplore, ACM Digital Libraries, MEDLINE, and conferences such as UbiComp and EAI MobiHealth.

The Patient-Centered Outcomes Research Institute (PCORI) [43] defines 'patient-centricity' in clinical and health services research as follows: *"Patient-centricity is a dynamic process through which the patient regulates the flow of information to and from him/her via multiple pathways to exercise choices consistent with his/her preferences, values, and beliefs. This fundamentally transformative concept affects how health care decisions are made and who has the authority to make them"*. In order to ensure that our selected studies prioritized the needs and outcomes of patients as a fundamental focus, we utilized the definition from PCORI to discern and exclude any studies that did not align with the principles of patient-centered research. Applied to the MCS paradigm, this refers to the relationship between study participants and researchers. Participants have the right to choose what information and data they provide, and it is essential for study creators and administrators to obtain consent and provide guidance to participants. Both parties should have equal power and not dominate the other.

B. SELECTION CRITERIA

We conducted a thorough study following several steps, including identification, screening, eligibility review, and inclusion. Our initial search was based on articles that contained the keywords 'mobile,' 'crowdsensing,' and 'health' in the title or abstract. We discovered numerous research papers that aimed to address specific challenges, such as reward mechanisms, identifying malicious activities, and developing strategies for user recruitment. These papers focus on general methodologies applicable to all MCS frameworks, but they do not describe specific real-world deployment details. After filtering out these papers, we were left with 32 relevant research publications. We then searched for keywords in the full text, including 'patient,' 'disease,' 'illness,' and 'wellness.' At this stage, we filtered out publications that lacked health-centric objectives, did not explicitly state the platform used, lacked participant details, or had no sensor specifications. Lastly, we considered only MCS systems that had been used in real-world scenarios and fell into one of three categories: Health Promotion, Health Research, or Health Maintenance [44]. Our selection process is illustrated in Figure 2.

Health promotion is a category that refers to the promotion of disease detection, behavioral interventions, and monitoring of human subjects [44], [45]. For example, a group of participants performs a series of physical activities. The result can be shared to motivate others to achieve their goals related to their personal health status. *Health research* includes studies that address issues in public health, clinical trials, health experiment methodology, and health research knowledge improvement [44]. *Health maintenance* is a category that includes treatment, medical practice, patients, and diagnostics [44].

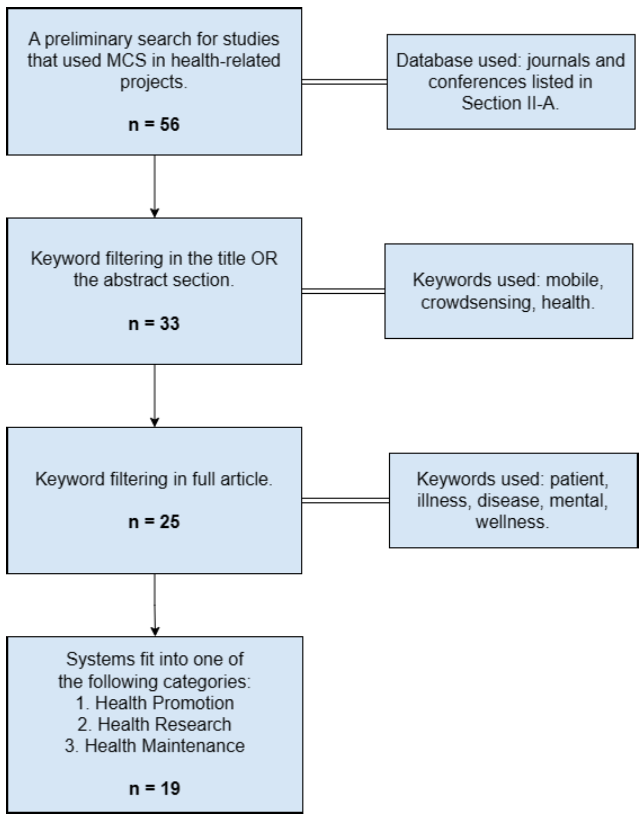

FIGURE 2. Flowchart outlining the process for selecting relevant studies.

C. SELECTED STUDIES AND DATA

We have selected 19 practical MCS systems based on 21 research studies that meet our selection criteria. These projects have been effectively implemented in the past. Moreover, we have compiled a list of valuable surveys related

TABLE 1. Selected 19 MCS systems [7], [34], [35], [36], [37], [38], [39], [40], [41], [46], [47], [48], [49], [50], [51], [52], [54], [55], [56] in the healthcare domain.

Selected mobile crowd sensing projects for healthcare					
Project	**Objective**	**Platform**	**Participants**	**Sensors Used**	**Year Published**
ImageScape [36]	Find dietary patterns from pictures and use them for chronic disease detection.	Mobile phone	6 unspecified users	Camera, microphone, GPS	2007
SPA [41]	Monitor one's body in real-time for chronic disease prevention or treatment.	Mobile phone	Patients with chronic diseases	GPS, accelerometer, BLE, pulse oximeter, blood pressure meter, actigraph	2008
HealthAware [34]	Obesity prevention through activity and food intake monitoring.	Mobile phone	Unspecified	Camera, accelerometer, GPS	2009
AndWellness [38]	Monitor participants' daily habits and behaviors from continuous sensing and survey responses.	Android phone, website	Unspecified	GPS, accelerometer	2010
EmotionSense [46]	Exploit mobile sensing to study human social behavior and provide real-time feedback and psychological help to users interactively.	Mobile phone	18 users from local Computer Science Department	GPS, accelerometer, microphone, Bluetooth	2010
Mental & Physical Assessment [47]	Measure mental well-being and physical well-being of older adults passively by automated and continuous sensing.	Mobile sensing device	8 elderly adults living in a retirement community	Accelerometer, barometer, light sensors, temperature sensors, humidity sensor, compass, microphone	2011
StressSense [40]	Recognize stress from human voice using smartphones.	Android phone	14 young college graduates	Microphone	2012
MSDC [35]	Demonstrate the usefulness of sensors with mobility for patient monitoring system.	Android phone	Unspecified	Accelerometer, temperature sensor, ECG	2012
StudentLife [7]	Use smartphone application to assess students' mental health, academic performance, and behavioral trends automatically and continuously.	Android phone	60 students from the same course	Majority of mobile phone sensors (GPS, accelerometer, audio, proximity, light, etc.)	2014
Mood Traces [39]	Explore whether the mobility behavior of an individual can provide information about his or her depressive state.	Android phone	46 mobile app users	GPS	2015
Patient monitoring [48]	Provides a novel way to record, aggregate, and visualize a large amount of raw data from long-term health monitoring systems.	Mobile phone, PC	Designed for 20 to 30 users	ECG; other bio-sensors based on demand	2015
NetHealth [6], [37]	Access participants' communication patterns, physical activity levels, and sleep to quantify health behaviors. Explore patterns from compliance level, Fitbit sensor data, and submitted surveys.	Mobile phone, website	400+ college freshmen	Fitbit wearable sensors	2016
Sensus [49]	To reduce the gap between human-subject researchers and MCS methods. Assist non-technical study designers in deploying tasks without knowing programming languages.	Mobile phone	10 Undergraduate students from psychology department; 10 from other departments	GPS, mobile phone sensors, consumer-grade wearable sensors	2016
Allergymap [50]	To address the aspects of allergic disease management, patient stratification, control of allergy, and monitoring treatment progress.	Mobile phone, website	Participants with allergic symptom	General mobile phone sensors	2018
TrackYourStress [51]	Investigate time trend of stress levels; test whether the perceived stress levels change or not while using the app.	Mobile phone, website	113 participants from social networks	GPS, microphone	2019
TrackYourTinnitus [52], [53]	To provide patients aggregated information about the variations of their tinnitus over time.	Mobile phone, website	Unspecified	Microphone	2020
BioBase [54]	Test the efficacy of the proposed system on improving the mental well-being of college students.	Mobile phone, wearable	262 college students attending university	Accelerometer, photoplethysmography sensor	2020
Koios [55]	Provide a platform that supports configurations and deployments of different types of studies.	Mobile phone, website	Undergraduate students	Smartphone sensors	2021
SocialSense [56]	Propose a distance monitoring strategy to ensure the minimum physical distance requirement is maintained.	Android phone	Unspecified	GPS, accelerometer	2023

to MCS systems, which are included in Table 3. These surveys address various topics and issues that are related to the selected projects, and they have aided in identifying potential solutions to the problems faced.

III. RESULTS

In this section, we categorize MCS systems based on their specific objective in the healthcare domain and describe their various architectural designs, providing a comprehensive breakdown of each layer of the proposed structure. Table 1 summarizes the chosen projects based on the search criteria defined in Section II. The projects are listed in ascending chronological order. The main objectives and other details about the deployments are also listed.

A. SYSTEM CLASSIFICATION

We categorize the selected MCS systems into three groups: *Activity Monitoring*, *Disorder Detection and Prevention*, and *Medical Treatment*. Some applications do not fit into any of these groups, because they have broader healthcare objectives. However, researchers can customize these more versatile applications to suit different purposes. They are discussed under the *Configurable* category. A detailed description of these categories can be found in Table 2. We also briefly highlight some *General-Purpose* MCS systems, i.e., systems that have not been designed specifically for healthcare application but that can be adapted to study health-related goals. In the end, we included an *Alternative Interpretations* section to highlight other possible classifications for the selected MCS systems aside from our application-centric approach.

1) ACTIVITY MONITORING

Activity is often understood to be physical (such as exercise, activities of daily living, indoor/outdoor mobility, etc.), but often MCS systems must collect many other forms of data that rely on a broader understanding of 'activity.' Examples include sleep [37], food consumption [34], [36], communication via text messages and phone calls [6], face-to-face and online social interaction, device usage patterns, and work or academic performance tracking [7], to name a few.

An example of such a system is MSDC (Mobile Sensor Data Collector) [35], one of the first systems developed for patient activity monitoring based on the Android operating system. MSDC collects three types of data from users: accelerometer, temperature, and ECG (electrocardiogram). Each mobile phone has a near field communication (NFC) tag at the back, which is connected to the smartphone via Bluetooth. The data is collected by the NFC tag and then sent to the smartphone, allowing individuals to view their own health data. After that, the data is sent to a server for real-time analysis and storage. As one of the earliest MCS systems, MSDC illustrates some of the advantages of MCS compared to wired sensor networks in the healthcare sector by making it easier to perform remote monitoring of patients.

To ensure that participants have healthy dietary patterns and to prevent obesity, HealthAware [34] and ImageScape [36] are designed to monitor food intake (e.g., using photos of the consumed food), locations, and activity levels of each participant. Caloric intake and expenditures are estimated so that researchers can predict whether the participant has a good dietary plan and sufficient amounts of exercise. In addition, ImageScape also collects other contextual information, such as timestamps of the photos taken and audio data, so that the collected data can be annotated with time and background noise levels. The clustering strategy used in the project also considered time, loudness, and location to reduce the redundancy of the photos.

StudentLife [7] monitors its participants' mental well-being and academic performance using automatic continuous sensing and self-report surveys. Using continuous sensing by the smartphones, students' activities are closely monitored through readings of the accelerometer, GPS, Bluetooth, microphone, and light sensors. Participants use scaled surveys to report their moods and indicate behavioral changes. Researchers use the data to perform various statistical analyses to find various patterns and correlations.

The COVID-19 pandemic has brought significant changes to people's lifestyles around the world. SocialSense [56] is a tool developed to monitor the physical distance between individuals. Whenever users get too close to each other physically or intend to do so, an alert is sent out as a reminder. Additionally, SocialSense addresses issues such as data quality and security using a federated learning approach.

2) DISORDER DETECTION AND PREVENTION

Many chronic and neurodegenerative diseases have early signs that can be detected, such as irregular heartbeat, sudden loss of mobility, and falling. A few MCS applications are explicitly designed to detect these early signs so patients and healthcare providers can take preventive actions and give timely feedback. For example, the SPA [41] system consists of three main components: a network of body area sensors that collect both biomedical and environmental data, a remote server that stores and analyzes this data, and a team of healthcare professionals who review records and provide healthcare recommendations. In addition, a personalized dynamic context-aware questionnaire is used to collect data and detect any unusual responses from participants. Depending on factors such as blood pressure readings, different sets of questions will be presented to different users. Researchers and health providers can quickly identify any dramatic changes from sensor readings and survey responses and then reach out to participants for more information. Alerts will be sent out automatically based on these unusual signs.

MoodTraces [39] takes a different approach than SPA. It minimizes the involvement of participants' active reporting and automatically monitors an individual's mood disorders through location information only. The goal is to find correlations between mobility patterns and depressive mood.

TABLE 2. Real-world MCS projects with different objectives in the healthcare domain.

Category	Description	Projects
Activity Monitoring	The main objective is to track the type, level, and frequency of users' daily activities and their sleep. Information is collected from various sources, such as the accelerometer, proximity sensor, location sensor, phone calls, photos, and survey answers.	HealthAware [34] MSDC [35] ImageScape [36] NetHealth [6], [37] StudentLife [7] SocialSense [56]
Disorder Detection and Prevention	This category represents systems designed for the early detection and prevention of mental or physical symptoms. Stress, depression, and other physiological signals are assessed from users' input data.	SPA [41] MoodTraces [39] StressSense [40] Mental & Physical Assessment [47] TrackYourStress [51] BioBase [54]
Medical Treatment	The purpose of these studies is to investigate prevailing medical conditions with the intention of scrutinizing symptom patterns and implementing preemptive measures in order to protect a wider population.	TrackYourTinnitus [52] AllergyMap [50] Patient Monitoring [48]
Configurable	Systems that can be customized easily by administrators to fulfill different study objectives and sensing tasks.	Koios [55] EmotionSense [46] Sensus [49] AndWellness [38]

The goal of StressSense [40] is to identify stress using audio data recorded using a smartphone's microphone. Due to different acoustic environments and individual variations of sensing stress, they present a stress detection method using universal adaptive stress models to adapt to specific individuals or environments, therefore predicting the occurrence of stress more accurately.

Stress and anxiety are common among university students and require attention. BioBase [54] aims to alleviate anxiety and promote mental wellness for college students. It offers a mobile app that allows participants to report their mental state and mood changes through ecological momentary assessments. The wearable device BioBeam also collects data on sleep, heart rate, and physical activity opportunistically.

3) MEDICAL TREATMENT

AllergyMap [50] is designed for the community of patients allergic to different allergens such as pollen and dust. This system collects two data sources: objective environmental data about humidity and dust and subjective data on location, time, and assessments submitted by the patients. AllergyMap aims to detect known allergens spatially from the objective sensor data and, based on patient input data (e.g., gender, age, the severity of specific allergies, and symptoms), to prevent patients from going to these identified areas. AllergyMap also stratifies patients based on their profile data so that each patient can learn the status of areas of interest in the level of allergens detected. Historical data from the patients were used to generate the ground truth of the specific individual; therefore, the allergic symptoms can be managed to avoid exacerbation.

The MCS platform TrackYourTinnitus (TYT) [52] tracks how participants perceive their symptoms of tinnitus using a smartphone. It records the environmental sound level and the assessment survey submitted by participants. This work discovered that patients' perception of tinnitus annoyance correlated with other factors, such as stress level. Such findings help control the level of symptoms of tinnitus, which was considered uncontrollable before. Such factors can also be manipulated to mitigate the stress caused by tinnitus.

4) CONFIGURABLE

There are also MCS applications designed for general usage in healthcare. They can be configured easily without the need for programming expertise and knowledge of technical details to design crowd sensing studies at scale and for different tasks. For example, EmotionSense [46] is designed to collect data that describes participants' emotions and activities and to analyze the data to discover correlations among a user's emotions, locations, and activities. The sensors used for this task are localization sensors (GPS, Bluetooth Low Energy or BLE), activity sensors (accelerometer), and microphones, which are all available on modern smartphones. The sampling rates can be configured based on the resources available on the device. The system is designed to minimize user involvement in any of these steps. EmotionSense's goal is to help researchers collect data that can be used for various psychology and sociology investigations. A limitation of the system is that it only runs on the Android operating system.

In contrast to EmotionSense, Koios [55] combines opportunistic and participatory sensing, i.e., in addition to sensor

TABLE 3. Surveys and reviews on mobile crowd sensing and related challenges.

Topic	Title
Mobile Crowd Sensing	Mobile Crowdsensing: Current State and Future Challenges [1]
	A Survey of Mobile Crowdsensing and Crowdsourcing Strategies for Smart Mobile Device Users [2]
	A Survey on Mobile Crowdsensing Systems: Challenges, Solutions, and Opportunities [4]
	A Survey of Mobile Crowdsensing Techniques: A Critical Component for The Internet of Things [5]
	Mobile Crowd Sensing – Taxonomy, Applications, Challenges, and Solutions [57]
	Mobile Health Crowdsensing (MHCS) Intervention on Chronic Disease Awareness: Protocol for a Systematic Review [58]
	A Classification Framework of Mobile Health CrowdSensing Research: A Scoping Review [59]
	Mobile Crowd Sensing and Computing: The Review of an Emerging Human-Powered Sensing Paradigm [60]
	Mobile Crowdsensing in Healthcare Scenarios: Taxonomy, Conceptual Pillars, Smart Mobile Crowdsensing Services [61]
	Referenceable Mobile Crowdsensing Architecture: A Healthcare Use Case [62]
	The Emergence of Visual Crowdsensing: Challenges and Opportunities [63]
	Data-Oriented Mobile Crowdsensing: A Comprehensive Survey [64]
	Mobile Crowd Sensing Architectural Frameworks: A Comprehensive Survey [65]
Security and Privacy	Emerging Security Mechanisms for Medical Cyber Physical Systems [66]
	Privacy-Preserving Mechanisms for Location Privacy in Mobile Crowdsensing: A Survey [67]
	Mobile Crowdsensing: A Survey on Privacy-Preservation, Task Management, Assignment Models, and Incentives Mechanisms [68]
Phone Sensing	Enhancement of Neurocognitive Assessments Using Smartphone Capabilities: Systematic Review [33]
	Participatory Epidemiology: Use of Mobile Phones for Community-Based Health Reporting [69]
	A Comprehensive Study of Mobile Sensing and Cloud Services [70]
Crowd Sourcing	Mapping of Crowdsourcing in Health: Systematic Review [71]
	A Review of Mobile Crowdsourcing Architectures and Challenges: Toward Crowd-Empowered Internet-of-Things [72]
IoT Sensing	Health Monitoring and Management Using Internet-of-Things (IoT) Sensing with Cloud-Based Processing: Opportunities and Challenges [73]
Data Collection	Possibilities, Problems, and Perspectives of Data Collection by Mobile Apps in Longitudinal Epidemiological Studies: Scoping Review [74]

data, it also uses triggers to request a user to answer a survey or questionnaire. This is particularly useful in studies where patient-reported outcomes are combined with sensor data. Koios also integrates with Fitbit wearable devices, so the types and quantities of physiological data collected are more comprehensive than with smartphones alone. It runs on both Android and iOS platforms, with data sent to a central repository, where the received data can be analyzed and displayed using a web portal. Koios data collections are highly configurable, i.e., researchers can use the web portal to design the surveys (questions and answer types, timing/frequency of surveys, rules to trigger survey requests). Researchers can also monitor user compliance, i.e., the number and timing of the surveys submitted and the amount of sensor data that has been collected. With these capabilities, Koios opens the door for many types of crowd sensing studies in healthcare and other domains.

Sensus [49] and AndWellness [38] have the same objective: to reduce the gap between human-subject researchers and the technical details behind MCS systems. AndWellness is another general type of MCS system that is similar to Koios [55]. It collects survey responses via mobile applications and has a visualization dashboard on the web. However, it can only operate on the Android system, while Sensus operates on both Android and iOS.

5) GENERAL-PURPOSE MCS SYSTEMS

Although not initially designed for healthcare, several MCS frameworks can be easily adapted to study health-related objectives. These systems are not included in Table 1, which only focuses on health-centric applications. One of these frameworks is MOSDEN [22], which follows an opportunistic sensing application architecture. It allows access to internal sensors of Android-based smartphones and external sensors of other infrastructure. MOSDEN is initially used for environmental monitoring, such as air and noise, and it also provides timely visualization based on the collected data. To make it suitable for healthcare-specific objectives, the only change needed is to switch the sensors it accesses from microphone to location, accelerometer, and camera as needed.

Medusa [75] makes it easy to obtain health data as it already accesses several sensors such as the accelerometer, audio, camera, and GPS. One of the main objectives of Medusa is video documentation. Video summaries and features are extracted from videos submitted by participants to keep helpful information and filter out irrelevant videos. Instead of extracting features from uploaded videos, it can be configured only to extract health-related information from selected raw data. This reduces overhead and allows for more efficient data collection and analysis.

Pub-SubMCS [76] focuses on solving issues related to efficient worker recruitment, improving data validation and resource consumption, and protecting workers' privacy. It facilitates data collection through sensors embedded in modern mobile phones. Due to its comprehensive mechanism for creating smart contracts for various task subscribers, it can be used to target specific groups, such as people with chronic diseases or other medical conditions, to collect health-related data from their mobile devices.

6) ALTERNATIVE INTERPRETATIONS

The classification of selected MCS systems can vary depending on various factors. One way to interpret the classification is through a system-centric approach. For example, sensor usage distinguishes systems that selectively activate sensors for participatory and opportunistic sensing [7], [39], [41], [46], [51] from those that need them constantly on [37], [47], and [50]. Another way to categorize the systems is based on user roles, with some systems involving users both as task initiators and recipients [41], [50] and others [6], [7], [39], [40], [46], [48] having a clear task flow between administrators and users. Additionally, systems can also be classified based on data collection and processing methods, such as centralized [35], [36], [37], [38], [39], [40] and distributed [34], [47], [56] approaches.

An infrastructure-based perspective can provide further categorization criteria that involve the underlying technologies and physical components that support crowd sensing tasks. These categories may include considerations of using mobile phones [34], [35], [36], [37], [38], [39], [40] or other portable devices [37], [47], Bluetooth utilization [41], [46], network connectivity requirements [50], [51], [52], sampling rate variations [38], [46], [55], [56], and battery life considerations [7], [39], [41], [55]. Furthermore, infrastructure-based categorization can encompass different data storage, data processing, and data analysis methods [46], [47], [48], [49], [50], [51], [52], and communication protocols [34], [35], [36], [37] as additional classification criteria.

Our work proposes a categorization of various MCS systems, focusing on practical objectives and diagnosis. It is crucial to be aware that there are other ways to categorize these systems, such as the system-centric and infrastructure-centric approaches mentioned above. The proposed categorization aligns well with the real-world MCS systems selected in our paper, which strongly focus on objectives.

B. MCS ANALYSIS USING A LAYERED ARCHITECTURE

Section III-A presented an overview of several MCS solutions and their specific applications. In this section, we take a top-down approach inspired by [4] and [72] to analyze these systems further by using a layered architecture approach. Unlike the frameworks used in previous research, our three-layered architecture (Figure 3) concentrates solely on the most crucial features required for healthcare MCS systems. We explain each feature in detail, how it benefits the system, and the goals of their respective studies. Additionally, we use this analysis to provide recommendations for improvements for each of the layers.

1) APPLICATION LAYER

The application layer (Table 4) covers several key requirements for initiating a human-centered research study. In this layer, we discuss participant recruitment, incentive methods, and task allocation.

a: PARTICIPANT RECRUITMENT

Researchers recruit participants for a study either through an open invitation to the public or by selecting targeted individuals. The first strategy is ideal for studies requiring a large and diverse dataset. By involving individuals from various backgrounds, researchers can collect comprehensive data and explore the research question from multiple perspectives. This approach is especially useful for studies that aim to establish generalizable findings or rely on statistical analyses.

- Public: Three studies [37], [39], [40] have employed a direct recruitment approach from the general public. NetHealth [37] targeted the incoming first-year class, aiming to secure a substantial number of participants and ensure appropriate representation across various demographic groups. MoodTraces [39] made its application freely available on the Google Play Store, enabling any user who installs and utilizes it to become a participant. By adopting an open-to-public approach, MoodTraces aimed to explore the relationship between mobility patterns and depressive moods across different age groups and backgrounds. SocialSense [56], like MoodTraces, uses an Android application to collect location and mobility data from users of different ages and geographical regions. StressSense [40] recruited participants within the entire university campus, aiming to incorporate individuals with diverse backgrounds into the research cohort.

- Targeted: On the other hand, the second strategy involves recruiting participants from a narrower and more specific group. This method is often used when the research question demands a specialized sample or when there is a particular target population. By concentrating on a specific demographic, researchers can thoroughly investigate the research topic within the context of the chosen group. This approach enables a more precise and detailed analysis,

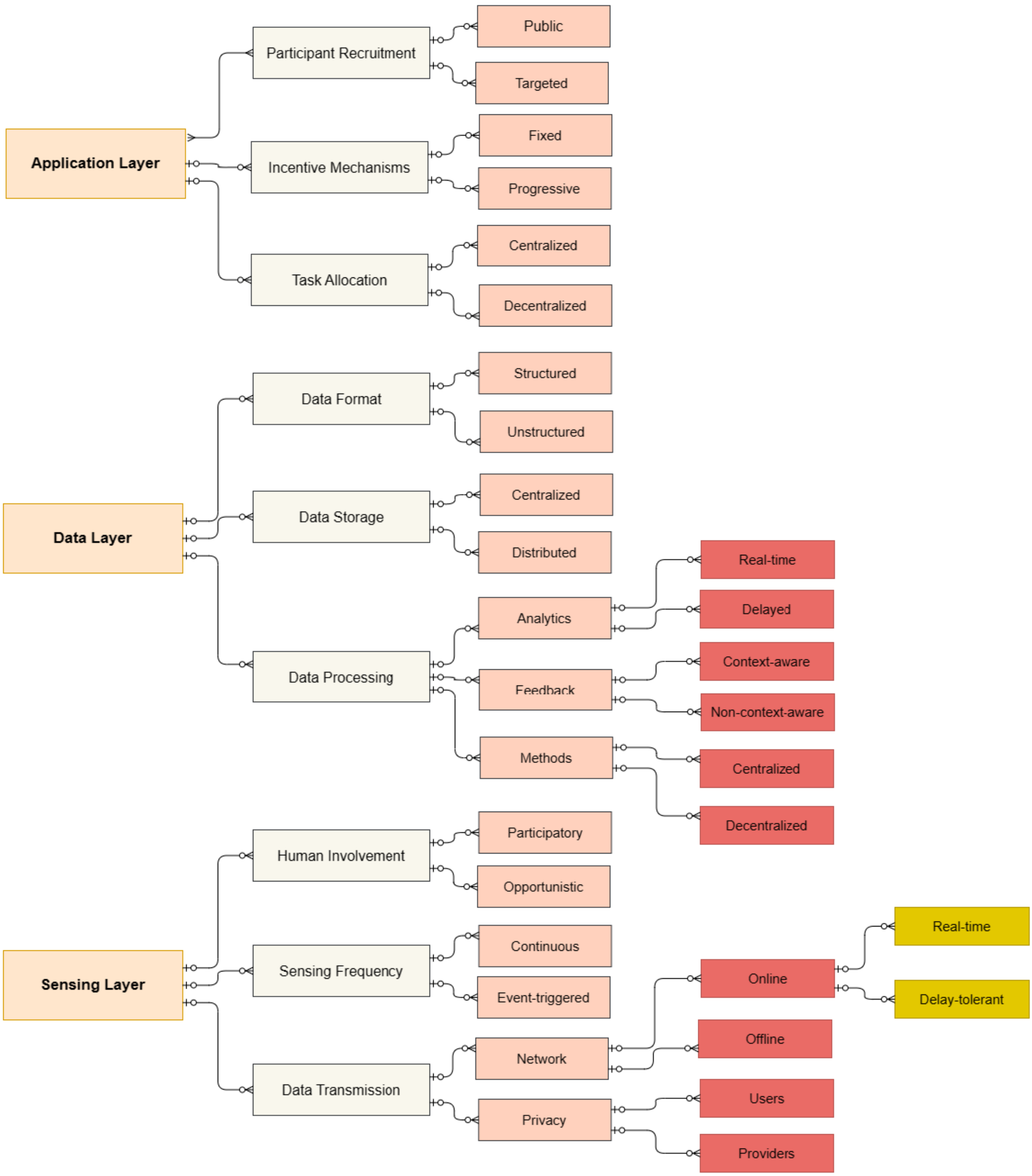

FIGURE 3. **An overview of the three-layer architecture and its different features that can be used for sensing tasks in various scenarios.**

yielding insights that are directly relevant to the target population. However, sometimes a targeted approach is also used out of convenience, i.e., ease of access to a particular group of participants, such as college students or current patients of a clinic.

The studies in [7], [49], [52], and [54] used a pre-screening process to select their targeted participants. In the StudentLife [7] study, participants were selected based on their academic performance and had to be from the same class to make meaningful comparisons. Participants were voluntarily recruited from a computer science programming class. For Sensus [49], participants were recruited from the same psychology class out of convenience. In [52], participants were patients with tinnitus with varying levels of symptom perception. The BioBase [54] study had detailed inclusion criteria to recruit participants, as they aimed to compare the results obtained from a randomized group with a waitlist control group to test the efficacy of their mobile app and wearable device.

Both strategies involve voluntary participation from individuals who have a personal interest in helping or who are directly affected by the health concern. The work in [37], [40], and [54] promoted their studies through emails, flyers, and social media pages, and the studies presented in [7] and [49] advertised solely to their own students in class.

Our analysis found that it is crucial to be aware of selection bias during participant recruitment [77]. This occurs when specific individuals or groups are more likely to be included in a study than others, leading to inaccurate research findings. One common cause of selection bias is convenience sampling, where participants who are easily accessible, such as classmates [46], [49], are chosen. Selection bias can result in a non-representative sample that excludes less accessible individuals. Targeting specific demographics or geographic areas can also lead to selection bias. For example, if a study only recruits participants from urban areas or specific age groups, the findings may differ from the broader population. Selection bias can have significant implications, including malicious results [78] and biased conclusions. To mitigate this, researchers should reach out to diverse populations and use random sampling when possible.

b: INCENTIVE MECHANISMS

The implementation of an incentive mechanism is crucial for MCS studies, because it sets the foundation for maintaining participant enrollment, retention, and high compliance. Incentives are usually rewards that have a monetary value.

- Fixed: Fixed incentive means that participants will get a set reward only after the end of the study. This reward can be predetermined and shared with participants beforehand, giving them confidence that they will get a specific reward for their contributions. This approach is transparent and ensures that participants know what to expect, which can motivate them to stay committed throughout the study. BioBase [54] used a fixed amount of incentives in their research studies. A lottery was used to reward participants in the initial screening process, regardless of whether they were ultimately chosen to participate. At the end of the study, all participants received the same compensation upon returning the wearable device.

- Progressive: Progressive rewards are given out periodically during the study period rather than as a lump sum at the end. These rewards are not finalized in terms of timing or amount, and they may be given out when certain milestones are reached. The specifics of when rewards are given out can change depending on the study's design and goals. This approach keeps participants engaged and motivated by providing rewards throughout their involvement in the study. Progressive rewards also allow researchers to tailor incentives to match the study's specific requirements or goals. Several studies used the progressive reward mechanism [7], [37], [39], [40] for different reasons. StudentLife [7] offered additional bonuses periodically to random top performers, such as participants with high compliance rates, to encourage higher task completion rates. Similarly, in the NetHealth study [37], participants received monthly compensation, and those with high compliance received an additional bonus. MoodTrace [39] wanted to ensure that participants complete a minimum number of surveys. In [40], an incentive was only given when the participant spent a certain amount of time performing the assigned tasks. Finally, the study in [49] only used extra credit for the course taken by the participants as incentives, and many participants withdrew before the study finished. The researchers suspected that the incomplete incentive mechanism directly affected retention. For several other research studies [34], [35], [36], [38], [41], [46], [48], [50], [51], no details are provided if and how incentives were offered.

Comparing the different studies shows that many MCS system developers have not fully considered how much and how often rewards should be given to ensure that their studies meet their recruitment and retention goals. However, a robust incentive mechanism is essential to the success of a study since it affects compliance and participation, data quality, and overall system effectiveness. It is essential to prioritize and address this issue, and researchers should consider the reward structure and frequency to match their study's requirements and objectives. Considerations include assessing factors such as task complexity and frequency, study duration, potential expenses and costs (e.g., traveling or taking breaks from work to be able to participate), and desired participant engagement level.

c: TASK ALLOCATION

Task allocations can be classified into two main categories: centralized and decentralized. We can have a better understanding of the strategies and mechanisms used to coordinate and distribute tasks among participating mobile devices. This distinction serves as a basis for analyzing and optimizing the performance, scalability, and resource utilization of MCS systems.

- Centralized: In centralized task allocation, researchers take the lead in organizing and assigning tasks to participants. They create the tasks, set guidelines and requirements, and make them mandatory for participants to complete. This approach gives researchers direct control over the tasks and ensures a coordinated approach to data collection. Participants receive specific tasks and must complete them according to concise instructions and deadlines. HealthAware [34]

TABLE 4. Three primary components of the application layer are participant recruitment, incentive mechanisms, and task allocation. These components are further categorized based on the strategies used in various works.

Application Layer		
Sub-categories	**Approach**	**Description**
Participant Recruitment	Public [37], [39], [40], [56]	Recruitment for participants is open to the general public population.
	Targeted [7], [49], [52], [54]	Recruitment involves targeting a narrower and more specific group of participants.
Incentive Mechanisms	Fixed [54]	Participants will receive a predetermined reward, which will be shared with them upon the conclusion of the study.
	Progressive [7], [37], [39], [40]	Rewards are distributed periodically throughout the study period instead of being provided as a single lump sum at the end.
Task Allocation	Centralized [7], [34]–[41], [46]–[50], [51], [52], [55]	Researchers exercise direct control over the sensing tasks and closely monitor data collection.
	Decentralized [54]	Researchers provide minimal guidelines and impact once the study commences.

applied centralized task allocation by requiring participants to perform physical activities and upload pictures of their food intake to generate accurate data. StressSense [40] is another system that used centralized task allocation, where participants were given tasks such as mock interviews and sales scenarios to collect emotion-related data. In [47], participants were required to wear a mobile sensing device on their body during the day, with clear instructions given, and adherence was mandatory.

- Decentralized: In contrast, decentralized task allocation involves minimal input from researchers after the study begins. Participants have the freedom to decide whether to complete tasks, making it a spontaneous decision. Researchers may define the study's scope and objectives, but participants can choose which tasks to complete and when to do so. This approach allows for a more flexible and participant-driven approach, potentially resulting in a larger pool of contributors and broader data collection. However, it may also introduce variability in task completion and timing due to different levels of participant engagement and task prioritization. According to one study [54], participants were given the option to use a mobile app or not. This option allowed researchers to test the effectiveness and long-term effects of using the app and paired devices while leaving the decision to participate up to the participants.

In the healthcare domain, the participants in an MCS system are distinct from those in emergency management or public safety domains. This is because the tasks have specific instructions and objectives, and prompt responses are usually necessary. All other systems (18 out of 19) in Table 2 applied centralized task allocation for their studies. Our analysis reveals that researchers face a crucial decision when allocating various sensing tasks: whether to adopt a centralized or decentralized approach. A centralized approach provides greater control and consistency but may result in less genuine data. A decentralized approach offers more freedom to the participants but may lead to challenges in ensuring task completion and data quality. It is essential for researchers to carefully consider this decision as it significantly impacts the overall dynamics and outcomes of the MCS system.

2) DATA LAYER

The data layer, shown in Table 5, describes components such as data format, storage options, and processing features. In this section, we discuss different implementations of these components.

a: DATA FORMAT

It is essential to consider how data is classified based on its format because it affects how the information is organized, structured, and interpreted. We categorize data format as either structured or unstructured.

- Structured: Structured data contains organized and explanatory information, such as demographic information, survey responses, or experiment measurements. The standardized format of structured data makes it easy to collect, store, and analyze. Researchers can quickly sort, filter, and query structured data for statistical analysis and data manipulation without extensive preprocessing.

Two MCS systems [49], [51] collect structured data only. TrackYourStress [51] uses ecological momentary assessments to study the participants' stress levels. The scales and subscales in the assessments are integers used to rate the participants' stress. It also collects the gender and date of birth of the participants. Sensus [49] acquires the participants' personal information from the social media account profile. The structured data has human-readable values and can be easily compared and analyzed.

- Unstructured: In contrast, unstructured data lacks a predefined organization or structure. It includes raw data from wearables, biosensors, smartphones, audio and video recordings, social media posts, and images. Unstructured data requires further analysis and processing to extract useful information and relevant insights. Researchers use techniques like natural language processing, machine learning, or qualitative analysis to uncover patterns. Although unstructured data may contain valuable insights, its lack of predefined

TABLE 5. The Data Layer includes data format, data storage, and data processing. Each category is further classified by the techniques used in our selected works.

Data Layer		
Sub-categories	**Approach**	**Description**
Data Format	Structured [49], [51]	Structured data is organized and easy-to-understand information, such as demographic data, survey responses, and experimental measurements.
	Unstructured [34]–[36], [38], [40], [46], [48]	Raw data comes from various sources such as wearables, biosensors, smartphones, audio and video recordings, social media posts, and images.
Data Storage	Centralized [7], [34]–[41], [46], [48], [49], [51], [52], [55]	All the data is collected and stored in a single location for easy access.
	Decentralized [47], [50], [56]	Participants' data is stored in various locations, which can be distributed across different storage locations.
Data Processing	**Analytics:** Real-time [34], [38], [41], [48]	The real-time analysis allows for quick detection and response to critical situations by immediately processing and analyzing incoming data.
	Analytics: Delayed [7], [46], [47], [50]	The delayed analysis allows for long-term trend analysis, retrospective evaluations, and predictive modeling by storing and analyzing data over extended periods.
	Feedback: Context-aware [34], [37], [40], [41], [46], [55]	Context-aware mechanisms use contextual information, such as location, time, or individual characteristics, to dynamically adapt tasks, recommendations, or system settings.
	Feedback: Non-context-aware [7], [35], [51], [54]	Non-context-aware mechanisms provide participants with consistent and standardized feedback through general instructions, progress updates, and acknowledgments.
	Methods: Centralized [7], [35]–[41], [46], [48], [50]–[52]	Centralized processing involves analyzing and aggregating data in a central location.
	Methods: Decentralized [34], [47], [56]	Decentralized data processing methods leverage the computing power of individual mobile devices.

structure makes it more challenging to analyze than structured data.

HealthAware [34] and ImageScape [36] require pictures of the food as the input data. The pictures cannot provide useful insights and are meaningless before classification and modeling. EmotionSense [46] collects audio data from the microphone. The audio data was used to extract features for analysis and emotion labeling. It is meaningless to compare the raw audio data alone. In fact, many MCS systems [35], [38], [40], [48] collect unstructured data only. Other systems [7], [37], [39], [41], [47], [51], [52], and [56] collected both structured and unstructured data from study participants.

Structured data is arranged in a specific format, while unstructured data captures a broader range of information. Structured data is clear and easily accessible but may overlook valuable insights. Unstructured data provides rich and detailed insights but requires sophisticated techniques to extract meaningful information. Future MCS platforms must find the right balance between structured and unstructured data collection methods.

b: DATA STORAGE

Data storage is crucial for MCS systems in healthcare because it affects the accessibility, scalability, and reliability of the MCS system. Generally, data storage can be categorized as either centralized or distributed.

- Centralized: In a centralized data storage system, all the data gathered from MCS systems are consolidated and stored in a single location. This approach offers the advantage of easy accessibility to all available data for analysis and visual representation, depending on the researchers' objectives. With a centralized system, researchers can process the entire dataset without searching and synchronizing information from various sources. This makes it easier to conduct a comprehensive analysis and better understand the data.

Various mobile health systems [6], [34], [37], [49] utilize a centralized data storage system for their collected health data. HealthAware [34] has its own database dedicated to storing health data, while Sensus [49] uses Amazon Web Services Simple Storage Service for data storage and management. NetHealth [37] used Fitbit to collect data and then stored it in their own database for convenient access. Most MCS systems in healthcare [7], [35], [36], [38], [39], [40], [41], [46], [48], [51], [52], [55] keep their collected raw data and metadata in a central repository for further analysis.

- Distributed: A distributed data storage system involves storing participants' data in different locations. This approach provides better data security and privacy as the data is distributed across multiple locations. However, querying and analyzing the data may be more difficult as researchers may need to gather and integrate data from different locations. The fragmented nature of data storage can make data retrieval and analysis more complex, which may require additional resources and effort.

Three systems, the Mental and Physical Assessment system (MPA) [47], AllergyMap [50], and SocialSense [56] used a distributed data storage approach. In MPA, each participant was given a mobile sensing device to carry individually during the study. The device was returned daily for data extraction and recharge, as there is no central repository for storing the data in one location for access and sharing. On the other hand, AllergyMap used sensor data from a public library online but also required user input to indicate the level of allergic symptoms they experienced. The two databases are independent of each other and stored in different locations. SocialSense collects and stores health-related data of the users' health status, COVID-19 testing status, symptoms, location, and accelerometer data from various geographical regions at each base station for future analysis. Decentralized data storage is considered safer than centralized storage [79] and facilitates data recovery.

Centralized data storage simplifies data management but raises concerns about security and privacy. Distributed data storage enhances data privacy and security but may require more time and resources for synchronization and analysis. Robust security measures and privacy safeguards must be implemented in centralized storage systems, and researchers must weigh the benefits of enhanced privacy against potential trade-offs when choosing distributed storage.

c: DATA PROCESSING

We analyze data processing techniques from three perspectives: analysis, feedback, and methods.

- Analytics: When analyzing data, we categorize the process as either real-time or delayed. Real-time analysis is crucial in healthcare scenarios, as it allows for prompt detection and response to critical situations. Immediate processing and analysis of incoming data enable timely notifications, alerts, or interventions. For example, real-time analysis can help identify abnormal vital signs or detect emergency events, triggering appropriate and timely interventions or notifications to healthcare providers.

Four MCS systems [34], [38], [39], [41] require real-time data analysis. Food pictures captured by [34] were analyzed immediately so that users could quickly locate and track the pictures under the same category. The corresponding required activity levels and calorie intake would be reflected on the main page of the mobile phone application. References [38] and [39] constantly monitored the system time and location of the participants and prompted them to perform actions if a specific trigger was initiated in real-time. Another similar system is the smartphone-assisted system [41], which continuously collects biomedical and environmental data. It detects unusual data changes in real time, and based on the emergency levels of different monitored parameters, the data will be reported to healthcare professionals at different frequencies. Real-time data analysis consumes more resources, but it is fundamental for MCS systems in healthcare as timely responses are necessary and sometimes required.

Delayed data analysis methods, on the other hand, have their own benefits in healthcare MCS systems. These methods support long-term trend analysis, retrospective evaluations, and predictive modeling. By storing and analyzing data over extended periods, healthcare researchers and professionals can identify patterns, trends, and potential risks or insights that may not be immediately apparent. Delayed analysis methods are particularly valuable for epidemiological studies, long-term health monitoring, or predictive analytics to identify disease outbreaks or predict health conditions.

There are four systems [7], [46], [47], [50] analyzed collected data in a delayed manner. StudentLife [7] collects survey responses and sensor data from the accelerometer, microphone, light sensor, and GPS. They were used as inputs to statistical analysis to predict the participants' mental health and academic performance. EmotionSense [46] continuously recorded the audio data of the participants; then, researchers used appropriate classifiers to cluster the data into emotion categories with different granularity. They can compare the accuracy results from emotion recognition, but it does not provide real-time feedback to the users. Another unique example is the system designed for mental and physical well-being assessment [47]. In this study, each participant is given their own sensing device. The data from these devices can only be retrieved by the researchers once the devices are returned. This data collection method is delay-tolerant, which helps conserve computing power and battery life. This ensures that the study can continue without interruption and allows for extended device usage. Reference [50] is a typical study for predictive analysis. The users will only acquire relevant information and feedback once a significant amount of data is collected and analyzed.

In healthcare MCS systems, delayed data analysis can also be beneficial. By analyzing data over extended periods, healthcare professionals can identify patterns and trends that may take time to become apparent. This method is beneficial for long-term health monitoring, epidemiological studies, and predictive analytics to identify disease outbreaks or predict health conditions.

Several systems have utilized delayed data analysis methods, including StudentLife [7], EmotionSense [46], mental and physical well-being assessment system [47], and AllergyMap [50]. StudentLife [7] collects survey responses and sensor data to predict participants' mental health and academic performance. EmotionSense [46] records audio data and uses classifiers to cluster the data into emotion categories. The mental and physical well-being assessment system [47] provides each participant with their own sensing device, and researchers can only retrieve the data once the devices are returned. AllergyMap [50] is an example of predictive analytics that provides feedback to users once a significant amount of data is collected and analyzed.

The real-time analysis ensures quick insights and enables timely interventions or adjustments based on the data. However, it may require significant computational resources and real-time processing capabilities to handle the continuous influx of data. While the delayed analysis may reduce the computational burden and resource requirements associated with real-time analysis, it can lead to delayed responses to users or study creators, potentially hindering real-time decision-making or feedback. It is crucial to strike a balance between real-time analysis and delayed analysis, taking into account the specific requirements and objectives of the study.

- Feedback: Feedback mechanisms in MCS systems encourage participation, enhance data quality, and customize interventions for individual participants. The classification of context-aware and non-context-aware feedback plays a significant role in ensuring effective communication and participant interaction.

Context-aware feedback mechanisms take advantage of contextual information, such as location, time, or individual characteristics, to adapt tasks, recommendations, or system settings accordingly. This approach enables personalized feedback and interventions based on the participant's specific context and needs. Context-aware feedback facilitates targeted interventions, personalized health recommendations, and adaptive task assignments, ultimately enhancing participant engagement and improving the accuracy and relevance of collected data in healthcare crowd-sensing systems.

There are several context-aware systems [34], [37], [40], [41], [46], [55] used in healthcare. For HealthAware [34], user information such as age, gender, weight, and exercise goal is stored in the database. After converting and analyzing the pictures of food consumed, the system will generate updated daily exercise goals and calorie intake. Nethealth [37] tracks users' compliance levels and triggers actions when they fall below the required threshold. StressSense [40] collects human voice from real-life acoustic surroundings and applies it to adapt universal stress models to participants based on user-labeled data. Therefore, each user has his or her universal stress model to predict the occurrence of stress. The SPA [41] will generate personalized surveys for its users based on previous survey responses. In EmotionSense [46], the system has declarative rules based on the 'facts' it perceives. The facts include the user's emotions and environment, and they are used as input to generate additional facts to trigger actions such as turning the GPS sensor on and off. Similar rules could be applied to other sensors as well. Koios [55] used similar context-driven logic to design its crowdsensing platform. Systems with context-awareness capabilities can adjust their behaviors, leading to more meaningful data analysis and efficient system operation. Although they do not consider specific contextual factors, non-context-aware feedback mechanisms are still valuable for healthcare scenarios. They offer consistent and standardized feedback to participants through general instructions, progress updates, and acknowledgments. These mechanisms are also more energy-efficient.

This work includes four non-context-aware systems [7], [35], [51], [54]. [7] does not provide any feedback to the students during the study because the researchers do not want to affect student behavior. The goal is to record their daily experiences discreetly. The system by [35] is designed to collect sensor data independently of external factors. TYS [51] and BioBase [54] track the stress and anxiety of participants by using responses submitted to ecological momentary assessment. The questions under each assessment remain the same during the study period. These systems aim to detect specific patterns from the collected data and do not require contextual information to adapt.

Sensitive data may be used for personalized feedback, which can raise concerns about privacy and security. Protecting participants' personal information and ensuring secure data handling in a context-aware feedback strategy is crucial. However, implementing such mechanisms can be complex and require sophisticated algorithms, data processing capabilities, and access to contextual data sources. This may impose additional demands on system development resources, such as computational power and memory. Moreover, contextual adaptations may not be easily applicable to different contexts or diverse user populations, posing a challenge for ensuring the scalability and applicability of context-aware feedback across various healthcare scenarios. On the other hand, non-context-aware feedback mechanisms may not consider individual differences or specific contextual factors, resulting in a one-size-fits-all approach. This may limit the effectiveness of the feedback, as participants may not receive feedback that aligns with their unique needs or circumstances. Additionally, non-context-aware feedback mechanisms may not adapt tasks, recommendations, or system settings based on changing circumstances or participant progress, resulting in static and less responsive feedback. Researchers need to evaluate these implementations before developing their own MCS platform.

- Methods: We divide methods used for data processing into centralized and decentralized. Centralized processing involves analyzing and aggregating data in a central location, which is ideal for healthcare scenarios. It offers comprehensive data integration, standardized analysis techniques, and enhanced security and privacy measures. With centralized processing, advanced analytics, machine learning algorithms, and data fusion from multiple sources can be applied more efficiently, leading to more accurate diagnostics, predictive modeling, and population health management.

Several systems, such as [37], [38], [40], and [55], use a centralized processing strategy. Reference [40] sends all collected data to a secure server for processing and sharing. AndWellness [38] uses a MySQL database to store all the data collected, and the database is only connected to one central server for processing. Koios [55] and NetHealth [37] used the same strategy to store and process collected data. Most of the systems [7], [35], [36], [39], [41], [46], [48], [50], [51], [52] we discussed in this work used a single server for data processing. Central processing gives researchers and study providers quick access and timely responses.

Decentralized data processing methods use the computing power of individual mobile devices. In healthcare crowd-sensing systems, decentralized processing allows participants to analyze data on their devices, reducing reliance on network connections and maintaining privacy. Decentralized processing is beneficial when real-time analysis or immediate feedback is necessary, as it minimizes delays and enables quick decision-making. Additionally, distributing the computational load across multiple devices can improve system scalability and resilience.

Three of the selected MCS systems [34], [47], and [56] used decentralized data processing. HealthAware [34] stores all data, including photos, on the mobile device for processing. In [47], each mobile device stores the data locally, and there is no central repository. This strategy is feasible and valuable because the system collects sensitive data directly from elderly participants. An advantage of this approach is that data security and privacy are enhanced since only the user can access their data. SocialSense [56] stores data from various sources in separate base stations, each developing its own knowledge graph based on node correlations and similarities. These graphs are then shared across base stations, allowing them to learn from each other while still maintaining user privacy.

As data volumes increase in MCS systems, centralized processing can face scalability issues. Network disruptions or limitations can also hinder data transmission. Mobile devices have limited capabilities, making complex data analysis resource-intensive. Decentralized processing presents challenges with managing and processing heterogeneous data from various devices, which can introduce inconsistencies and errors in processed data. Ensuring data integrity and reliability across heterogeneous devices is an ongoing challenge in decentralized processing.

3) SENSING LAYER

Table 6 illustrates the sensing layer in MCS systems. It includes three main components: human involvement, sensing frequency, and data transmission. This section describes the different approaches to structuring the sensing layer.

a: HUMAN INVOLVEMENT

In [1], it was found that MCS tasks are categorized as either participatory or opportunistic based on the extent of user involvement during sensing tasks.

- Participatory: Participatory sensing requires active and continuous contributions from participants. It involves participants actively engaging in data collection tasks, providing real-time and periodic updates, and actively participating in the sensing process. Participatory sensing is ideal for scenarios where active user engagement and personal data collection are crucial, such as health monitoring or environmental sensing. Two out of eighteen systems [34], [51] used participatory sensing only. HealthAware [34] relies heavily on input data entered by participants manually. One important index used to categorize the food pictures in the database was the name of the food, and it required the user's input directly. TrackYourStress [51] is another system used for participatory sensing only. All the input data comes from the surveys submitted by the participants.

- Opportunistic: Opportunistic sensing tasks require minimal user input compared to participatory sensing. This method utilizes participant mobile device sensors to collect data without additional user involvement. Participants can passively contribute data as they do their daily activities without manual input. Opportunistic sensing is particularly useful for scenarios requiring large-scale datasets where continuous user engagement is not practical or necessary.

Our study showed that most systems, such as [7], [35], [36], [37], [38], [39], [41], [47], [49], [50], [51], [54], and [56], took an opportunistic sensing approach. For instance, [35] collects data from the accelerometer, temperature, and electrocardiogram signals. There is no participant involvement other than equipping the device. Unlike [34], ImageScape [36] automatically captures pictures of food intake and collects additional context information such as location, timestamp, and audio environment. However, participants need to tag pictures manually to share with others. MoodTrace [39] only collects location data, which requires minimal participant involvement, and [47] only instructs participants on how to wear the mobile sensing device, with all sensing tasks implemented opportunistically. SocialSense [56] collects location and accelerometer data in an opportunistic manner. However, users need to submit their COVID-19-related questionnaires manually. Overall, opportunistic sensing is pervasive in MCS systems. Many MCS systems in healthcare use both participatory and opportunistic sensing because data from participants' daily activities and their surrounding environment are both crucial and sometimes necessary.

One major drawback of data collection through active engagement is that it can discourage widespread participation. This is because it requires participants to invest effort and time, which can lead to reduced participation rates. Additionally, relying on users to initiate and maintain sensing processes may result in inconsistent data collection, as participants may only sometimes be available or motivated to contribute. Opportunistic sensing, on the other hand, has limitations because the collected data may lack context and detailed information due to the passive nature of data collection. This makes it challenging to ensure data quality and reliability. Furthermore, opportunistic sensing heavily relies on mobile device sensors, which vary across different devices, leading to potential inconsistencies in data collection. There are also privacy concerns as data is collected without explicit user consent or awareness, requiring careful consideration of privacy protection measures.

b: SENSING FREQUENCY

The sensing frequency refers to how often the sensing task should be performed. Two main approaches to collecting raw sensed data are continuous and event-triggered sensing.

TABLE 6. Sensing Layer is divided into human involvement in sensing tasks, sensing frequency, and transmission of sensed data. They are further classified by different requirements of selected systems.

Sensing Layer		
Sub-categories	**Approach**	**Description**
Human Involvement	Participatory [34], [51]	Sensing which requires active and continuous contributions from participants. It involves participants actively engaging in data collection tasks manually.
	Opportunistic [7], [35]–[39], [41], [47], [49]–[51], [54], [56]	Opportunistic sensing requires minimal user input manually. It utilizes participant mobile device sensors to collect data without additional user involvement.
Sensing Frequency	Continuous [7], [34]–[37], [40], [52], [54]	Collecting raw sensed data continuously at a predefined sampling rate.
	Event-triggered [39], [41]	Sensing tasks are activated based on the detection of specific actions or events.
Data Transmission	**Network:** Real-time [35], [56]	Data is sent to be stored or analyzed immediately after collection.
	Network: Delay-tolerant [7], [36], [37], [39], [41], [48], [50]–[52]	Data can be temporarily stored before being transmitted to the next destination.
	Network: Offline [34], [47]	Data is collected and stored on the mobile device during the sensing task and will only be collected once the study ends.
	Privacy: service users [7], [34]–[36], [47], [49], [56]	For service users, privacy concerns including risks related to identity and location exposure.
	Privacy: service providers [7]	Users engage in harmful behavior and exploit the study, which could have negative consequences on data accuracy and the service providers' privacy.

Continuous sensing involves collecting raw sensed data continuously at a predefined sampling rate, which is suitable for applications that require real-time monitoring or capturing fine-grained variations. This method is commonly used in health tracking systems.

- Continuous: Some systems, such as [7], [34], [35], [36], [37], [40], [52], and [54], used continuous sensing only. One representative example of continuous sensing is accelerometer data sensing for activity recognition [7], [34], [35], [36]. Physiological and environmental sound data also require continuous and independent sensing [37], [40], [52]. Reference [54] used a wearable device on the wrist for data collecting through biosensors. Continuous sensing is required for these systems because coherent and time-series data are fundamental for researchers to analyze the insights and provide meaningful feedback. Some systems implemented both continuous and event-triggered sensing in their crowd-sensing system, such as [38], [46], [49], and [55].

- Event-triggered: Event-triggered sensing, on the other hand, activates sensing tasks based on specific actions or events. When a particular action or event occurs, such as a location change or a sensor threshold being crossed, the system initiates the data collection process. Event-triggered sensing conserves resources by collecting data only when relevant events occur, making it suitable for applications where data collection is focused on specific occurrences or specific conditions.

Two systems, [39] and [41], implemented event-triggered sensing only. In [39], the GPS sensor is activated only when the user starts moving, with the movement detected through changes in accelerometer readings serving as the trigger. The participants in [41] received a personalized survey based on their previous answers. In this case, the previous submission serves as the triggering event.

An event-triggering mechanism can help conserve resources by turning on the sensor only during specific time intervals. Additionally, labeling the raw data with different tags or groups can improve the efficiency of data pre-processing. Many other systems selected in our work used both continuous and event-triggered sensing.

Continuous sensing can consume many resources, such as battery power and network bandwidth. This can cause the device's battery to drain quickly, which limits how long the MCS system can operate. Additionally, continuous data collection generates a large amount of information that can be challenging to process and analyze in real-time, which leads to delays or inefficiencies in data processing and analysis. For event-triggered sensing, it is crucial to accurately detect events or actions that trigger data collection to ensure that the MCS system is effective. False positives or missed events can result in complete or accurate data, affecting the system's reliability and validity. Event-triggered sensing relies on specific actions or events to initiate data collection, but there may be a delay between when the event occurs and when data collection begins. This delay can cause a delay in data collection, impacting the system's real-time responsiveness and the timeliness of the collected data.

c: DATA TRANSMISSION

In healthcare scenarios, it is crucial for MCS systems to transmit data in an effective and reliable manner. It is required to be capable of maintaining and sending information in different situations. We analyze data transmission from two aspects: the network connection's availability and privacy rules. We also examine how systems operate with or without network access and consider both user and service provider perspectives on data privacy during transmission.

- Network: Based on the operational requirements of communication networks, we classify the MCS systems into online and offline modes. Online transmission refers to the process of transmitting data when a network connection is available. This can include cellular networks, Wi-Fi, or GSM. Online transmission can be further classified into two types: real-time-only transmission, where data is sent immediately after collection, and delay-tolerant transmission, where data can be temporarily stored before being transmitted to the next destination.

Two systems [35], [56] must have a consistent network connection to work correctly. In [35], the sensor data needs to be streamed and analyzed in real-time, and the results will be presented to users in the shortest time for health monitoring purposes. SocialSense [56] is a tool designed to monitor physical distancing, ensuring that users maintain a minimum distance of two meters to help reduce the spread of COVID-19. The data is transmitted and processed in real-time so that alerts can be sent out quickly. This allows for prompt action to be taken, helping to keep people safe and healthy.

For systems that have delay-tolerant transmission, such as [7], [36], [37], [39], [41], [48], [50], [51], and [52], network connection is also required to complete the data transmission process. However, the data can be temporarily stored on the device until a connection becomes available. This approach prevents data loss in the event of network instability or unavailability. Reference [37] has a very similar data transmission procedure compared to [35]. The wearable Fitbit device will record the sensed data locally first. When a Bluetooth connection is available, the device will transmit the data to the user's mobile phone. Finally, the data is uploaded to the Fitbit server if the mobile phone establishes an internet connection.

Real-time data transmission relies on a stable network connection, which can lead to disruptions in areas with limited coverage or network congestion. Delay-tolerant transmission has its own challenges, including delays caused by internet connection and device storage limitations. Participants may also prioritize other activities, further delaying the process.

Offline transmission, as the name suggests, refers to the scenario where data is collected and stored locally on the mobile device during the sensing task without any network connection. Offline MCS systems typically have their own on-device databases to store the collected data. The stored data is shared or uploaded later when there is a chance for data synchronization.

Two systems, [34] and [47], implemented offline mode for data transmission. HealthAware [34] stored the pictures of food and data collected from the accelerometer. Another system that operates under offline mode is [47]. Each user carries the mobile sensing device around the waist. All sensing tasks are performed offline, and users return the device to researchers daily. The data collected is stored locally on the device and can only be uploaded and shared after the study has ended. This approach ensures that sensing tasks can be completed without network connections and minimizes the computing and transmission overhead.

Data synchronization delays can affect real-time decision-making and analysis. Offline networks limit interaction and hinder the responsiveness of some MCS applications. Storing data only on mobile devices risks data loss without backup mechanisms. Offline transmission also requires adequate storage capacity and can impact device processing power and battery life. When considering whether to integrate offline data transmission into their MCS platform, researchers must carefully examine the specifics of their studies and the nature of the data they collect. Factors such as the size and complexity of the data, the frequency and urgency of updates, and the availability and reliability of network connections all play a role in determining the feasibility and benefits of offline data transmission.

- Privacy: To maintain the confidentiality of users' data and ensure the accuracy of information received by service providers, the privacy component of the MCS system is essential. In the upcoming paragraphs, we will examine the importance of privacy for both service users and service providers.

Privacy concerns for service users include the risk of exposing their identity and location and a lack of awareness regarding privacy risks. Many MCS systems [7], [34], [35], [36], [47], [49], [56] implement privacy measures for their participants or service users. StudentLife [7] provides more comprehensive privacy considerations than other systems. It uses random IDs to anonymize user identities and one-way hashing to conceal phone calls and message information. Data uploading is also encrypted with SSL to prevent third-party interception, and when participants leave the study, their data is removed from the server. Some systems [34], [36], and [56] used distributed repositories for data storage to minimize data sharing and communication, while others [35], [47] focus more on privacy concerns after the data has arrived at central repositories. Sensus [49] uses run-time data anonymization for the GPS and survey data. SocialSense [56] utilized Federated Learning to protect user privacy. The models were trained on decentralized data sources and later connected by sharing individual knowledge graphs. In healthcare MCS systems, user privacy is typically protected by anonymizing identities. This is especially important because many participants are patients who prefer to keep their identities confidential.

The importance of privacy for service providers is often overlooked, especially regarding data reliability. This is particularly evident in crowdsensing tasks, where users are rewarded for completing periodic surveys or assessments. However, if a user submits multiple identical surveys, the data becomes useless and can mislead the study. This issue is discussed in [7], which suggests that rewarding users based on the total number of tasks completed may lead to abuse.

MCS systems have a significant vulnerability when safeguarding users' privacy. The risk of revealing their identity and location is a significant concern, which could result in compromising personal data. There is a possibility that participants unintentionally divulge sensitive information, thereby raising concerns about security breaches. Users may be inclined to complete multiple identical surveys to maximize rewards, generating repetitive or misleading data that could impair the study's reliability. To address this weakness, future MCS platforms should implement mechanisms to identify and prevent fraudulent or duplicate submissions. Data validation, integrity checks, and outlier detection can help identify and eliminate unreliable or suspicious data. Clear guidelines and protocols should be established to discourage fraudulent behavior and ensure data quality.

IV. DISCUSSION

In this section, we discuss essential considerations when designing and using MCS systems for healthcare and how researchers have addressed them so far. Figure 4 presents a visual representation of these complex and demanding aspects that require careful consideration. To address each topic separately, we will first summarize some of the techniques used in selected systems. Then, we summarize current techniques that could be used to address the challenge. Finally, we point out potential future development directions.

FIGURE 4. Main challenges in designing mobile crowd sensing systems.

A. PRIVACY PRESERVATION

MCS systems in healthcare applications and settings are designed to collect personal and sensitive information about their users, and consequently, there is a need for stringent security and privacy considerations [80]. User privacy should always be prioritized, especially when handling sensitive health information. Besides the risks of breach of confidentiality, concerns about privacy could also prevent users from enrolling in a study in the first place [67].

Anonymization is a critical step used to protect participants' privacy, e.g., in [7] and [41], each participant's identity was anonymized with a random user ID, which was kept in a separate database. Further, the sensed data was transmitted to a central database using an encrypted SSL connection to prevent interception, i.e., MCS data collections must also use state-of-the-art network and systems security features to prevent unauthorized access to and use of personal data. Very often, after a study ends (or after a certain time period beyond a study's conclusion), all data is deleted. In [47], the researchers applied a privacy-sensitive method for processing the data so that the recorded audio data is protected before being stored in the database. In [34] and [47], the data was processed and stored locally on the user's device. When the processed data needs to be uploaded to a central repository, only the results of some initial processing will be uploaded. In SocialSense [56], a Federated Learning approach was used to establish correlations of data collected from each base station. Since each base station across different geographical regions is independent of each other, data privacy is enhanced.

Privacy preservation techniques have also been the focus of several recent studies. For example, CrowdBLPS [81], a blockchain-based system for MCS, protects both the user's location and identity. During the participants' selection phase, it replaces users' actual location with a corresponding cloaked region (calculated by an anonymous spatial area and probability density function). It also implements pseudonymous addresses to represent researchers and users, which provides privacy preservation without submitting the true identity of the selected participant. Privacy-preserving collaborative reputation system (PCRS) [82] is a framework used to preserve user privacy. Participants in this framework collect sensing data and send the data as a report to another participant. The receiving participant can choose to evaluate the report based on the local trust value, which is calculated using past reports, or choose to skip to the next report. Both reports are then sent to a server for storage. This protects user privacy by breaking the connection between real identities and the contextual information of the reported data.

Location privacy [83] is another major concern for MCS systems, as users' location data can be easily compromised by attacks from multiple data sources. Tracking individuals' locations can reveal sensitive information about their daily lives, including their home addresses, workplace locations, and doctor or hospital visits. One solution is to decrease the accuracy of location data or intentionally introduce unique noise to make it harder for attackers to determine a participant's actual location [67]. For instance, the coordinates collected from sensing tasks can be transformed such that only the researchers know how to decrypt them. A potential direction for future research in privacy preservation involves protecting data from leakage and fake sensing attacks by using deep learning methods [84].

B. RESOURCE LIMITATIONS

Mobile sensing devices, such as smartphones, often have stringent resource constraints, including limited energy, low network bandwidth, and limited computational power [1]. Due to the high variability in the resource capabilities of state-of-the-art mobile devices, building a model that can precisely predict resource requirements is challenging. This also makes scheduling and context-aware sensing more difficult.

Over the years, researchers have consistently addressed the energy consumption issue in MCS systems. One approach to tackle this issue is through energy-efficient algorithm design. It involves optimizing task scheduling to reduce idle periods and conserve energy by selectively participating in tasks based on data trends. In [34], researchers designed an efficient algorithm to differentiate and quantify physical activities based on accelerometer readings. This algorithm aimed to balance energy consumption and acceptable data accuracy. Users were prompted to perform walking and running activities to train the system with initial parameters before initiating the study. The obtained parameters are then continuously compared with the base filter to detect and differentiate activities such as walking and running. In [38], researchers compared resource utilization of CPU, GPS, and network usage under different activity inference rates. This data collection system can be configured to change the inference rate from once a second to once a minute to conserve energy and improve the usability of the mobile application. In [47], the authors use delay-tolerant strategies to reduce the resource requirements for real-time continuous sensing. The data collection and upload processes can be performed after sensing task completion. In [55], the authors divided a complete sensing cycle into different intervals based on triggering rules to save resources. For example, to track users' locations, the GPS sensor will be turned on when Wi-Fi connectivity is unavailable and turned off when the connection is available, thereby preserving energy.

Collaborative sensing and task offloading have become increasingly popular recently. These techniques enable nearby devices to work together, sharing the burden of sensing tasks and data collection. In [85], the authors proposed a blockchain-based architecture to ensure energy efficiency. All the registered devices in a research study are grouped under a software-defined network (SDN). Every activity and transaction occurring on each user's device is closely monitored by the SDN controller. If one device's remaining resource goes below a certain threshold, the packet (all data collected) will be transferred to another device for further transmission. With the proliferation of mobile devices, the volume of data collected in future experiments will only increase. Reference [79] suggests that using a compressive data schema is also an effective solution. Sensed data is initially stored on participants' mobile devices, and the entire dataset is reconstructed later using signal recovering, requiring less central storage capacity.

C. DATA QUALITY

Ensuring that data quality is high is a fundamental concern because the quality of the data impacts what we can do with and learn from the data. We divide issues related to data quality into two areas: data inconsistency and data redundancy.

One typical example of inconsistent data is location data, which is often a critical data source needed to understand a user's context, provide location-aware services, or request user activities based on the user's current location. One approach to ensuring data correctness is to verify the proximity of the submitted data from the recorded GPS by their registered devices [69]. Due to the different sensing and computing capabilities of mobile devices, the same task accomplished by different users may give us different inference results [68]. Many systems rely on participatory sensing or users' manually provided data, thus introducing the risk of malicious or unintentional data input that could affect the study's outcomes. The work in [86] proposed a cross-validation framework to address these concerns. They recruited a validating crowd to assess the quality of sensed data through stochastic optimization. Useful features were extracted from the raw dataset using a unique sampling technique and then presented to validators. The researchers in [87] developed an efficient algorithm to detect label errors (walking, lying, sitting) from self-reported data to improve data quality. In [81], the researchers focused on improving the quality of participants, i.e., they proposed a participant selection stage before pre-registration to select workers that meet the working condition by quantifying the selection criteria to a local optimization problem. The authors of [32] and [88] proposed improving data quality by enhancing the design and usability of digital health systems.

To improve the reliability of data, researchers have explored using the trustworthiness of sensed data [77] and user reputation scores, as well as maximizing the consistency of data collected by different mobile devices. Additionally, improving the accuracy and efficiency of manually submitted assessments by users through the integration of objective sensor data from smartphones is an area that requires further exploration [33].

Continuous sensing is ubiquitous in the healthcare domain, and the enormous amount of data collected can lead to data redundancy. For instance, [36] keeps taking pictures at a fixed rate; therefore, many similar and duplicated pictures were stored and analyzed. Researchers reduced the number of pictures for data processing by feature comparisons and classifications to remove duplicated and unrelated images. Data are partitioned into different groups, and then duplicated or remarkably similar pictures will be grouped based on the comparison metrics. After removing redundant data, only the ones with unique tags and references will be stored. The work in [41] uses adaptive sampling on predefined features to filter out redundant data. Moreover, data will be aggregated by a defined algorithm when the storage capacity has been reached. AndWellness [38] implemented survey configuration, preventing participants from answering repetitive surveys and reducing data volume.

Another recent strategy for removing redundant data is provided by Compressive CrowdSensing [89], [90]. This approach tries to make correct predictions of collected data by using only a few samples. Researchers found inherent correlations within the data in a small subset, and it becomes unnecessary to collect data continuously at a high sampling rate, thus mitigating the data redundancy problem. This technique could lead to various research directions in areas such as data reconstruction, data accuracy issues, energy management, or managing sampling costs.

D. USER COMPLIANCE

To track users' activities and health conditions efficiently, we need to ensure high compliance. Monetary incentives have been investigated in [37], showing the correlation between reward and participation rate, but it does not necessarily give us more reliable contributions from participants simultaneously. Other factors preventing users from actively participating are fear of sensitive information leakage (privacy concerns) and concerns over resource consumption on their personal devices [2]. Therefore, a more comprehensive incentive mechanism must be developed, with guidelines and explanations available to potential users.

The work in [91] proposed a blockchain-based MCS with a decentralized reward mechanism. Each sensing task is treated as a contract associated with the participant's profile. Participants are rewarded instantly or periodically based on the size of the sensing task and their stored reputation scores. In [2], a well-designed user interface can assist users in achieving higher compliance and better quality of sensory data. To ensure reliable contribution from users, intelligent contracts like those used in [92] can be implemented to evaluate past performance and select potential participants with high compliance. It is necessary to use a model during the recruitment process to identify reliable participants who are likely to complete tasks and comply with tasking rules [93].

During the study pre-registration, potential participants can also evaluate the usability of the system. For example, the work in [32] tested the usability of a neurocognitive assessment application designed for individuals with Parkinson's Disease. User interactions and system layouts should be carefully considered in MCS applications in healthcare, especially for those who may have difficulties completing assigned tasks or using the system.

V. LIMITATIONS

As mentioned in Section III-A6, the interpretation of the selected systems can vary among researchers. The boundaries between 'Activity Monitoring,' 'Disorder Detection and Prevention,' and 'Medical Treatment' are not fixed. Monitoring physiological data can be utilized as input data for disorder detection, and the outcomes from disorder detection can lead to future medical treatment. The highly scalable nature of these MCS systems makes them applicable in a wide range of fields within healthcare. In the future, developing a standardized classification framework that accounts for the interdependencies of the systems' objectives could help address ambiguities and categorize the different facets of MCS systems more effectively.

VI. CONCLUSION

Due to the rapid development of sensor networks, the mobile crowd sensing paradigm has been well-established for different domains. In this paper, we presented a survey of practical mobile crowd sensing systems used for healthcare purposes, and we found significant variations within the proposed architectural frameworks. We classified the selected systems by their primary objectives to show their diverse design choices and robust scalability to fulfill different sensing tasks. We introduced a three-layered architecture and applied it to analyze the chosen research studies. This architecture aims to classify systems based on the methods used in each layer, simplifying future reviews and summaries. Each system must make trade-offs in light of the overlapping challenges in each layer, depending on its objectives. We also offered solutions for existing and potential challenges. Additionally, we identified future research directions for mobile crowd sensing that stem from current challenges.

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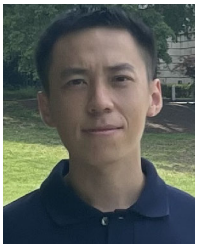

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