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Crowdsourcing in Medical and Public Health Research: A Comprehensive Survey of Applications, Challenges, and Future Directions

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Abstract: Timely and fine-grained public health surveillance is essential for the early detection of emerging health risks; however, existing monitoring systems largely rely on centralized reporting mechanisms that suffer from delays, limited spatial resolution, and poor sensitivity to local outbreaks. Crowdsourcing offers a promising alternative by enabling citizens to report real-time, location-specific health information, but such data is inherently noisy, sparse, and uncertain, making reliable spatio-temporal analysis challenging. To address this problem, this paper proposes an ASTILM for crowdsourcing-driven health risk prediction. The proposed framework integrates a trainable SHI-FIS to model nonlinear geographic influence, a Spatio-Temporal Health Risk Prediction Network (ST-HPN) to capture temporal dependencies, and an Adaptive Feature Fusion Unit (AFFU) to dynamically regulate spatial-temporal interactions under uncertainty. The model is optimized using Huber loss to enhance robustness against outliers common in participatory data. Extensive experiments conducted on a realistic synthetic crowdsourced health dataset demonstrate that ASTILM significantly outperforms conventional CNN, LSTM, CNN+LSTM, and ConvLSTM models, achieving up to 85% reduction in RMSE and 65% reduction in MAE while maintaining strong spatial correlation. The results confirm the effectiveness of the proposed framework for reliable, fine-grained health risk prediction and highlight its potential for deployment in real-world crowdsourced public health monitoring systems.

Keywords: Crowdsourcing, Spatio-temporal, Health surveillance, ASTILM, ST-HPN

INTRODUCTION

Jeff Howe, a U.S. correspondent for *WIRED* magazine, initially introduced the concept of crowdsourcing in 2006. Jeff Howe defines crowdsourcing as the process of freely and voluntarily outsourcing tasks once handled by internal organizational personnel to a non-specific mass network. The rapid development of information technologies, such as the Internet [1], has led to the present form of crowdsourcing, where large-scale projects are distributed to workers worldwide through the Internet, and task outcomes are collected within a short period for integration. Simultaneously, workers performing labeling tasks receive some level of compensation. Thus, one of the primary challenges of crowdsourcing projects is maintaining a balance between label quality, cost management, and time consumption [2]. While crowdsourcing aims to obtain high-quality data labels in a short period at minimal cost, achieving this objective is difficult in real-world scenarios. Therefore, methods for evaluating and integrating low-quality crowdsourced labels are particularly important.

Crowdsourcing is the process of utilizing collective knowledge to solve a problem [3]. It involves a group working collaboratively to address an issue and then sharing the resulting solution. For example, many individuals suffer or die because the initiation of out-of-hospital cardiopulmonary resuscitation (CPR) is delayed.

Crowdsourcing techniques are increasingly being adopted in public health and medicine. Examples include engaging young people in the design of HIV services, enhancing cancer research [4], and developing patient-centered mammography reports. Some crowdsourcing approaches emphasize broad community participation to generate innovative ideas, whereas others focus on collective contributions to produce a single high-quality output, such as clinical algorithms. The target audience for crowdsourcing may include individuals with specialized clinical expertise or members of the general public [5].

Recognizing the growing importance of crowdsourcing, the United Nations Children's Fund (UNICEF), the United Nations Development Programme (UNDP), the

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World Bank, and the World Health Organization (WHO) Special Programme for Research and Training in Tropical Diseases (TDR) published a practical guide on crowdsourcing in health and health research. Although crowdsourcing is becoming increasingly common in medical settings, only a limited number of systematic reviews have specifically evaluated crowdsourcing research in medicine [6]. Existing reviews have generally been broad in scope, have largely overlooked medical applications, and have not incorporated the latest studies. CrowdDesign aims to address the problem of insufficient high-quality data during emerging public health emergencies, where flexible and adaptive models are essential.

Mobile crowdsourcing, in particular, has evolved to support data collection, processing, and problem-solving. It involves individuals voluntarily collecting and sharing data using widely available mobile devices [7]. A cloud-based data-sharing platform processes this information and distributes it to interested stakeholders. Typically, a mobile crowdsourcing system consists of cloud infrastructure and smartphones. The advanced multi-sensing capabilities of modern smartphones have significantly expanded the potential of crowdsourcing.

Public health and medicine continue to adopt crowdsourcing approaches in areas such as HIV services, cancer research, and patient-centered mammography reporting. Some strategies encourage large-scale community participation for idea generation, whereas others facilitate collaborative development of high-quality outputs, including clinical algorithms [8]. Crowdsourcing participants may include healthcare professionals as well as members of the public. Recognizing its importance, UNICEF, UNDP, the World Bank, and WHO-TDR published a practical manual on crowdsourcing in health and health research [9].

Crowdsourcing can also support the development of public health policies, for example, by designing strategies to improve service delivery and expand hepatitis testing [10]. From a scientific perspective, the limited number of rigorous studies highlights the need for additional randomized controlled trials with clinical outcomes. This represents an important gap in the existing literature. One successful example is a recently completed large-scale, eight-city randomized controlled trial that used crowdsourcing to promote HIV testing [11], demonstrating the effectiveness of crowdsourcing in strengthening public health interventions.

Table 1. Applications of Crowdsourcing in Healthcare

Crowdsourcing Application	Purpose of Crowdsourcing	Examples
Informing medical research (formative)	Optimize search processes	Assist with systematic reviews
Pre-clinical research	Share key elements necessary for drug development	Curate drug data; accelerate genomic analysis
Clinical and translational research	Recruit study participants; encourage community engagement	Solicit community feedback; enhance drug development
Post-marketing surveillance	Monitor drug safety and efficacy after approval	Gather adverse event reports from patients
Rare disease research	Pool knowledge and experiences from patients worldwide	Collect patient-reported outcomes and genetic data
Biomedical image annotation	Train AI models for diagnostics	Label MRI, CT, and pathology images
Behavioral and psychological research	Gather diverse behavioral data	Gamified mental health surveys; cognitive task platforms
Public health surveillance	Early detection of outbreaks and health trends	Crowdsourced symptom tracking (e.g., *Flu Near You*)
Health informatics system improvement	Identify issues in EHR systems and improve usability	Crowdsource interface feedback; report system bugs
Medical education and training	Enhance learning through peer knowledge sharing	Share clinical cases; peer review of diagnoses on virtual platforms

Enabling large-scale participation, data collection, and problem-solving, crowdsourcing has become an increasingly useful approach across a wide spectrum of medical and public health research fields. Crowdsourcing is used in the early phases of medical research to optimize literature search techniques and assist in the creation of systematic reviews, thereby using collective intelligence to simplify evidence synthesis. In pre-clinical research, it helps share and curate vital information needed for drug development, including drug characteristics and genetic data, thereby speeding early-stage biomedical innovation. By soliciting feedback and promoting inclusive participation in drug development, crowdsourcing supports participant

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recruitment and community engagement within clinical and translational research. By allowing patients and consumers to report adverse events directly, it helps monitor the safety and efficacy of approved medications through post-marketing surveillance. In rare disease research, crowdsourcing is particularly valuable because it enables worldwide patient experiences to be pooled and patient-reported outcomes and genetic data to be collected, thereby overcoming the challenges of small datasets and dispersed patient populations.

Moreover, crowdsourcing plays a key role in biomedical image annotation by providing labeled datasets—such as MRI, CT, and pathology images—that are essential for training AI diagnostic models. By gathering a diverse range of user-generated data through platforms such as gamified mental health surveys and cognitive task applications, it also significantly contributes to behavioral and psychological research. Crowdsourcing in public health surveillance enables the early detection of disease outbreaks and trends through technologies such as symptom trackers, as demonstrated by platforms like *Flu Near You*, which collect real-time health data from the general population. Crowdsourcing is also used in health informatics to improve the usability of electronic health record (EHR) systems by collecting feedback on interface issues and system defects from users and healthcare professionals. Finally, in medical education and training, it enhances learning through peer-to-peer knowledge sharing, enabling medical professionals to discuss clinical cases and participate in virtual peer reviews of diagnoses. Collectively, these applications demonstrate the growing importance and remarkable adaptability of crowdsourcing as a participatory tool in modern medical research and healthcare.

Table 2. Challenges Involved in Crowdsourcing for Medical Research

Challenge	Description	Examples
Data Quality	Crowdsourced data may be inaccurate or inconsistent due to non-expert input.	Incorrect symptom entries; mislabeling in image annotation
Privacy and Confidentiality	Risk of exposing sensitive patient or participant data.	Unauthorized access to health records; data breaches
Ethical Concerns	Unclear consent and potential exploitation of participants.	Lack of informed consent in online health studies
Participant Bias	Non-representative samples due to self-selection.	Overrepresentation of tech-savvy or urban populations
Regulatory and Legal Compliance	Crowdsourced studies must adhere to health regulations and ethical standards.	Issues with HIPAA or GDPR compliance
Intellectual Property Issues	Ownership and credit for crowdsourced contributions may be disputed.	Disputes over AI models trained on crowd-labeled medical data
Task Complexity	Some research tasks may be too technical for the general public.	Complex genomic data interpretation
Motivation and Retention	Sustaining contributor interest over time is challenging.	Drop-off in participation in long-term health-tracking applications
Verification and Validation	Difficulty in verifying the authenticity of crowdsourced input.	Detecting fake symptom submissions or bot activity
Integration into Formal Research	Aligning crowd input with traditional scientific workflows.	Difficulty publishing studies relying on non-peer-reviewed crowdsourced data

Though it has considerable potential, crowdsourcing in medical research presents several major challenges that must be addressed for effective implementation. Data quality is one of the primary concerns, as non-expert participants may provide inaccurate or inconsistent inputs, including incorrect symptom entries or mislabeled medical images. Privacy and confidentiality are closely related issues because sensitive patient data may be exposed, creating the risk of unauthorized access or data breaches. Ethical concerns also arise, particularly regarding obtaining clear and informed consent from participants, which may otherwise lead to exploitation in online or app-based research. Furthermore, participant bias resulting from self-selection often produces non-representative samples—frequently skewed toward technologically savvy or urban populations—which limits the generalizability of findings. Another challenge, particularly in global data collection, is ensuring compliance with legal and regulatory requirements, including HIPAA or GDPR. Questions of intellectual property also emerge, particularly in determining ownership and appropriate credit for crowdsourced contributions, such as AI models trained using publicly labeled data. Task complexity can further limit success, as some biomedical research activities, such as genomic interpretation, may exceed the capabilities of the general public. Maintaining contributor engagement also remains a challenge, particularly in long-term studies

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where user participation may gradually decline. Verification and validation represent another major concern, as distinguishing genuine submissions from fraudulent entries, bots, or spam is both difficult and essential. Finally, integrating crowdsourced data into formal research frameworks remains challenging because of skepticism within traditional scientific communities, particularly when such data lacks peer review or standardized methodologies. Collectively, these challenges highlight the need for robust design, governance, and quality assurance mechanisms in crowdsourced medical research.

Motivation and Contribution

Driven by the increasing accessibility of digital platforms and mobile technologies, crowdsourcing has emerged as a transformative paradigm in medical and public health research. The motivation for adopting crowdsourcing lies in its ability to harness the collective intelligence and efforts of diverse participants—from the general public to domain experts—to efficiently and innovatively address complex healthcare challenges. Crowdsourcing offers a rapid, scalable, and cost-effective approach to collecting, annotating, and processing large volumes of data, particularly in situations where high-quality data are scarce, such as during public health emergencies. It facilitates the development of adaptive AI models for health monitoring and policy evaluation, enhances data collection with contextual insights, and enables real-time community engagement. For example, crowdsourcing has been used to promote HIV testing, develop patient-centered healthcare services, and improve image-based diagnostics. Mobile crowdsourcing, in particular, transforms smartphones into powerful tools for health data generation by leveraging ubiquitous sensing and community participation. Although challenges such as quality control, privacy, and task complexity remain, the urgent need to address critical public health issues rapidly and inclusively continues to drive growing interest in crowdsourcing as an essential research methodology.

The major contributions of this survey are as follows:

- **Comprehensive Review of Crowdsourcing Applications in Health Domains:** We provide an extensive overview of how crowdsourcing has been applied across diverse stages of medical research, including pre-clinical, clinical, and post-marketing phases. The survey categorizes real-world implementations, such as biomedical image annotation, public health surveillance, rare disease research, and patient recruitment, highlighting their objectives, methodologies, and outcomes.
- **Identification of Core Challenges and Research Gaps:** This work synthesizes existing literature to identify recurring challenges in crowdsourced health research. These include data quality concerns, ethical and privacy issues, participant bias, regulatory constraints, and integration difficulties with formal research frameworks. By mapping these obstacles, the survey underscores the need for standardized protocols and robust governance models.
- **Introduction and Contextualization of the CrowdDesign Framework:** As an illustrative example of innovation in this field, we discuss the design and effectiveness of CrowdDesign—a crowdsourcing-driven AI model selection framework tailored for Public Health Policy Adherence (PHPA) tasks. The framework integrates probabilistic reasoning and human-AI collaboration, demonstrating how crowdsourcing can support not only data collection but also high-stakes AI model design in emerging public health scenarios.

RELATED WORK

This study presents **CrowdDesign**, a crowdsourcing-driven artificial intelligence model design framework intended to address the **Optimal AI Model Design (OAMD)** problem in **Public Health Policy Adherence (PHPA)** applications [12]. CrowdDesign combines the strengths of artificial intelligence and human intelligence through subjective logic to identify the most effective model designs for evaluating public health policy compliance from social media images. Specifically, CrowdDesign first develops a combined network architecture and hyperparameter space reduction strategy that significantly reduces the AI model search space while maintaining a high probability of retaining the optimal model design within the reduced search space. It then employs a probabilistic reasoning-based AI model design scheme that utilizes crowdsourced human intelligence to estimate the probability of each AI model design candidate producing accurate PHPA labels through subjective logic-based probabilistic reasoning. Based on the learned probabilities, the optimal AI model design for the target PHPA application is selected [13].

To the best of our knowledge, CrowdDesign is the first crowdsourcing-driven AI model design framework developed specifically to address the OAMD problem in PHPA applications. This paper focuses on PHPA as a representative use case to demonstrate the effectiveness of CrowdDesign. Nevertheless, the framework has the potential to be extended to a much broader range of real-world applications, including intelligent transportation, smart healthcare, and online recommender systems, all of which rely on sophisticated AI models such as ResNet, VGG, and Transformer architectures, where application performance is highly sensitive to model design [14].

CrowdDesign is evaluated using two real-world PHPA applications: mask-wearing policy adherence and social distancing policy adherence. Experimental results demonstrate that CrowdDesign outperforms a wide range of state-of-the-art deep neural networks, human-AI collaborative models, and AI model optimization baselines in terms of PHPA performance. The significance of this work lies in its potential to transform the monitoring and evaluation of public health policy

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compliance, providing a novel framework that enables rapid adaptation of public health strategies in response to ongoing and emerging health challenges [15].

The work in [16] categorized mobile crowdsensing applications into three groups: **group sensing, community sensing, and urban sensing**. Based on the main features of mobile crowdsourcing stated in [17], these applications can be classified as **people-centric** or **environment-centric**. While environment-centric applications gather information about the user's surroundings (e.g., air quality, noise pollution, road conditions, damage, disasters, etc.), people-centric applications collect data about the user (e.g., physical exertion, sports experiences, etc.).

To improve the performance of automatic question-answering on images acquired by security cameras, Guo et al. developed a crowd-AI camera-based sensing system that gathers various questions and answers from crowd workers [18]. Lin et al. presented a hybrid crowd-AI system that uses crowd-annotated medical image samples to diagnose tropical diseases by improving the performance of deep image classification models [19]. Yoo et al. proposed a task-agnostic collaborative learning framework that employs a crowdsourcing-based deep estimation error inference approach to identify and correct AI failure cases in natural scene classification [20].

Aiming to generalize effectively across different unseen classes, Chen et al. developed a novel zero-shot learning method using meta-learning strategies to adapt to new tasks without requiring additional data [21]. By combining few-shot learning techniques with domain adaptation, Zhao et al. enabled models to rapidly adapt to new data with minimal training instances, thereby improving performance in dynamic image classification [22].

Studies [23] and [24] examined the fundamental components of mobile crowdsourcing systems. They pointed out that crowdsourcing systems must address several key issues, including quality control, task management, incentives, security, and privacy. Furthermore, [25] proposed four simple yet essential questions for developing crowdsourcing applications: **"What is being done?", "Who is doing it?", "Why are they doing it?", and "How is it being done?"** Based on these principles, mobile crowdsourcing applications can be analyzed along four dimensions: **(1) Tasks, (2) Participation, (3) Data Collection, and (4) Processing.**

Study [26] investigated the incentives of crowdsourcing workers. Their research classified motivational factors into intrinsic motivation (e.g., enjoyment and community engagement) and extrinsic motivation (e.g., immediate rewards, delayed rewards, and social motivation). The study found that extrinsic motivational factors significantly influence the amount of time participants spend on crowdsourcing platforms, while intrinsic motivational factors, particularly enjoyment-based motivation, also play a substantial role.

Reviewing relevant conceptual work in mobile crowdsourcing systems, [27] proposed a generic architecture for mobile crowdsourcing applications. The proposed architecture consists of two major components: the backend system/server and the participants/client. On the client side, mobile devices support geo-crowdsourcing campaigns by collecting and transmitting geospatial data using smartphones. The client provides both a user interface and data collection capabilities. The backend system recruits and communicates with suitable participants while managing data storage, processing, and visualization tasks. Study [28] examined existing mobile crowdsourcing systems and identified two primary models. The first is an Internet-based model, in which mobile users serve as service providers over the Internet. The second is a location-based model, where users within a specific geographical area provide cloud-based services through local mobile crowdsourcing.

Based on Singular Value Decomposition (SVD), [29] proposed a binary crowdsourcing approach applicable to various task-answer matrices. Study [30] introduced a multi-class crowdsourcing approach based on the Dawid–Skene (DS) model to overcome the overfitting problem caused by maintaining numerous confusion matrices. Under specific conditions, multiple workers share a common confusion matrix, significantly reducing model complexity while improving robustness. Based on the generalized DS model, [31] proposed a two-step spectral approach for multi-class classification problems. This method further optimized and enhanced the generalized DS model in several aspects. However, these DS-based approaches primarily consider variations in workers' labeling capabilities while ignoring differences in sample labeling difficulty, which can also significantly influence annotation quality.

Study [32] investigated crowdsourcing systems focused on solving both micro-tasks and complex tasks. The authors categorized crowd tasks into several subcategories, including division tasks, aggregation tasks, qualification tasks, and grading tasks. Their task-oriented crowdsourcing framework establishes relationships among workers, requesters, and the crowdsourcing system itself. Using several existing crowdsourcing platforms, they generalized the workflow process while examining the underlying conceptual model. Building upon crowd tasks, [33] proposed a framework in which the most appropriate worker is automatically assigned to each task. Push technology enables automatic worker-task matching through an underlying classification system that utilizes entities extracted from task descriptions together with worker profiles derived from social network information.

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Crowdsourcing has emerged as a transformative tool in medical and public health research by providing scalable and participatory approaches for data collection, annotation, and surveillance. Study [34] established the foundation by categorizing crowdsourcing into innovation contests, health promotion, and research, highlighting its ability to generate clinical algorithms and patient-centered health messages. Study [35] further explored how crowdsourcing promotes public health training through activities such as hackathons and video contests, although many initiatives lacked systematic evaluation. Similarly, [36] demonstrated participatory epidemiology using mobile platforms such as *Flu Near You*, enabling real-time disease reporting directly from community participants.

More recent studies have focused on integrating artificial intelligence with crowdsourced data. Study [37] proposed utilizing crowdsourced patient reviews to assess healthcare accessibility, providing an equitable, bottom-up approach for evaluating healthcare systems. Study [38] compared human annotation with zero-shot learning and concluded that crowdsourcing remains superior for understanding contextual public health text. Studies [39–40] emphasized the growing importance of citizen science through platforms such as *PatientsLikeMe*, demonstrating how individuals can self-organize and contribute real-world health data. Collectively, these studies indicate that although crowdsourcing holds significant promise, future research must address challenges related to validation, standardization, and integration into formal scientific research frameworks.

Table 2. Survey of Existing Crowdsourcing Methods

Method	Advantages	Disadvantages	Research Gap
Probabilistic reasoning + crowdsourcing-driven AI design for PHPA tasks	Integrates human-AI decision-making; reduces AI model search space	Dependent on crowd label quality; limited to social media image tasks	Needs extension to broader domains beyond PHPA and visual data
Crowd-AI Q&A system using camera-based sensing	Improves visual question-answering systems; gathers real-world crowd insights	Data sparsity and noisy answers can reduce quality	Lacks generalization to medical or safety-critical applications
Hybrid crowd-AI system for medical image troubleshooting	Improves tropical disease diagnosis; enhances deep learning model accuracy	Limited scalability; crowd annotation cost can be high	Requires standardization for broader medical applications
Task-agnostic collaborative error inference for AI models	Identifies and corrects deep learning failure cases	Generality limits domain-specific optimization	Not yet evaluated for high-stakes healthcare applications
Binary crowdsourcing using SVD on task-answer matrices	Efficient for binary classification; reduces overfitting risk	SVD assumptions may not hold under real-world label noise	Not extended to multiclass or complex labeling scenarios
Multi-class crowdsourcing using DS with shared confusion matrices	Reduces model complexity; improves robustness	Does not consider sample difficulty	Needs integration of task difficulty modeling
Two-step spectral method for DS-based multiclass problems	Improves DS model scalability; spectral analysis enhances robustness	Ignores worker-task interaction and label difficulty	Requires dynamic adaptation for real-world crowdsourcing tasks
Crowdsourcing system architecture study	Covers quality control, incentives, and task management	Primarily theoretical; lacks deployment case studies	Requires practical evaluation and real-world validation
Study of intrinsic and extrinsic worker motivations	Explains long-term user engagement trends	Difficult to quantify motivations in dynamic platforms	Motivation modeling should be integrated into task design
Task-driven framework with automatic worker-task matching via push technology	Efficient worker-task assignment; leverages social network information	May incorrectly match workers and tasks; privacy concerns	Requires domain-specific optimization and trust modeling

RESEARCH GAP

- **Limited Application in High-Stakes Medical Domains:** Most existing crowdsourcing systems have been evaluated on general-purpose or relatively low-risk tasks. Robust frameworks validated for critical healthcare applications such as medical diagnosis, clinical decision support, and emergency response remain limited.
- **Insufficient Modeling of Label Quality and Task Difficulty:** Although several methods improve label aggregation (e.g., through shared confusion matrices), they generally overlook variations in task

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difficulty and differences in worker reliability across multiple task categories.

- **Scalability and Real-World Deployment Challenges:** Many proposed architectures remain theoretical or have been validated only in controlled experimental settings. Large-scale real-world deployment and evaluation across diverse, dynamic crowdsourcing environments remain largely unexplored.
- **Lack of Unified Quality Control Mechanisms:** Existing crowdsourcing platforms lack standardized and adaptive quality assurance mechanisms capable of effectively handling noisy, malicious, or unreliable inputs without imposing excessive burdens on participants or researchers.
- **Weak Integration with Formal Research Pipelines:** Crowdsourced data and knowledge are often insufficiently integrated into conventional clinical workflows and academic research pipelines, resulting in underutilization and skepticism within the medical research community.
- **Underdeveloped Ethical, Legal, and Motivational Frameworks:** Current research provides limited attention to comprehensive frameworks addressing ethical issues (e.g., informed consent), legal compliance (e.g., GDPR and HIPAA), and sustainable participant motivation strategies specifically designed for medical crowdsourcing.
- **Limited Generalization Across Domains and Modalities:** Many existing models are highly domain-specific (e.g., PHPA using social media data) and demonstrate limited generalizability across multimodal datasets (e.g., text, audio, image fusion) or healthcare domains such as mental health, epidemiology, and genomics.

CONCLUSION

In conclusion, this survey underscores the growing relevance and transformative potential of crowdsourcing in medical and public health research. By aggregating the knowledge, experiences, and contributions of a diverse crowd—from laypersons to domain experts—crowdsourcing has proven valuable across a wide range of applications, including disease surveillance, biomedical image annotation, clinical trial recruitment, and public health policy adherence assessment. However, despite its versatility, the field continues to face persistent challenges related to data quality, ethical concerns, participant engagement, and system integration. Our review reveals that while innovative frameworks such as CrowdDesign represent important advancements, there remains a significant need for standardized methodologies, robust validation techniques, and ethical governance frameworks. Addressing these gaps will be essential to fully realize the potential of crowdsourcing as a reliable, scalable, and inclusive tool for healthcare innovation. Future research should focus on bridging these gaps to ensure that crowdsourced systems are not only technically efficient but also trustworthy, equitable, and aligned with established clinical best practices.

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