Credibility on Crowdsensing Data Acquisition: A Systematic Mapping Study

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***Abstract*—This paper focuses on the credibility of crowd sensed data. The ubiquity of crowdsensing platforms has enabled the capture of sensed information useful for several applications domains. However, one concern with crowdsensing is the information credibility and, over the last few years, we have seen a variety of approaches to leverage credibility on the crowdsensing platforms. Here, we carried out a systematic mapping study on 177 credibility-related articles about crowdsensing. The results show that the absence of standard models in the data capture process and the human factors such as individualism, inattention, and the possibility of errors (whether they are intentional or not), are the primary harmful to the credibility on these platforms. Additionally, we propose a three-level taxonomy that classifies crowdsensing credibility into two broad branches: direct and indirect approaches. To the best of our knowledge, we believe this is the first systematic mapping to address both credibility approaches and the factors that negatively impact the data credibility on crowdsensing platforms.**

***Index Terms*—Crowdsensing, Credibility, Systematic mapping, Data acquisition.**

I. Introduction

Devices of our daily use, such as smartphones, have significantly evolved in their computing, sensing, and communication capabilities [1]. Although we can collect empirical data in several ways, mobile devices have played a crucial role in data sensing tasks as they typically have many sensors attached. The smart devices popularization, together with mobility features, allow these devices to be used to capture large volumes of data, which have contributed to the development of low cost and large scale sensing solutions [2].

A smart data acquisition process is particularly attractive on the Internet of Things (IoT) environments. In there, the sensors can perform not only normal sensing functions but also make optimal decisions without or with minimal human intervention [3].

Open data capture paradigms where information comes from a variety of sources have become quite popular with cloud computing growth, and social networks evolution [2], [4]. The combination of the observations from the fixed urban IoT infrastructure and the crowdsensing devices then contributes to more accurate knowledge about the urban physical phenomena [5]. Despite the advantages of creating a large-scale, low-cost sensing network for data capture, the inherent openness of crowdsensing systems where any individual can contribute to data collection leads to some problems related to information credibility [6]. Systems are susceptible to inadequate, erroneous, and malicious data submission [7].

In this systematic mapping study, we aim to identify and classify a range of credibility approaches on crowdsensing platforms, including the factors that negatively impact the credibility of the data on these platforms. Systematic mappings have been adopted for extraction and classification of knowledge in several application domains [8] [9] [10] [11]. Previous works have addressed at different levels the credibility from crowdsensing systems as presented in table I. However, due to the rapid evolution on this complex and relevant subject, here we propose an up-to-date classification on the crowdsensing and crowdsourcing literature works to cover approaches that directly or indirectly leverage the credibility of information on this kind of platforms. We believe that our proposal has a complementary nature in comparison to the related works.

Our findings must be useful for crowdsensing platform users and practitioners by enabling them to broaden the credibility approaches options available to these platforms and to understand what factors most negatively impact these platforms. It is noteworthy that the systematic mapping here proposed does not perform an in-depth comparative analysis. Instead, it categorizes credibility approaches and the factors that impair their adoption (through Sysmap).

The remaining of the paper is organized as follows. Section II presents a brief background. The systematic mapping method is described in Section III. Section IV reports the mapping results concern each research question. In Section V, the findings of this mapping study are discussed. Finally, Section VI presents the conclusions of this paper.

II. Background

In this section, we briefly discuss systematic mappings, crowdsensing, and credibility-aware approaches.

A. Systematic Mapping

An empirical study that investigates a specific research question is called the primary study. On the other hand, secondary studies review primary studies related to a question in search of evidence on a given problem [19]. Systematic mapping is a type of secondary study that aims to identify and classify studies on an area or topic of interest [20]. This type of study aims to answer research questions such as *What do we know about the topic T?* and can be used to guide further research in area [21].

Although systematic mappings made use of the same methodology as systematic reviews, they have different objectives. Systematic mappings identify and classify the research

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TABLE I
SOME RELATED WORK ON CROWDSENSING CREDIBILITY

Work	Year	Summary
Allahbakhsh et. al. [12]	2013	Focused on quality-control in crowdsourcing systems under a life-cycle perspective to classify existing quality approaches.
Mousa et al. [6]	2015	Separated the existing trust systems in two main classes (Trusted Platform module and Reputation) and analyzed vulnerabilities and attacks in participatory sensing applications.
Gao et al. [13], Jaime et al. [14] and Zhang et al. [15]	2015	They reviewed the state-of-the-art incentive mechanism schemes for crowdsensing, as well as their design issues, including data quality.
Pouryazdan and Kantarci [16]	2016	Surveys the state-of-the-art reputation-based crowdsensing in smart cities and discuss the smart citizen factor in smart city crowdsensing.
Restuccia et al. [17]	2017	Explored the main aspects of QoI applied to MCS campaigns. Their main foci were truth discovery algorithms and trust frameworks for mobile crowdsensing.
Agarwal et al. [1]	2017	They examined how human behavior (perception, comprehension, and projection) attributes work in different situation contexts in the MCS system.
Liu et al. [18]	2018	Their main focus was on MCS techniques for reducing resource cost and achieving QoS (Quality of Service). They also discussed MCS applicability toward the IoT.
Our work	2019	A systematic mapping on mobile crowdsensing with an emphasis on data credibility and the factors that negatively influence the credibility of information on these platforms. Moreover, from credibility, we also show that elements created for purposes other than credibility can also indirectly increase the data trustworthiness by working cooperatively with other components of the crowdsensing ecosystem.

related to a topic, the systematic reviews answer questions about the relative merits [20]. Secondary studies such as systematic mappings have been widely employed as a method for extracting and synthesizing knowledge in evidence-based research practices [22].

B. Crowdsensing

In crowd-based data capture paradigms, there is a common idea based on participatory or opportunistic data collection to compose crowd intelligence, which will then be used to solve a variety of specific tasks. Mobile Crowdsensing (MCS) refers to an activity where data is sensed and generated by multitudes of people using devices that they carry with them, typically, mobile devices [23]. It is a new sensing paradigm that empowers ordinary citizens to contribute data sensed or generated from their mobile devices and aggregates and fuses the data in the cloud for crowd intelligence extraction and human-centric service delivery [4].

On the same context, crowdsourcing is closely related to the crowdsensing paradigm. In crowdsourcing, a network of people forms an open call on projects that benefit from the crowd' strength. Crowdsourcing is a form of outsourcing where there is no formal hiring to perform specific tasks [8]. Crowdsourcing tasks may involve crowdsensing activities.

The need for dynamic and smarter data collection in IoT environments leverage the adoption of new sensing paradigms such as participatory sensing and crowdsensing networks to gather data from portable smart devices [3]. In IoT, the emerging techniques integrate multiple sensor types into physical terminals as data sources, and the MCS ecosystem can be used as contributing nodes [24].

MCS is emerging as a distributed paradigm, and it lies at the intersection between the IoT and the volunteer/crowd-based scheme. MCS creates a new way of perceiving the world to significantly extend the service of IoT and explore a new generation of intelligent networks, interconnecting things with things, things with people, and people with people [18]. Human-centered MCS characteristics bring together advantages and disadvantages. The intelligence and mobility of humans can be leveraged to help applications collect higher-quality and context-dependent complex data. On the other hand, humans naturally have personal preferences and behavior issues that are not necessarily aligned with the end goals of the MCS ecosystem [25].

A typical crowdsensing architecture consists of three main components: A crowdsensing platform in general in the cloud, data collectors and service requesters [26]. The crowdsensing platform provides sensing tasks that involve data capture that is performed by the data collectors through their mobile devices. Data collectors send the data to the platform. This data is processed and made available to the end-users or service requesters in the form of information as shown in figure 1.

C. Credibility approaches

Crowd-based systems are susceptible to inadequate, erroneous, and malicious data submission [6]. The data provided by collectors may be misleading, such as intentionally falsified data, hardware/software failure, network issues, and noise in sensed data. There are other indirect challenges, such as user privacy and user incentives [23]. Due to the open nature of the crowd sensed data, crowdsensing platforms not only collect data from various sources but also try to process the data to ensure their credibility [27].

To ensure the credibility of data on crowdsensing platforms, practitioners expand crowdsensing architecture by adding elements that can act directly or indirectly on credibility. We present some of the credibility-aware elements and activities encountered in the literature and its main foundations:

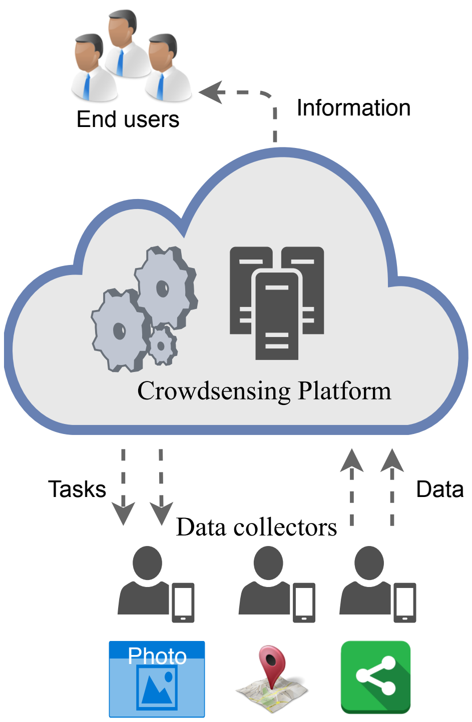

Fig. 1. Simplified crowdsensing architecture.

- *Incentive Mechanisms*: It is an approach in which users receive some reward for collaborating on different levels with the crowdsensing ecosystem. One of the objectives of this approach is to indirectly leverage data quality by attracting honest and skillful data collectors [28]. There are intrinsic incentives, such as personal enthusiasm or altruism, and extrinsic incentives such as a monetary reward. Suitable incentive mechanisms can affect the crowd's performance and produce contributions with higher credibility [12].
- *Reputation Systems*: It is an approach in which reputation scores, based on the previous user contributions, are used to evaluate the trust level of the collector [29]. A reputation system is used to help filter the unreliable participants and reduce the noise that affects data integrity in a crowdsensing platform [23].
- *Task allocation*: Task allocation or task assignment is an activity in which the aim is to achieve a good tradeoff between task quality and task cost. In general, tasks are expected to be assigned to proper data collectors to satisfy specific requirements [30].
- *False-data detection*:Crowdsensing platforms can receive erroneous (unintentionally) and malicious (intentionally) data input [23]. False-data detection is an approach that focuses on detect and correct false or missing values on sensed data due to malicious users actions, security breaks, or faulty sensor readings [31]. False-data detection modules act as a filter and reinforce the credibility on crowdsensing platforms.
- *Privacy Mechanisms*: Privacy concerns cold steer the collectors away from the crowdsensing platform [1]. Security and privacy are essential components of trust, and from a credibility point of view, this approach can stimulate expert user participation and indirectly leverage the data quality.
- *Credibility estimator*: Also known as trust estimators, they compute trust scores which are then used to infer the quality of information (QoI) of the data submitted [17]. Credibility estimators is a direct approach and can be used as a module by other elements to achieve and enforce data credibility.

Despite the individual presentation of credibility approaches. Some of these approaches may act in a complementary way, that is, reputation systems may adopt false-data detection and credibility estimators as part of the calculation of reputation-scores [31]. Task allocators and Incentive Mechanisms can take reputation-scores in decision making [32]. Privacy mechanisms can power incentive mechanisms, credibility estimator, and reputation mechanisms to attracting expert collectors and indirectly contributing to high-credibility data [33].

III. Research Method

This section presents how we organize the systematic mapping concerning research questions, search strategy, exclusion, and inclusion criteria as well as the classification criteria used to aggregate the primary studies. Information on selected and excluded publications at each stage of this mapping is available in the data repository[1] as electronic spreadsheets.

A. Research Questions

The main objective of our work is the identification and classification of the primary studies that address credibility on crowdsensing data acquisition. For this, we used the following research questions (RQ)s to analyze each primary study:

- RQ1: What is the strategy used to ensure the data credibility? This research question aims to identify and classify credibility-aware approaches on crowdsensing platforms. This question includes articles that specifically address proposals to ensure credibility, as well as those that just have made strong use of known credibility-aware approaches on their systems.
- RQ2: Which element or activity has negatively impacted the credibility of information on crowdsensing platforms? This research question aims to map specific factors that directly influence the credibility of information on crowdsensing platforms negatively.

B. Search strategy

Considering the research questions, we used a set of keywords which involve terms that refer to crowdsensing activities as well as quality control, data credibility, and error detection. The keywords used broadly covers the area for credibility on crowdsensing data collection and is sufficient not only for the known privacy/security or reputation mechanisms but also for other indirect categories.

- *Crowdsense: participatory sensing, opportunistic sensing, crowdsensing*.

[1]http://siswebfree.alwaysdata.net/crowdsysmaprepo/

- *Credibility: false data detection, anomaly detection, data correction, confidence level, data accuracy, data quality, data integrity, reliability, information credibility*.

We used the keywords as mentioned earlier to define the search query (SQ), applied to the digital libraries as follow:

SQ. (("participatory sensing" OR "opportunistic sensing" OR crowd-sensing OR crowd-sense OR crowdsensing OR crowdsense) AND ("false data detection" OR "anomaly detection" OR "data correction" OR "data accuracy" OR "data quality" OR "quality of sensing" OR "confidence level" OR "data integrity" OR reliability))

We selected a set of scientific databases to execute the electronic search as stated on Kitchenham [20] guidelines, which contains a collection of recommended digital libraries for evidence-based research. Four digital libraries were used to identify the studies: IEEE Xplore digital library, Engineering Village, ACM Digital Library, and Scopus. Our selected digital libraries indexes relevant peer-reviewed journals and conference proceedings, gathering together studies covering the fields of computer science, social science, and engineering. The Scopus was used to obtain other studies since it explores other digital databases and a significant amount of literature. We also include the reference list of the approved studies for manual searches to expand the results. Table II lists the data sources used in this work.

TABLE II
DATA SOURCES

Source	Details
ACM Digital Library (ACM)	dl.acm.org
Compendex (Elsevier)	www.engineeringvillage.com
IEEE Xplore (IEEE)	www.ieeexplore.ieee.org
Scopus (Elsevier)	www.scopus.com
REF	References of the approved studies

C. Selection of primary studies

To ensure that primary studies unrelated to research questions are eliminated from the search process, as well as ensuring that related are selected for analysis, criteria for inclusion and exclusion should be defined [20]. We divided the studies examination and separation process into stages as per recommendations of Silva Neto *et. al* [11]. In the first stage, we apply selection criteria on reading the title and abstract of primary studies. On the second stage, we read the text in its entirety. We repeat the process on the references list of approved studies. We present the selection criteria in table III, and show an overview of the application of these criteria as a filter in figure 2.

Well-defined selection criteria reinforce the replicability of evidence-based research [21]. We adopt a five years period, from 2013 to 2018 for digital library searches to obtain recent primary studies. However, our manual search stage in the reference list included some studies published before the year 2013. We interested only in studies written in English because of this language adoption in relevant scientific events on different geographic areas [11]. The complete listing of primary studies analyzed is available in our data repository[2].

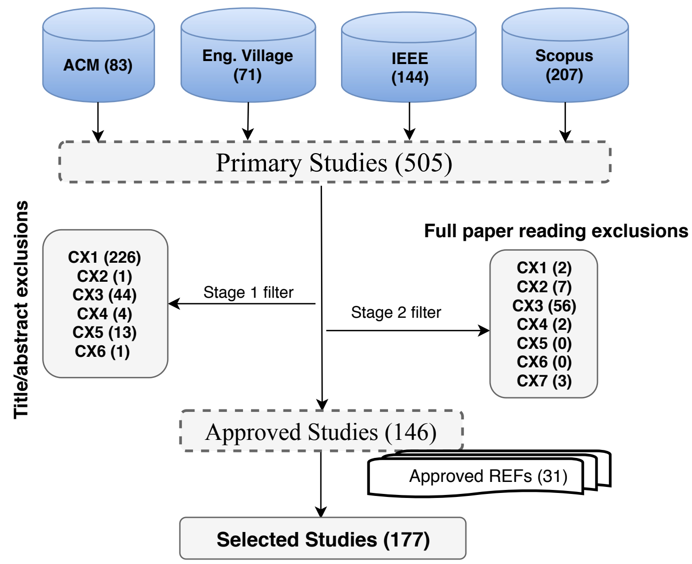

Fig. 2. Selection process.

IV. SYNTHESIS OF EXTRACTED DATA

To identify clusters of evidence, we rank the publications based on their common factors concerning research questions (RQ).

A. RQ1: What is the strategy used to ensure the data credibility?

This research question investigates which item was proposed or actively approached aiming the credibility of the information. The literature lists the credibility-aware approaches in crowdsensing systems in different ways. Some authors are dividing credibility-aware approaches according to the methodology used for trust assessment; they adopt reputation mechanisms and hardware-based solutions as main classifications [6].

We adopt a classification based on the crowdsensing ecosystem data credibility. Our study divides approaches of credibility into direct and indirect categories. In indirect approaches, the focus is on behavioral aspects of the data collector, which indirectly contribute to increasing the overall credibility of the crowdsensing system. Figure 3 presents a three-level taxonomy in which we identify two broad branches: direct and indirect approaches. The former can be classified as credibility estimator, false/missing data detector, and reputation mechanisms. The latter contains task allocators, incentive mechanisms, and privacy/security mechanisms. Within this classifications, we present the credibility approaches more comprehensively.

Table IV presents the publications grouped by their classification extracted from the primary studies concerning RQ1. During the analysis, if the adopted solutions indicate more than one approach, we chose the item most strongly referenced by

[2]http://siswebfree.alwaysdata.net/crowdsysmaprepo/

TABLE III
INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria
1) Primary studies published between January 2013 and December 2018 for searches in digital libraries.
2) Primary studies that have as main theme or that have sections explicitly dedicated to the credibility on crowdsensing data acquisition.
Exclusion criteria
CX1: Repeated primary studies.
CX2: *Short Papers*, where it is difficult to extract answers to research questions.
CX3: Primary studies with no relation to research questions.
CX4: Secondary studies: Surveys, literature reviews and systematic mappings.
CX5: Promotional stuff on electronic searches.
CX6: Primary studies published in a language other than English.
CX7: Full text unreachable.

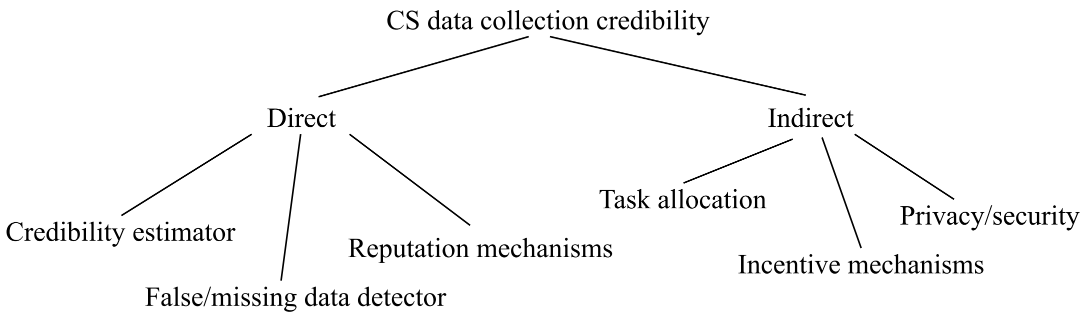

Fig. 3. Proposed taxonomy for crowdsensing (CS) credibility.

the author of the primary study. We group the publications as follows:

1) Incentive mechanism: In this classification, the authors assume that users should have some incentive in the form of rewards that justify the efforts in the data collection. Data acquisition requires an appropriate reward for each contribution, acting as a motivator in capturing relevant data and thus indirectly influencing the credibility [46]. Since the focus of this work is credibility, we present the incentive mechanisms with an emphasis on how they improve the credibility of crowdsensing systems.

As an indirect approach, incentive mechanisms can use other credibility approaches as an intermediary way of assisting in decision-making and leverage credibility. A number of the analyzed publications adopts a long-term approach, using the history of contributions in the decision making of the incentive mechanisms. The primary studies that adopt reputation-scores include that of Sun and Ma [34], Hu *et al.* [36], Yang *et al.* [38], Restuccia and Das [39], Dilruba and Naznin [125], Yang *et al.* [40], Song *et al.* [41], Song *et al.* [43], Sun [45], Peng *et al.* [46], Jin *et al.* [48], Song *et al.* [49], Wang *et al.* [50], Wen *et al.* [51], Sun *et al.* [32], Li *et al.* [52], Sun *et al.* [55], Sun *et al.* [58], Wang *et al.* [69], Wang *et al.* [72], and Xiong *et al.* [74]. They used reputation-scores into the incentive mechanism design to quantify the credibility and reward the best collectors. They explicitly adopted quality and quantity objectives by using incentive mechanisms to attract a large number of collectors and providing rewards to those who provided the most relevant data. The studies are firmly based on the motivation and skills of the collectors to improve the data quality and leveraging the credibility.

Incentive mechanisms also improved the collector's recruitment activities. Zheng *et al.*[37], Zhao *et al.* [42] and Kawajiri *et al.* [54] used spatiotemporal criteria, using the collector's location and availability, and the location of the sensing tasks to reward the most suitable participant. Messaoud *et al.* [57] introduce incentives in task assignment schemes. They investigate the impact of rewards on the commitment level of participants. Li and Cai [61] designed an online auction optimization problem by considering the tasks arriving on the fly, cost capacities of smartphone users, and the QoI requirement of each task. Jiang *et al.* [75] made use of the reputation of the participants and the designs of the task to leverage the quality-aware incentive mechanism. They adopted a greedy approach to achieve high quality with a minimum social cost. Pouryazdan and Kantarci [78] employed coalitional game theory to coordinate the collaboration between participants in which the crowd-sensors built a community for collaborative data acquisition based on mutual trust. Guo *et al.* [79] applied dynamic worker selection in conjunction with quality-based dynamic rewards to motivate hight quality data contributions.

To maintain valuable data collectors engaged in sensing activities, some researchers focus on discover efficient incentive mechanisms from collectors motivation perspective. Jin *et al.* [59] present a payment mechanism, which is used in pair with a truth discovery algorithm to improve data quality by controlling the level of participant sensing effort. Pouryazdan *et al.* [60] and Abdallaoui *et al.* [71], presented gamification-based rewarding schemes to ensure trustworthiness in user recruitment. Gong and Shroff [63] incentivize strategic users to truthfully reveal their private qualities and truthfully make efforts as desired by the requester. Jin *et al.* [64] present

TABLE IV
CREDIBILITY STRATEGIES

Classification	Description	References
Incentive Mechanism	Indirectly leverage data credibility by attracting honest and skillful data collectors	Sun and Ma [34], Hu *et al.* [35], Wu and Luo [36], Zheng *et al.* [37], Yang *et al.* [38], Restuccia and Das [39], Yang *et al.* [40], Song *et al.* [41], Zhao *et al.* [42], Song *et al.* [43], Jin *et al.* [44], Sun [45], Peng *et al.* [46], Yang *et al.* [47], Jin *et al.* [48], Song *et al.* [49], Wang *et al.* [50], Wen *et al.* [51], Sun *et al.* [32], Li *et al.* [52], Mohite *et al.* [53], Kawajiri *et al.* [54], Sun *et al.* [55], Guo *et al.* [56], Messaoud *et al.* [57], Sun *et al.* [58], Jin *et al.* [59], Pouryazdan *et al.* [60], Li and Cai [61], Li *et al.* [62], Gong and Shroff [63], Jin *et al.* [64], Dai *et al.* [65], Krishna [66], Peng *et al.* [67], Gao *et al.* [68], Wang *et al.* [69], Anawar *et al.* [70], Abdallaoui *et al.* [71], Wang *et al.* [72], Yang *et al.* [73], Xiong *et al.* [74], Jiang *et al.* [75], Pei and Hou [76], Liu *et al.* [77], Pouryazdan and Kantarci [78], Guo *et al.* [79] and Wang *et al.* [80]
Task Allocation	Assign tasks to proper data collectors to satisfy especific credibility requirement	An *et al.* [81], Zeng and Li [82], Hao *et al.* [83], Wang *et al.* [84], Hassani *et al.* [85], Wang *et al.* [86], Ben *et al.* [87], Wang *et al.* [88], Azzam *et al.* [89], Yang *et al.* [90], Xu *et al.* [91], Hao *et al.* [92], Gao *et al.* [93], He *et al.* [94], Amintoosi and Kanhere [95], Ben *et al.* [96], Ren *et al.* [97], Wang *et al.* [98], He *et al.* [99], Mrazovic *et al.* [100], Riahi *et al.* [101], Wang *et al.* [102], Gao *et al.* [103], Wang *et al.* [104], Baja and Singh [105], Wang *et al.* [106], Khatib *et al.* [107], Li *et al.* [108], Tao and Song [109], Liu *et al.* [110], Wang *et al.* [111], Wei *et al.* [112], Liu and Li [113], Zhu *et al.* [114], Yang *et al.* [115], Lin *et al.* [116], Yang *et al.* [117], Wu *et al.* [118], Duan *et al.* [119], and Hu *et al.* [120]
Credibility Estimator	Directly infer or estimates data credibility	Venanzi *et al.* [121], Freschi *et al.* [122], Amin *et al.* [123], Xiang *et al.* [124], Dilruba and Naznin [125], Mohssen *et al.* [126], Bhuiyan *et al.* [127], Yang *et al.* [26], Dickens and Lupu [128], Oleson *et al.* [129], Mashhadi and Capra [130], Naderi *et al.* [131], Wang *et al.* [132], Wang *et al.* [133], Hung *et al.* [134], Ouyang *et al.* [135], Meng *et al.* [136], Wang *et al.* [137], Mousa *et al.* [138], Ren *et al.* [139], Prandi *et al.* [140], Wu *et al.* [141], Shao *et al.* [142], Luo and Zeynalvand [143], Gao *et al.* [144], Liu *et al.* [145], Amintoosi and Kanhere [146], Alswailim *et al.* [147], Restuccia *et al.* [148], Li *et al.* [149], Kaptan *et al.* [150], Gad-ElRab and Alsharkawy [151], Liang *et al.* [152], and Folorunso and Mustapha [153]
False or Missing Data Detector	Detect false data or correct missing values on sensed data	Cheng *et al.* [7], Cheng *et al.* [31], Delpriori *et al.* [154], Barnwal *et al.* [155], Saroiu and Wolman [156], Talasila *et al.* [157], Tongqing *et al.* [158], Xiang *et al.* [159], Restuccia *et al.* [160], Ding *et al.* [161], Gilbert *et al.* [162], Dua *et al.* [163], Gilbert *et al.* [164], Budde *et al.* [165], De Araujo *et al.* [166], Miao *et al.* [167], Chang and Chen [168], Kang *et al.* [169], Zhou *et al.* [170], and Restuccia *et al.* [171]
Reputation Mechanism	Use reputation scores to filter unreliable participants and reduce the noise that affects data credibility	Amintoosi and Kanhere [172], Alswailim *et al.* [29], Huang *et al.* [173], Wang *et al.* [33], Yu *et al.* [174], Huang *et al.* [175], Yuan *et al.* [176], Manzoor *et al.* [177], Yang *et al.* [178], Bhattacharjee *et al.* [179], Yu *et al.* [180], Yang *et al.* [181], Wang *et al.* [182], Mousa *et al.* [183], and Pouryazdan *et al.* [184]
Privacy Mechanism	Privacy guarantee stimulates expert user participation and indirectly leverage the data quality	Yao *et al.* [185], Miao *et al.* [186], Wang *et al.* [187], Zeng *et al.* [188], Xie *et al.* [189], Qiu *et al.* [190], Erfani *et al.* [191], Vergara-Laurens*et al.* [192], Kazemi and Shahabi [193], Xu *et al.* [194], Mousa *et al.* [195], Wang *et al.* [196], Miao *et al.* [197], Cai *et al.* [198], Jin *et al.* [199], Zheng *et al.* [200], Alswailim *et al.* [201], Chen and Zhao [202], Wu *et al.* [203], and Alsheikh *et al.* [204]

a double auction-based incentive mechanism which involves auctions among not only the collectors, but also the data requesters, and can incentivize the participation of both data requesters and collectors.

Anawar *et al.* [70] introduced a design guideline for non-monetary incentive mechanism by mapping a set of behavioral incentive constructs into incentive features for mobile health participatory sensing. The author's guidelines evaluated participants' performance in a participatory sensing campaign regarding four incentive mechanics: Autonomy, mastery, purpose, and social. Pei and Hou [76] take the social relationship of participants on the incentive mechanism design. The authors proposed a social aware incentive mechanism to perform the collection of video clips in the crowdsensing network efficiently. On a similar manner, Liu *et al.* [77] explored the social relationship between participants by stimulating the cooperation between users. In order to perform a task, participants need to cooperate with their social friends and can exert pressure on then to achieving optimal results. Wang *et al.* [80] addressed the problem of motivating the participants to behave truthfully. They presented a location-privacy-preserving incentive mechanism that employs the trust degree and privacy sensibility level as decision criteria.

On the other hand, some incentive mechanisms try to leverage quality directly, making quality requirements explicit in the rewards decision making. Hu *et al.* [35] considered collector's bidding profiles and their sensing quality together. They used the task quality requirements as constraints to ensure better sensing performance. Peng *et al.* [67] designed a quality-based incentive mechanism in which the estimated quality of the contribution determines the rewards to the participants. Li *et al.* [62] present a quality-aware contract-based incentive mechanism in which the platform determines a contract that specifies the expected quality and a payment function. Gao *et al.* [68] present a Quality of Data (QoD) incentive mechanism for vehicle-based crowdsensing in which consisting of a QoD-aware winning-bid selection algorithm and a payment determination algorithm. Yang *et al.* [73] presented a user incentive-based scheme that computes the sensing truth and estimates the quality of user-reported data without the use of historical information. The authors considered that there is no available ground truth on MCS and used the current task to estimate the quality and maximize the profit of honest users.

Finally, based on the idea of reinforcing trust scores between collectors and the crowdsensing platform, studies made use of the relationship between collectors or collector groups to reward the most reliable collectors. Krishna [66] presents a group-based incentive and penalizing schemes for participatory data sensing in IoT Network in which considers group-wise incentive factor (based on QoI) and group-wise penalizing factor (based on faulty event updates). Yang *et al.* [47] used the correlation of credibility among collectors as reward criteria. They stimulate cooperation and joint submission of correlated participants via social networks. Dai *et al.* [65] propose a contract theory based incentive scheme. By additionally considering the recommendations of other mobile users and a threshold value, they establish the trust scheme between the crowdsensing platform and mobile data collectors.

2) Task allocation: The task allocation category selects the collector that best suits the capture of specific data in sensing tasks. The authors argue that collectors should be selected under some criterion before performing crowdsensing tasks. The central idea to ensure credibility would be to restrict the openness that allows less skilled participants to contribute [99]. The authors aim to filter the most suitable collectors to perform specific tasks and thus to obtain data with a high degree of credibility.

Since crowdsensing platforms use large numbers of individuals to perform tasks, a part of the task allocation studies adopts information regarding the relationship between the participants or information from groups of participants with characteristics in common to assist in decision making in determining the most appropriate tasks for each collector. An *et al.* [81] present a trusted task assignment scheme, which leverages the usage of social relationships by LRF(Link Reliability Factor), activity patterns by SQF(Service Quality Factor), and coherent subgroups of participants by RHF(Region Heat Factor). In the proposed model, the task is achieved by discovering the communities and credible routes between participants. Amintoosi and Kanhere [95] use social networks as the underlying infrastructure by transmitting messages via routes consisting of social links for recruiting social friends to participate in a sensing campaign. The authors consider the trust and privacy level of a route on the recruitment scheme. They obtain the trust score of a route by multiplying the respective trust rates of all links along the routes. Lin *et al.* [116] considered the similarity between users for the quality prediction and made use of the predicted data quality to guide user recruitment in a time-based sensing scenario.

Some studies considered spatiotemporal correlations and task-time requirements to select collectors whose sensing scenarios were compatible with their daily activities. Zeng and Deshi [82] introduced a behavior-aware recruitment scheme in which participants are engaged in their daily activities when they take part in the sensing campaign. The recruitment metrics that the authors consider in the scheme include spatiotemporal behavior characteristics of participants, data quality, and budget that users can afford. The author modeled the problem as a linear programming optimization for recruitment objectives. Hao *et al.* [83] presented a trajectory-based recruitment strategy by using temporal availability, trust, and energy. They clustered participants who have a high similarity of moving patterns into a group and select the optimal participant who can satisfy the availability, trust, and energy constraints at each time. Mrazovic *et al.* [100] model spatiotemporal participant's expertise by using third-order tensors to represent the correlation between participant, location, and time.

He *et al.* [94], [99] addressed the problem of allocating location-dependent tasks, by taking into account both the geographical characteristics of sensing tasks and the spatial movement constraints of participants. They mathematically formulated this problem as NP-hard. Thus, they designed an approximation algorithm that decomposes the problem into several subproblems to solve the proposed allocation problem. Hassani *et al.* [85] employed contextual information as criteria to select the best data collector by creating a collector profile that best suits the task. Yang *et al.* [90] considered the spatial and temporal constraints in both tasks quality requirements and collectors availability on minimizing the total penalty caused by the tardiness of sensing tasks. They revealed that the problem is NP-hard and combine the earliest-Completion-Time (ECT) heuristic with a genetic algorithm to solve this problem.

Wu *et al.* [118] studied the influence of user characteristics on the probability of completing sensing tasks. The authors evaluated the (hight and low)-heat of different sensing scenario regions based on the number of active users, average residence time of users, and the history of regional sensing tasks. Wei *et al.* [112] studied location-based tasks and considered both multi-source and spatial coverage level for each task. The authors designed a genetic algorithm-based solution for the multi-source optimization problem and a greedy algorithm to the spatial coverage problem. Yang *et al.* [117] proposes a personalized task recommender system which considers users' preferences and reliability. The authors applied a semi-supervised approach to estimate the reliability and a hybrid metric to compute the users' preferences based on historical records and the preferences of similar users.

We identified task allocation studies that focus on minimizing sensing resource consumption and efforts. These studies aim to reduce collector's resources consumption while executing sensing tasks. Wang *et al.* [86] presented an Integer Linear Programming formulation and a polynomial-time heuristic algorithm for Minimum Energy Single-sensor task scheduling problem. They scheduled sensor data collection activities for a given set of tasks to minimize energy consumption. They also avoid redundant efforts by sharing sensor data among multiple sensing tasks. Ben *et al.* [87], [96] addressed the problem of finding the subset of participants that maximize quality concerning spatial and temporal metrics while minimizing the overall energy consumption. They use a Tabu-Search based algorithm to provide a sub-optimal solution for the multi-objective optimization problem. Hao *et al.* [92] propose a trajectory-based strategy for participant recruitment on a joint consideration of the temporal availability, trust, and energy. They used Dynamic Tensor Analysis algorithm to predict future participants trajectory and infer their availability. Liu *et al.* [110] explored the spatial correlations of the data collected by neighboring participants. The authors propose a task-centric approach to select a minimum portion of the users as active participants while maintaining the sensing data integrity. They modeled a bound optimization problem to find the optimal number of participants that achieve the desired performance.

An alternative task allocation approach is to select only a few sub-areas for physical data sensing of the target area. Wang *et al.* [84], [98], [104] proposed to minimize the number of the collector by actively selecting a minimal number of cells for task allocation. They employed the overall sensing data accuracy as the data quality metric and exploited the temporal. The authors considered spatial correlations among the sensing data to deduce the missing information of unsensed cells from the sensing data in selected cells. Wang *et al.* [106] present the DR-Cell, a cell selection mechanism in which a Deep Reinforcement learning minimizes the sensed cell number. They mathematically modeled the reward scores, state, and action to further use in a recurrent neural network structure. The state represents the current data collection condition of the task. Action means all the possible decisions that may make in cell selection and reward indicates how good it is. Yang *et al.* [115] proposed to steer the participant's movements in location-dependent crowdsensing to leverage the sensing quality and coverage. The authors used a greedy algorithm to achieve a suboptimal solution for sensing scenarios based on the users' starting location and destinations.

On the other hand, a part of the studies used the idea of maximizing the number of tasks per collector or reusing participants in more than one task. Riahi *et al.* [101] formulated an optimal data acquisition problem as multi-query optimization with the objective of maximizing the total utility. They take into account the factors pertinent to data acquisition context to enable sustainability and to efficiently shares sensor data among different requisition types. Khatib *et al.* [107] formulated a multitask user selection problem to minimize the total number of recruited collectors subject to task requirements and collector's sensing capability while preserving coverage uniformity. They showed that the problem is NP-hard and proposed a greedy solution. Wang *et al.* [88] proposed a multitask allocation framework, which assigns a subset of tasks to each participant in each cycle. They employed an iterative greedy process to achieve near-optimal allocation solution. The authors also made use of an attention-compensated incentive model that paid extra compensation to participants that assign more than one task type. Zhu *et al.* [114] investigated the multitask allocation problem by considering the heterogeneity of participants. The authors designed a particle swarm optimization with a genetic algorithm to manage the number of tasks, sensing capacity, and time constraints.

A number of studies made use of shared approaches involving the incentive mechanisms and reputation-scores on task allocation decision-making. Xu *et al.* [91] focuses on time-window dependent tasks and introduced the social optimization user selection (SOUS) problem as an incentive mechanism consisting of a participant selection function. Since the general SOUS problem is NP-Hard, they used a greedy-based approximation algorithm. Gao *et al.* [93] addressed the problem of maximizing both the total reputation values of all participants and the number of sensing blocks that can collect data. They present a selection algorithm to obtain a near-optimal solution. Ren *et al.* [97] considered social attributes, expected delay and reputation-scores in participant selection scheme. They proved that the participant selection scheme is an NP-hard problem. The authors adopted a pseudo-polynomial time algorithm to provide an approximated solution.

Li *et al.* [108] presented a collector recommender system where the participant's data qualities for sensing tasks derives from historical statistical data. Gao *et al.* [103] introduced a dynamic-trust-based recruitment framework that dynamically updates the maximum number of history records (reputation-scores) and aggregate requester feedback for future interactions. Azzam *et al.* [89] proposed a group-based recruitment model that uses a genetic algorithm to select the most appropriate group of participants concerning the coverage of the area of interest, participant's reputation scores and devices capability to sense the requested data. Duan *et al.* [119] considered continuous and discontinuous workers patterns in participants' task allocation and auction mechanism. The authors used dynamic programming to achieve the optimal solution for the continuous case and adopted an NP-hard approach with a suboptimal solution for the discontinuous case. Hu *et al.* [120] presented a flexible task and reward assignment model that considers the sensing cost, sensing quality, and traveling cost to the location of tasks. The authors modeled an NP-hard problem and proposed a greedy approximation solution. Liu and Li [113] studied vehicular participatory sensing and used a greedy algorithm to evaluate the participants' sensing and mobility features in both temporal and spatial requirements.

Finally, we identified studies that explicitly considers both restrictions of collectors and service requesters, the managers of crowdsensing platforms. Bajaj and Singh [105] introduced a task allocator framework - Mew - which offers plug-n-play functionality for implementing custom task allocation algorithms to allow developers to reach out to the required set of participants. Tao and Song [109] formulated the task allocation problem from the perspectives of both requesters and collectors. First, they focus on data quality and propose a genetic algorithm (GA) to maximize data quality. Then, the authors took the competition of collectors into account and proposed an algorithm to improve the profit. Wang *et al.* [102] proposed a two-phase participant selection that takes into consideration requesters and collectors perspectives. They aligned the platform tasks quality requirements with collectors availability and skills. Wang *et al.* [111] considers platforms and participants benefits. The authors proposed a QoI satisfaction metric to accomplish platforms quality requirements and the Difficulty of task metric to maximize the participants' rewards.

We observed that the studies using spatiotemporal correlation or energy consumption criteria resulted in the modeling of NP-Hard problems for task allocation, which adopted approximate or greedy algorithms such as the genetic algorithms in their solution.

3) Credibility estimator: The credibility estimators is a direct approach and attempt to numerically infer quality and credibility indexes of information in crowdsense platforms [135]. In this classification, the goal is quantitatively express the credibility of the information or compute a quality index.

A representative number of studies concern location-dependent scenarios in which both the data itself as the collector's location information are mutually relevant. Ouyang *et al.* [135] used unsupervised probabilistic models to estimate the credibility of the information in geolocation tasks where the mobility and the credibility of the participants were uncertain. The authors modeled location popularity, location visit indicators, truths of events, and personal visit tendencies to discovering truths without location tracking. Wang *et al.* [132], [133] studied dependencies among variables by a Bayesian network representation and used the correlation between the observed data and the credibility among the data collectors to estimate the degree of global credibility of the information. The authors employed an expectation maximization-based algorithm that jointly estimates the reliability of each source and the ground truth value of each reported variable. In a similar scenario, Meng *et al.* [136] formulated the truth discovery on correlated entities as an optimization problem that considers both truths and participants reliability as variables. Their proposed objective function measures the differences between the participant-input observations and the unknown truths and integrates participant's reliabilities as unknown weights.

Mashhadi and Capra [130] proposed to record the participant's mobility pattern and combine participant's mobility information with contextual data to estimate a credibility weight for each contributor. Gao *et al.* [144] employed Binomial-Poisson distribution (BPD) to model the quality level of the participant's contribution. The authors introduced a two-level iterative algorithm that estimates the parametric values of the used BPD by applying the expectation-maximization (EM) method. Bhuiyan *et al.* [127] made use of an idea of zones in which a distance function measures the difference between zone sensor values and the estimated ground truths. Alswailim *et al.* [147] proposes a participant contribution trust (PCT) schema for crisis response system. The PCT split crisis area into sectors and compared intra- and inter-sector contributions to estimate the accuracy of sensed data. Li *et al.* [149] explored data sparsity characteristics and took advantage of the spatial correlations to reuse contributors' data. The authors reutilize data from an adjacent point of interests to estimate the truth of nearby points. Kaptan *et al.* [150] used probabilist values and a threshold-based approach to compute the trustworthiness in a vehicular crowdsense recruitment system. The authors averaged historical trust values as thresholds and decision criteria.

We identified studies that focus on quantifying and qualifying information in social sensing scenarios. Taghizadeh *et al.* [131] presented two metrics to represent the quality of the claims. The first one was based on the content of the claim, and the second was based on the popularity and propagation of the claim in environments where the data comes from social networks. Shao *et al.* [142] discussed the source selection problem in social sensing applications. They modeled an optimization problem and proposed a reliability-based pruning heuristic and a similarity-based lossy estimation algorithm. The proposed algorithm calculates the ratio for sources reliability to cost and then sorts of sources based on the descending order of ratios. Amintoosi and Kanhere [146] introduced an application-agnostic trust framework for social-participatory sensing in which a system independently assesses the quality of the data and the trustworthiness of the participants and combine these metrics using fuzzy logic to arrive at a trust rating for each contribution. Dilruba and Naznin [125] presented a population-based reliability estimation (PBRE) by using a genetic algorithm to estimate the reliability. Amin *et al.* [123] introduced an algorithm that performs polarity-informed maximum-likelihood estimation of statistical credibility for reported observations. Wang *et al.* [137] modeled human participants as sources of unknown reliability by generating binary measurements of uncertain provenance. The authors proposed an enhanced EM algorithm to model the data uncertainty.

On the other hand, part of the studies presented solutions for general-purpose scenarios. Yang *et al.* [26] measured the credibility level of the information by applying unsupervised learning algorithms in conjunction with outliers detectors. They used a cluster centroid distance-based algorithm for computing the quality of each collector contribution. Hung *et al.* [134] adopted a trust model where the trustworthiness of the sensor and their data are measured concurrently and explicitly. They associated each sensor with a trust score, which shows its accuracy. The authors also assigned a trust score to sensor data, which represents its probability of correctness. They employ the Kullback-Leibler(KL) divergence to measure the similarity between two sensors data distributions. Venanzi *et al.* [121] estimated the credibility by using a Bayesian model for computing a community-based trust estimation. Dickens and Lupu [128] used Bayesian probabilistic models and expectation maximization to estimate reliability on binary labels.

Freschi *et al.* [122] combined statistical bootstrap with uncertainty propagation techniques for evaluating the quality of data. Xiang *et al.* [124] quantified the sensor noise using the confidence interval by using expectation maximization-based algorithm to compute the maximum likelihood estimation. Mohssen *et al.* [126] applied statistical analysis techniques to the inertial sensors available on the cellphone to estimate both the phone and user orientation. They fuse the phone's energy-efficient inertial sensors and applies the PCA (Principal Component Analysis) technique to detect the user direction. Folorunso and Mustapha [153] presented a fuzzy-expert system in which a fuzzy inference system (FIS) compute trust values, priority values, and generate access decision rules to the participants. The system ranks the participant's level of skills by considering events performed by participants and historical records.

We also identified studies that adopt shared approaches involving the historical contributions, i.e., reputation-scores on credibility index computations. Liu *et al.* [145] presented a context-aware data quality estimation scheme. Using historical sensing data, they trained a context-quality classifier, which captures the relation between context information and data quality, to estimate data quality in an online manner. The authors applied such a context-aware data quality estimation scheme to guide user recruitment in mobile crowdsensing. Wu *et al.* [141] introduced a dynamical credibility assessment of privacy-preserving (CAPP) in which they divide the trust into two dimensions: the quality of contribution(QoC) trust and social trust. The authors' schema established how likely a node could fulfill its function and how trustworthy the relationship between a node and other nodes will be, respectively. CAPP evaluate the trust by using the history information of nodes and the similarity between sensing data.

In order to increase credibility confidence level, some studies adopt external validators to reinforce the credibility estimation process. Pradi *et al.* [140] presented a trustworthiness model used in mobile Pervasive Accessibility Social Sensing (mPASS) in which they compute the trustworthiness by combining the accuracy of sensors, source credibility of users, and authoritative reports coming from authoritative data sources. Luo and Zeynalvand [143] introduced a cross-validation approach which seeks a validating crowd to verify the data credibility of the sensing crowd and uses the verification result to reshape the original sensing dataset into a more credible posterior belief of the ground truth. Oleson *et al.* [129] applied the programmatic gold approach, that relies on manual spot checks and detection of collector errors. Restuccia *et al.* [148] employed a mobile trusted participants (MTP) approach, those who are hired by the sensing application to generate reliable reports and provide ground truth periodically. The authors studied the trade-off between the number of MTPs and the desired accuracy in classifying the collected reports as reliable and unreliable. They also evaluated their proposal resilience against corruption, on-off, and collusion attacks.

Finally, the work of Mousa *et al.* [138] experimentally evaluated different reputation trust mapping functions to measure which of them has higher capabilities to enable the trust system to aggregate more accurate data. They revealed that EM function enables the system to assign more accurate trust scores and subsequently aggregate more accurate data. Ren *et al.* [139] presented a Quality Utilization (QU) metric that quantifies the ratio of quality of the collected sensing data to the cost of the system. Three data collection algorithms were proposed to maximize QU under different application requirements. Gad-ElRab and Alsharkawy [151] introduced a statistical MCS data quality model. The authors presented equations to measure the data quality quantitatively based on the experience of the user and the device context. Liang *et al.* [152] proposed a blockchain-based crowdsensing quality control model. The authors used quality grading evaluation (QGE) for data evaluation by applying Bayesian probability and fuzzy mathematics to compute the correctness degree.

4) False/missing data detector: In this classification, the authors explicitly attack the fact that crowdsensing systems are prone to false, corrupted, and incomplete data submission and address ways of detecting and correcting this data.

A considerable number of studies use prediction models to estimate a ground truth for decision making in the detection of false data. Xiang *et al.* [159] presented a participatory sensing and filtering scheme for identifying the truthful pollution sources (PassFit) in which they cluster noise data according to the reported locations and estimate the parameters of the pollution sources. The authors employed the Mutual Information Based Clustering Algorithm for clustering and later application of an Expectation Maximization-based (EM) probabilistic model to detect false data. Barnwal *et al.* [155] proposed the use of conditional probability to compute confidence scores that determine if a particular event is anomalous by estimating the statistical confidence intervals.

On the other hand, a part of the studies addressed the problem of missing data. Cheng *et al.* [7], Cheng *et al.* [31], Delpriori *et al.* [154], Tongqing *et al.* [158], and Restuccia *et al.* [160] discussed false data detection in environments where this data also comes with incomplete information. They replaced missing values by estimated ones, and with the complete data, it was possible to detect if these are false or not. Kang *et al.* [169] used signal and temporal correlation to generate sensing images, the expression of a distribution status of environment phenomenon as two-dimensional(2D) signal. The authors applied a tensor decomposition approach to infer the missing items of target signals through signals' correlation.

Saroiu and Wolman [156], Gilbert *et al.* [162], Dua *et al.* [163], and Gilbert *et al.* [164] used hardware-based credential modules to detect false data. Ding *et al.* [161] presented a data cleansing-based robust cooperative sensing scheme in which the under-utilization of licensed spectrum bands and the sparsity of nonzero abnormal data are jointly exploited to robustly cleanse out the nonzero abnormal data component, not the sensing data itself. The authors propose only the explicit separation between incorrect and correct data rather than the entire disposal of the defective data.

We identified studies that focus directly on false data and address security issues. Miao *et al.* [167] studied two types of data poisoning attacks, the availability attack, and the target attack, against a crowdsensing system empowered with the truth discovery mechanism. They proposed an optimal data poisoning attack framework, based on which the attacker can not only maximize his attack utility but also successfully disguise the attack behaviors when attacking a crowdsensing system employing the truth discovery mechanism. Chang and Chen [168] proposed a cloud-based trust management scheme (CbTMS) for detecting Sybil attacks in mobile crowdsensing (MCS) networks. CbTMS framework includes a passive checking scheme (PCS) and active checking scheme (ACS) that simultaneously keep Sybil identity nodes in check, including traffic volume, signal strength, and network topology. In the proposed framework, the trust credit of a node is evaluated by Trust Credit Assessment (TCA) scheme using historical records.

Zhou *et al.* [170] exploited spatial correlation and provenance knowledge (reputation and co-located events) to defend against the potential data falsification threats. The authors handled Sybil, on-off, and location spoofing threats. Restuccia *et al.* [171] presented location validation system to secure sensing campaigns from location-spoofing attacks. The authors used the collaborative actions of the users and the WiFi capability of smartphones to validate the location of the collector.

Finally, we identified studies that try to determine the incorrectness sources on crowdsensing ecosystems. Budde *et al.* [165] presented an empirical study of errors exhibited in non-expert smartphone-based sensing by using four small exploratory studies. They analyzed and compiled ways in which human-errors may lead to incorrect data submission. Talasila *et al.* [157] also address human-errors, but that focus was human intervention in data validation activities. De Araujo *et al.* [166] investigate the behavior of smartphone's environmental sensors under different situations that are inherent to participatory sensing scenarios. They revealed that the existing smartphones are not ready yet to act as user-centric data-collectors without any data-treatment, mainly due to the observed issues in data quality when the devices are being handled or used.

5) Reputation mechanism: Reputation mechanisms use information based on contribution history to indicate collectors with the highest potential to provide quality data [29]. In this classification, the authors use the idea of registering data with high-quality index and using these records in decision making on future contributions. The studies of Amintoosi *et al.* [172], Alswailim *et al.* [29], Huang *et al.* [173], Wang *et al.* [33], Yu *et al.* [174], Manzoor *et al.* [177], and Yang *et al.* [178] records the collector's reputation score for further use in crowdsensing ecosystem decision making. Huang *et al.* [175] proposed the use of sensor reputation-score at the hardware level and not at the human collector's measurements. Yuan *et al.* [176] adopted a reputation-score threshold to improve the accuracy and credibility of the reputation mechanisms themselves. Pouryazdan *et al.* [184] studied the reputation approaches and introduced a collaborative reputation score that incorporated statistical reputation scores and vote-based reputation scores.

Bhattacharjee *et al.* [179] introduced a reputation model that segregate different user classes such as honest, selfish, or malicious based on their reputation scores. To classify an event as true or not, a generalized linear model was used to transform its truthfulness into the quality of information (QoI). The QoI of various events in which a collector participates was aggregated to compute a collector's reputation score. The resultant score is then used as an indicator to decide an incentive (reward) for a collector.

Mengyang *et al.* [180] presented a Data Trustworthiness enhanced Reputation Mechanism (DTRM) in which integrates a sensitivity-level based data category, a meta-graph theory-based user group division and a reputation transferring into the evaluation process. DTRM computes the direct reputation-score of a user, and, if the direct reputation-score cannot lead to a decision, the system computes an indirect reputation-score from other users to reinforce a final reputation-score. Yang *et al.* [181] proposed a reputation-aware data collection mechanism, that analyzes reputation state, quantifies historical reputation of participants according to the willingness and data quality, and then updates the reputation of participants by using a logistic regression function.

Wang *et al.* [182] addressed the problem of the real-time road information acquisition based on crowdsensing and proposed a reputation system to evaluate the reliability of each contributor, which takes both location and time deviation factors into account. Mousa *et al.* [183] presented a Dynamic Trusted Set based Reputation System (DTSRS) that incorporates a mechanism to defend against corruption, collusion, and on-off attacks. The proposed system depends on a dynamic trusted set of participants to identify the reliable data in each campaign.

6) Privacy Mechanism: In this classification, the authors argue that the insertion of privacy and security in the crowdsense platforms will allow active participation of the collectors and indirectly imply a better data collection.

A portion of the studies approached the privacy of the participant's location-based information on the crowdsense ecosystem. Vergara-Laurens *et al.* [192] proposed a hybrid mechanism that dynamically changes the cell sizes of the grid of the area of interest according to the variability of the variable of interest being measured and chooses different privacy-preserving mechanisms depending on the size of the cell. In small cells, where users can be identified easier, the algorithm uses encryption techniques to protect the participant's privacy, as the reported location is the correct location. On the other hand, the algorithm uses anonymization and data obfuscation techniques in bigger cells where the variability of the variable of interest is low, and therefore it is more important to protect the correct location (privacy) of the participant.

Kazemi and Shahabi [193] introduced the trustworthy privacy-aware framework for participatory sensing (TAPAS) in which each participant determines his privacy level, which is only available to himself. The TAPAS also assigned a pseudonymous identity for the queries between participants and the Server Platform, which is unrelated to the participant's private information. Erfani *et al.* [191] proposed a privacy-aware data aggregation scheme by applying secret perturbation (additive homomorphic encryption-based) and data splitting on participant's sensitive information. Xie *et al.* [189] presented a privacy-aware data aggregation scheme in which they replace location data by an anonymous location and apply an erasure code on the sensing data for the content privacy preservation. Similarly, Qiu *et al.* [190] designed an erasure coding based sensing record coding scheme to encode each sensing record into many data slices, each of which can be delivered to the service provider through the other participants or the record's generator herself.

Some studies adopt the idea of protecting the collector data from both other collectors and the data requesters responsible for the crowdsensing platform. Yao *et al.* [185] proposed a anonymity-based privacy-preserving data reporting protocol. They broke the link between any data and the participant who reports the data. Wang *et al.* [187] adopted differential privacy in Sparse mobile crowdsense to provide participant's location privacy regardless of an adversary's prior knowledge. They applied a linear program to select an optimal location obfuscation function. Zeng *et al.* [188] addressed the problem of keep data privacy from different participants while maintaining low energy consumption. By integrating pairs of asymmetric cryptography keys techniques and modular operation, they achieve both participant's and service requesters privacy in the platform ecosystem.

We identified studies that are focusing on privacy and security issues. Mousa *et al.* [195] define a new attack (RR attack) that aims to link multiple contributions from the same participant, and subsequently re-identify participant's identities. They proposed a privacy-preserving and reputation-aware mobile participatory sensing system (PrivaSense) in which reputation scores are anonymized and transferred in the form of anonymous certificates. PrivaSense detaches the link between each contribution and its provider as well as among multiple contributions provided by the same participant, i.e., prevent the associations between consecutive contributions.

Wang *et al.* [196] explored security and privacy issues on incentive mechanisms. They proposed a blockchain-based solution in which node cooperation based privacy protection method was used not only to protect the privacies of sensing data and identity information but also prevent the impersonation attacks. Chen and Zhao [202] distributed a receiver filtering policy (RFP) along with tasks to guarantee that only those participants whose data attributes satisfy the RFP, transfer the sensing data. In the authors' schema, the participants encrypt the sensing data under a set of attributes such that only the receiver who holds these attributes obtain these data. The schema is resilient against collusion attacks.

We also identified studies that insert privacy on truth discovery activities. Miao *et al.* [186] [197] presented a privacy-preserving truth discovery framework (PPTD) for MCS systems, in which the sensory data and reliability of each participant are both protected from being disclosed to others. The proposed framework was implemented by involving two non-colluding cloud platforms and adopting additively homomorphic cryptosystem. In PPTD, the aggregated results (referred to as truth) was cooperatively estimated by the two cloud platforms without disclosing any participant's private information. Xu *et al.* [194] addressed the problem of add privacy to the truth discovery process by completing every aggregated operation in an encrypted environment. Cai *et al.* [198] proposed a crowdsensing framework that enables privacy-preserving knowledge discovery and full-fledged blockchain-based knowledge monetization. To achieve both privacy protection and cost efficiency in streaming truth discovery, they adopted a lightweight cryptographic technique, that is, additive secret sharing, to encrypt the client's sensory data.

Jin *et al.* [199] presented a crowdsensing framework that integrates an incentive, a data aggregation, and a data perturbation mechanism. Their data perturbation mechanism ensures the protection of participant's privacy, as well as the accuracy of the final perturbed results by adding controlled noises to the aggregated results to achieve differential privacy and small degradation of aggregation accuracy. Zheng *et al.* [200] introduced a privacy-aware crowdsensing design with truth discovery. They integrated splitting-based encryption with homomorphic encryption to build a secure truth discovery protocol that protects individual sensory data and reliability degrees throughout the truth discovery procedure. Alswailim *et al.* [201] presented a context-aware privacy scheme to protects participants' private data based on the context decisions. The authors proposed to balancing the conflicting privacy-accuracy trade-off by adjusting a high level of privacy protection in safe areas and a high level of data accuracy in risk/areas situations. Wu *et al.* [203] combines the public key distributions with trust management by allowing each node to determine the authenticity of their received public keys in a mutual verification process. Alsheikh *et al.* [204] studied the privacy-accuracy trade-off in MCS and proposed a coalition strategy to allows users to cooperate in providing their data under one identity. The authors used a k-anonymity metric to measure the participants' privacy level when the participants select their level of anonymization.

The next sub-section presents the classifications for RQ2.

B. RQ2: Which element or activity has negatively impacted the credibility of information on crowdsensing platforms?

This research question investigates which element or activity has the most significant impact or negative influence in decision-making for a particular credibility approach. We group the elements that negatively impacted the credibility of the data on crowdsensing platforms. Table V presents the list of publications grouped according to the classifications obtained for RQ2.

An interesting fact revealed by our analysis is that some of the publication's objectives grouped in RQ1 are precisely to address specific factors that negatively affect the credibility of the information. The primary studies present evidence of many factors that negatively impacted the credibility of the

TABLE V
ELEMENTS OF NEGATIVE IMPACT ON DATA CREDIBILITY

Description	References
Collectors contributions may be misleading such as intentionally falsified	An *et al.* [81], Amintoosi and Kanhere [172], Alswailim *et al.* [29], Zeng and Li [82], Hao *et al.* [83], Huang *et al.* [173], Wang *et al.* [33], Venanzi *et al.* [121], Hassani *et al.* [85], Amin *et al.* [123], Zeng *et al.* [188], Ben *et al.* [87], Restuccia and Das [39], Wang *et al.* [88], Azzam *et al.* [89], Yang *et al.* [90], Yu *et al.* [174], Hao *et al.* [92], Zhou *et al.* [158], Gao *et al.* [93], He *et al.* [94], Yang *et al.* [26], Huang *et al.* [175], Xie *et al.* [189], Restuccia *et al.* [160], Amintoosi and Kanhere [95], Oleson *et al.* [129], Ben *et al.* [96], Mashhadi and Capra [130], Naderi *et al.* [131], Ren *et al.* [97], Kazemi and Shahabi [193], He *et al.* [99], Wang *et al.* [133], Xu *et al.* [194], Mrazovic *et al.* [100], Manzoor *et al.* [177], Ouyang *et al.* [135], Meng *et al.* [136], Wang *et al.* [137], Yang *et al.* [178], Riahi *et al.* [101], Wang *et al.* [102], Budde *et al.* [165], Mousa *et al.* [138], Sun *et al.* [58], Bhattacharjee *et al.* [179], Bajaj and Singh [105], Wu *et al.* [141], Yu *et al.* [180], Miao *et al.* [197], Yang *et al.* [181], Shao *et al.* [142], Li *et al.* [62], Liu *et al.* [145], Amintoosi and Kanhere [146], Wang *et al.* [69], Wang *et al.* [72], Yang *et al.* [73], Liu *et al.* [110], Yang *et al.* [115], Alswailim *et al.* [147], Restuccia *et al.* [148], Li *et al.* [149], Kang *et al.* [169], Zhou *et al.* [170], Restuccia *et al.* [171], Folorunso and Mustapha [153], and Wu *et al.* [203]
Collector's motivation to participate	Sun and Ma [34], Hu *et al.* [35], Wu and Luo [36], Zheng *et al.* [37], Yao *et al.* [185], Miao *et al.* [186], Yang *et al.* [38], Wang *et al.* [187], Yang *et al.* [40], Song *et al.* [41], Zhao *et al.* [42], Song *et al.* [43], Xu *et al.* [91], Jin *et al.* [44], Sun [45], Peng *et al.* [46], Qiu *et al.* [190], Vergara-Laurens *et al.* [192], Yang *et al.* [47], Jin *et al.* [48], Song *et al.* [49], Wang *et al.* [50], Wen *et al.* [51], Sun *et al.* [32], Li *et al.* [52], Mohite *et al.* [53], Kawajiri *et al.* [54], Sun *et al.* [55], Guao *et al.* [56], Jin *et al.* [59], Wang *et al.* [196], Pouryazdan *et al.* [60], Cai *et al.* [198], Jin *et al.* [199], Gong and Shroff [63], Li *et al.* [108], Dai *et al.* [65], Wang *et al.* [182], Peng *et al.* [67], Gao *et al.* [68], Zheng *et al.* [200], Anawar *et al.* [70], Abdallaoui *et al.* [71], Xiong *et al.* [74], Jiang *et al.* [75], Pei and Hou [76], Liu *et al.* [77], Pouryazdan and Kantarci [78], Guo *et al.* [79], Wang *et al.* [80], Hu *et al.* [120], Wang *et al.* [111], Wei *et al.* [112], Lin *et al.* [116], Yang *et al.* [117], Wu *et al.* [118], Duan *et al.* [119], Alswailim *et al.* [201], Chen and Zhao [202], and Alsheikh *et al.* [204]
Variety of hardware sensors and social networks as data sources	Freschi *et al.* [122], Cheng *et al.* [7], Cheng *et al.* [31], Delpriori *et al.* [154], Barnwal *et al.* [155], Dilruba and Naznin [125], Xiang *et al.* [159], Erfani *et al.* [191], Wang *et al.* [132], Hung *et al.* [134], Prandi *et al.* [140], Jin *et al.* [64], Krishna [66], Liu and Li [113], and Zhu *et al.* [114]
Precision issues in the hardware sensors	Xiang *et al.* [124], Saroiu and Wolman [156], Talasila *et al.* [157], Mohssen *et al.* [126], Bhuiyan *et al.* [127], Ding *et al.* [161], Gilbert *et al.* [162], Dua *et al.* [163], Gilbert *et al.* [164], De Araujo *et al.* [166], Chang and Chen [168], and Kaptan *et al.* [150]
Collector overload and high resource consumption	Wang *et al.* [84], Wang *et al.* [86], Wang *et al.* [98], Messaoud *et al.* [57], Ren *et al.* [139], Gao *et al.* [103], Wang *et al.* [104], Wang *et al.* [106], Li and Cai [61], Khatib *et al.* [107], and Tao and Song [109]
Credibility approaches itself	Yuan *et al.* [176], Miao *et al.* [167], Mousa *et al.* [195], Gao *et al.* [144], Mousa *et al.* [183], Liang *et al.* [152], Gad-ElRab and Alsharkawy [151], and Pouryazdan *et al.* [184]
Human Validation Errors	Dickens and Lupu [128], and Luo and Zeynalvand [143]

data, as presented in Table V. We identified the negative factors as follow. *(i)* The equipment used for sensing, either due to problems of precision in the data collection or in the possibility of obtaining incorrect data. *(ii)* The absence of standardization in the data capture process, including the use of mobile devices sensors and the human as a sensor in social networks. *(iii)* The motivation of the data collector was also a factor of negative impact on the credibility of the sensed data, which makes the platforms prone to incomplete or even falsified information. *(iv)* The reliability of the credibility approaches already in use.

One of the most important characteristics of MCS is the involvement of humans in the whole loop of the data-to-decision process, including sensing and transmission [205]. Since the crowdsense ecosystem is typically human-centered, the most considerable portion of the primary studies points out the data collector's behavior issues. The studies present human factors such as individualism, inattention, and the possibility of errors (whether they are intentional or not), as the primary harmful instrument that impacts credibility. We present on table VI a list with the main attributes and requirements that explicitly guided the approaches grouped as data collector's behaviors. We observe that the presence of corrupted/malicious participant's contributions, user's skillfulness, the relationships between participants as well as participant's willingness, and participant's spatiotemporal availability play an essential role in addressing human-behavior data credibility issues. Some works as those of Dickens and Lupu [128] and Luo and Zeynalvand [143] point to human error, but it does not refer to data collector's behavior, but rather to the possibility of failure by human validators on crowdsense platforms who need manual validation.

A number of studies discuss the reliability of the credibility approaches itself as presented by work of Miao *et al.* [167], Mousa *et al.* [195], Gao *et al.* [144], Mousa *et al.* [183]. Anawar *et al.* [70] introduced a design guideline for non-monetary incentive mechanisms within the context of participants' performance in sensing campaigns. Liang *et al.* [152] suggested a quality model based on blockchain to reflect the non-centered behavior of crowdsensing platforms. Gad-ElRab and Alsharkawy [151] designed a statistical data quality model for MCS to represent the factors that affect the data quality. Pouryazdan *et al.* [184] introduce a collaborative reputation score to expand the scores computation approaches. Yuan *et al.* [176] focus the problems related to the efficiency of reputation mechanisms used on the crowdsense platforms and proposes metrics that aim to balance the acceptable level of credibility in information regarding the number of collectors.

Finally, Wang *et al.* [84], Wang *et al.* [86], and Wang *et al.* [98] point out that the excess of sensing tasks attributed to the data collector, may negatively impact the quality and credibility of their resulting data.

V. Discussion

In this systematic mapping study, 177 papers on credibility on crowdsensing data acquisition were analyzed and classified in order to provide an overview of the current status. This section discusses the principal findings of this mapping study.

The studies provide evidence that credibility on crowdsensing platforms is addressed directly and indirectly at different levels. Because it is an ecosystem strongly dependent on human actions, the use of incentive mechanisms has played a fundamental role in motivating, satisfying and encouraging the participation of honest and skillful collectors who minimize the costs of data collection and reach the quality requirements.

Since the selection of the most suitable collectors can leverage the final credibility of the sensed data [30], the studies present task allocators that aim to satisfy the quality requirements of the sensing tasks. Factors related to the location and time required to perform the activities or availability of the participant are widely adopted; however, more recent studies address the use of contextual information aligned with cross-validation of data to add value in the composition of the requirements of the tasks and selection of collectors less susceptible to errors.

Crowdsensing platforms try to ensure that the contextual, location, and time information of the collectors travel privately and safely in the crowdsensing ecosystem. The studies point to the use of privacy mechanisms to protect the information used mainly in aggregation, selection of collectors, and in the calculation of the quality index.

The credibility estimators numerically represent the degree of confidence of specific elements in the crowdsensing ecosystem. Concerning data credibility, studies point to the use of probability-based solutions involving techniques such as maximum likelihood estimation, Machine Learning techniques, and variations that adopt specific metrics as quality requirements. The studies also present hardware-based solutions, where the application of trusted platform modules estimates the credibility directly in the sensors.

False or missing data detection activities can be used individually as a credibility criterion or applied as reinforcement to quality requirements in the crowdsensing ecosystem. The studies present spatiotemporal and contextual approaches for the detection of incomplete data and their reconstruction. Concerning the detection of false data, we identified the use of credibility estimation techniques.

The studies indicate that reputation mechanisms have a long-term character and their primary function is to calculate and update the reputation scores that can serve as criteria for decision making in other parts of the crowdsensing ecosystem. Reputation scores can act on task allocation activities, or as a direct quality criterion in incentive mechanisms. A credibility estimator can process the participant's data and compute an updated credibility indicator which saves the new reputation score for use in future iterations. The recent study of Bhattacharjee *et al.*[206], which is an extension of the Bhattacharjee *et al.*[179], reinforces the idea of an ecosystem with components that are currently acting cooperatively to enhance credibility.

A considerable amount of the analyzed studies presented proposals for new metrics, approaches, models, or use of technologies for each of the different segments or groups. However, we have observed a slight variation in some recent publications concerning the type of research performed. These are experimental studies in which the crowdsensing ecosystem is analyzed and diagnosticated on a controlled form by empirical evaluation. De Araujo *et al.* [166] investigate the behavior of specific smartphone's environmental embedded sensors (temperature, pressure, and humidity) under different situations that are inherent to participatory sensing scenarios. They concluded that the existing smartphones are not ready yet to act as user-centric data-collectors without any data-treatment, mainly due to the observed issues in data quality when the devices are being handled or used. Budde *et al.* [165] present an empirical study of errors exhibited in non-expert smartphone-based sensing by using four small exploratory studies. They analyzed and compiled ways in which participant's behavior, i.e., human-errors, may adversely affect data quality. Mousa *et al.* [138] experimentally evaluate different reputation trust mapping functions to measure which of them has higher capabilities to enable the trust system to aggregate more accurate data. Pouryazdan *et al.* [184] introduced a hybrid model within a collaborative reputation score. Due to the variety of approaches available, we believe that similar studies are promising for future crowdsensing credibility evaluation.

As discussed by Alsheikh *et al.* [204] and Alswailim *et al.* [201], we note contradicting incentives of privacy preservation and data quality maximization in MCS. By recognizing the accuracy-privacy trade-off, the authors revealed the need for new privacy-aware incentive mechanisms. In this way, Gong and Shroff [63] dealt with this issue by incentivizing the strategic users to truthfully reveal their private qualities and truthfully make efforts as desired by the requester. Alsheikh *et al.* [204] managed this trade-off by allowing the participants to select their level of anonymization.

As an indirect credibility factor, security has played a role

TABLE VI
STUDIES CLASSIFIED AS COLLECTOR'S BEHAVIOR - RESEARCH KEY ATTRIBUTES

References	Attributes that guided the approach
An *et al.* [81],Amintoosi *et al.* [172], Amintoosi and Kanhere [95], and Meng *et al.* [136]	Trust relationships between users.
Alswailim *et al.* [29], Huang *et al.* [173], Venanzi *et al.* [121], Yu *et al.* [174], Restuccia *et al.* [160], Oleson *et al.* [129], Manzoor *et al.* [177], Wang *et al.* [137], Mousa *et al.* [138], Wu *et al.* [141], Yu *et al.* [180], Shao *et al.* [142], Alswailim *et al.* [147], Yang *et al.* [73], Zhou *et al.* [170], Restuccia *et al.* [148], Restuccia *et al.* [171], Folorunso and Mustapha [153], and Wu *et al.* [203]	Corrupted/malicious user's contributions.
Wang *et al.* [33], Kazemi and Shahabi [193], Xu *et al.* [194], and Miao *et al.* [197]	Privacy and security requirements.
Tongqing *et al.* [158] and Yang *et al.* [26]	Accuracy, realibility
Restuccia and Das [39], Gao *et al.* [93], Huang *et al.* [175], Mrazovic *et al.* [100], Yang *et al.* [178], Riahi *et al.* [101], Budde *et al.* [165], Sun *et al.* [58], Bhattacharjee *et al.* [179], Yang *et al.* [181], Li *et al.* [62], and Wang *et al.* [72]	User's skillfulness, willingness, data quality.
Mashhadi and Capra [130], Ouyang *et al.* [135], Wang *et al.* [102], Bajaj and Singh [105], Liu *et al.* [145], Wang *et al.* [69]	Participant's contextual data.
Amin *et al.* [123]	Polarized networks
Hao *et al.* [83], Yang *et al.* [90], He *et al.* [94], Xie *et al.* [189], Naderi *et al.* [131], Ren *et al.* [97], He *et al.* [99], Amintoosi and Kanhere [146], Kang *et al.* [169], and Li *et al.* [149]	Spatiotemporal requiriments, data quality.
Zeng and Li [82], Ben *et al.* [87], Wang *et al.* [88], Azzam *et al.* [89], Liu *et al.* [110], and Yang *et al.* [115]	Coverage, data quality, and budget.
Hassani *et al.* [85], Zeng *et al.* [188], Hao *et al.* [92], Ben *et al.* [96]	Energy efficiency, accuracy, coverage.

in crowdsensing ecosystems, and the credibility solutions have incorporated mechanisms to defend against attacks. The use of a trusted set of participants was efficient against corruption, collusion, and on-off attacks in reputation systems [183]. Chen and Zhao [202] proposed a task allocation schema resilient against collusion attacks. A Blockchain-based mechanism was used to prevent impersonation attacks on incentive-based schemas [196]. By preventing the associations between consecutive participants' contributions in a reputation-based crowdsensing scenario, Mousa *et al.* [195] dealt with RR attacks. These works indicated that even in credibility solutions, the security should not be negligency.

The human-centered quality of the CS ecosystem brings together the collector's misbehavior issues. However, studies have been used the strength of the human-crowd itself to fight these problems. Some aspects addressed to leverage the credibility of successful crowdsensing data acquisition include: collaboration among crowd sensing participants [78], their social networking relationships [76][81][95], schemes group incentives [66], the recommendations of other mobile users [65] and the similarity between users indicating the contextual correlation of participants to quality [116].

VI. CONCLUSION

Here we presented an overview of the credibility-aware approaches on crowdsensing platforms from a systematic mapping over 177 publications. Our analysis showed that credibility solutions are not limited to reputation mechanisms, hardware-based solutions, or direct computation of truth scores, but rather an ecosystem acting at different levels to ensure the credibility of the data. We showed that current approaches could act at different levels that directly and indirectly leverage the credibility on crowdsensing platforms. Briefly, this discussion is showed in the proposed taxonomy (please see Figure 3).

Based on the diversity of approaches found and the possibility of their use in a cooperative way, the studies here used pointed out to the shared use of credibility solutions. Our results suggest that, from an ecosystem point-of-view, there is a contradicting accuracy-privacy trade-off which indicates the need for new privacy-aware approaches. Besides, credibility solutions have embbeded mechanisms to protect against security attacks.

As future work, we suggest an in-depth analysis of the Mobile Crowdsensing (MCS) challenges and open issues. The advances in obtaining a certain degree of credibility on the crowdsense platforms are undeniable; however, the diversity of credibility-aware approaches on crowdsensing platforms indicate potential research on empirical evaluation of credibility-aware metrics and standards to these platforms. We plan to use these mapping study findings as baseline to design novel methods for measuring the credibility of crowdsensing data acquisition.

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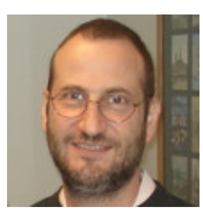

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