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Critical Review

Key Themes, Trends, and Drivers of Mobile Ambient Air Quality Monitoring: A Systematic Review and Meta-Analysis

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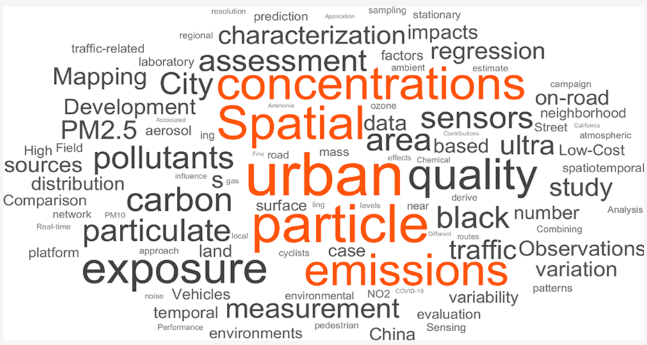
ABSTRACT: Mobile ambient air quality monitoring is rapidly changing the current paradigm of air quality monitoring and growing as an important tool to address air quality and climate data gaps across the globe. This review seeks to provide a systematic understanding of the current landscape of advances and applications in this field. We observe a rapidly growing number of air quality studies employing mobile monitoring, with low-cost sensor usage drastically increasing in recent years. A prominent research gap was revealed, highlighting the double burden of severe air pollution and poor air quality monitoring in low- and middle-income regions. Experiment-design-wise, the advances in low-cost monitoring technology show great potential in bridging this gap while bringing unique opportunities for real-time personal exposure, large-scale deployment, and diversified monitoring strategies. The median value of unique observations at the same location in spatial regression studies is ten, which can be used as a rule-of-thumb for future experiment design. Data-analysis-wise, even though data mining techniques have been extensively employed in air quality analysis and modeling, future research can benefit from exploring air quality information from nontabular data, such as images and natural language.



KEYWORDS: *Air Quality, Pollutants, Mobile Monitoring*

1. INTRODUCTION

A majority of the world's population is exposed to air pollution levels exceeding the World Health Organization guideline limits, which led to 4.2 million premature deaths worldwide in 2016.[1] Moreover, this health burden is disproportionately imposed on low- and middle-income countries. Accurate air quality data is crucial for tracking adverse health impacts of poor air quality and developing effective pollution mitigation plans. However, levels of different pollutants can vary on the order of a few meters in complex urban environments,[2,3] potentially rendering even a dense network of stationary air quality monitors unable to capture hyperlocal pollution variation.

The miniaturization and cost decrease of air quality sensors provide new measurement and study opportunities to air pollution researchers and practitioners in various settings, stationary or mobile, and closed or open spaces. Mobile monitoring techniques exhibit great flexibility in various applications, including indoor air quality characterization,[4] automated air quality monitoring,[5,6] or wearable sensors as the base for crowd-sourced environmental monitoring.[7] In ambient air quality monitoring practices, mobile monitoring is a highly scalable method that significantly enhances the spatiotemporal resolution of air quality data. Recently, it has been attracting prominent attention from both the scientific community and the public to trace emission sources, evaluate ambient air pollution's spatiotemporal distributions, and assess personal exposures and related public health burdens, among many other applications.[8−11] Besides being used as a standalone measurement technique, mobile monitoring has been an indispensable data source to complement traditional stationary air sampling, satellite remote sensing, and physical and empirical model simulations.[12−15] The growing body of mobile monitoring literature has presented a myriad of confounding factors to consider in study design for future studies, which urgently calls for a systematic organization of existing knowledge in this field. While we acknowledge the diversity and versatility of mobile monitoring studies, we have defined the scope of this review only to address studies on the mobile monitoring of ambient air quality, where measurements are conducted while the sensors are in motion (e.g., carried by

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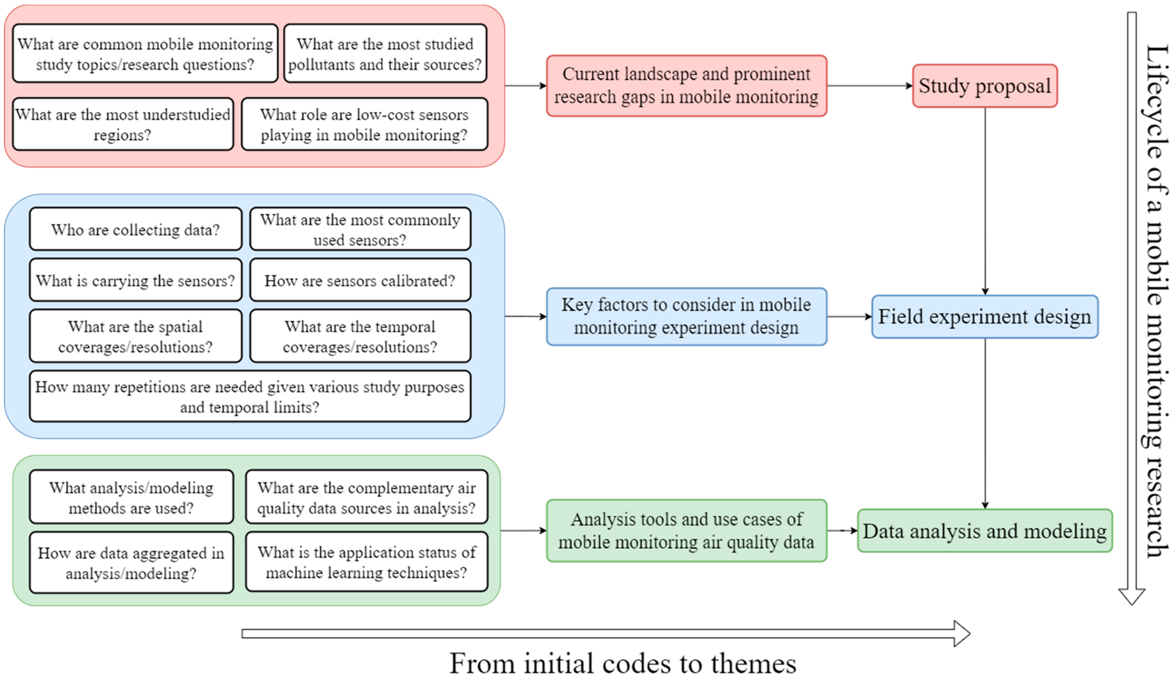

Figure 1. Conceptual flowchart of a mobile monitoring study.

a pedestrian or deployed on a vehicle). We use the term "mobile monitoring" to refer to the studies using such a monitoring scheme for simplicity. It is worth noting that studies using portable instruments for short-term stationary measurements are not in our review's scope.

Previous reviews mainly concentrate on two distinct areas of the sensing platforms and the data application. On the one hand, a great amount of attention has been paid to the rapid development of air quality sensing tools, firmware, or software, for mobile uses. Idrees and Zheng[16] reviewed recent low-cost air pollution monitoring systems, emphasizing their integration with enabling technologies, such as wireless sensor networks and the Internet of Things. They find the enabling technologies are not ready at the current stage but fast-evolving. Similarly, Villa et al.[17] reviewed the applications of small unmanned aerial vehicles (UAVs) as the platform for ambient air quality monitoring. They argue that, even though the potential of UAVs in air quality monitoring has been established, the strict civil aviation regulations and laws are the biggest challenges in its wider adoption. Król et al.[18] and Baron and Saffell[19] examined the development of VOC sensor and amperometric gas sensor technology, respectively. Specifically, Król et al.[18] categorized the sensors by the ability to be transported into those for stationary and mobile use. However, several types of equipment designed for stationary monitoring have also been adapted later for successful mobile deployments.[20−22] It demonstrates the necessity of reviewing the current sensor technology in an application-oriented scope, as in this paper.

On the other hand, environmental researchers and practitioners are interested in how data collected by mobile monitoring platforms can be used to inform air pollution mitigation and management strategies. Kumar et al.[23] and Morawska et al.[24] both focused on reviewing low-cost air quality sensors from the application perspective. The two reviews discussed low-cost sensor use cases and opportunities on mobile platforms while recognizing the potential of these sensors' integration with smartphones and wearables for opportunistic and ubiquitous air quality monitoring. Similarly, Thompson[25] reviewed the current establishments of high spatiotemporal "crowd-sourced" air quality monitoring networks, identifying that the bottleneck of such large-scale networks is low-cost sensor data quality rather than data communication. They also suggest that more investment should be directed to the fundamental analytical chemistry of the sensing platforms rather than to the immediate deployment of large smart-city systems. To the authors' knowledge, Gozzi et al.[26] wrote the only review on mobile particulate matter (PM) monitoring studies. They covered multiple facets of mobile PM monitoring, including instrumentation, current status, and critical issues and perspectives. However, they did not adopt comprehensive literature searching and exclusion criteria, which might lead to biased conclusions. Despite the substantial number of reviews performed within the perimeter of mobile monitoring in the past decade, very few have rooted their narratives on the values, opportunities, and challenges that being "mobile" can bring from an air pollution research perspective. Moreover, there has not been a study that systematically reviews the past decade's literature with a significant meta-analysis part to provide unbiased quantitative insights into the field.

In this review, we aim to provide a timely and comprehensive landscape of studies that employ mobile monitoring to understand, quantify, and mitigate the impacts of air pollution, emphasizing the rapidly expanding applications of low-cost sensing and data mining techniques. We distilled over 300 papers out of the initial 3200+ ones, focusing on those from the past decade. A taxonomic system was developed to extract standardized information from key aspects of mobile monitoring studies, borrowing concepts from thematic analysis. We employed a meta-analysis approach to summarize the information and provide insights into the three stages of a typical study's life-cycle, including study proposal, experiment design, and data analysis and modeling. Our work

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

is one of the first to review the rapidly growing field of mobile ambient air quality monitoring in the past decade, revealing current gaps in research and practices. It sheds light on the robust design and implementation of mobile monitoring studies, including practical and innovative research topics, valid experiment design, and rigorous data analysis. Our taxonomic information extraction method is highly transferable to other studies with a significant systematic review element, which minimizes the effects of authors' preferences and biases on knowledge extraction from the literature. Lastly, the review provides a quantitative reference to future applications, covering essential aspects throughout the entire life-cycle of a typical mobile monitoring study. It is of great interest and relevant to air pollution researchers, citizen scientists, and practitioners at all experience levels, which can be used as a guide for future mobile monitoring study designs.

2. REVIEW METHODOLOGY

In this study, we borrowed the concept of thematic analysis, a research method that identifies, analyzes, and reports patterns within data, typically texts, such as interviews, transcripts, questionnaires, and scientific literature. We followed the well-recognized six-step thematic analysis framework by Braun and Clarke:[27] familiarization with the data, generation of initial codes, search for themes, review of themes, the definition of themes, and writeup. The methodology adopted in this work is presented in Figure 1. We first screened out the papers for final review using a systematic and reproducible literature search and selection criteria. A series of codes is developed iteratively in the reviewing process to extract standardized information from the papers, which are in the form of small, self-contained questions that can be answered in standardized responses for further meta-analysis. The codes are then grouped under three themes: (1) the current landscape and prominent research gaps in mobile monitoring; (2) key factors to consider in mobile monitoring experiment design; (3) analysis tools and use cases of mobile monitoring air quality data. Each theme is further related to the main stage in the life-cycle of a mobile monitoring study, including the study proposal stage, the field experiment design stage, and the data analysis and modeling stage. By addressing the questions in the three themes, we provide critical insights into a typical mobile monitoring study's life-cycle and recommendations for the design and execution of future mobile monitoring studies.

2.1. Literature Search, Selection, and Screening Criteria.

To identify an initial group of papers for review, we employed Web of Science as the main search engine for publications that contained the relevant keywords "air quality", "air pollution", and "mobile". Supplemental Google Scholar searches were conducted to cross-check that relevant literature was included. In total, our first-round search returned over 3200 papers. It is important to emphasize that we define the scope of this review only to address studies on the mobile monitoring of ambient air quality. Meanwhile, we still use "mobile monitoring" to refer to these studies for simplicity. Therefore, the initial results were screened to identify which papers fell within our review's scope. It should be noted that this review did not include "gray literature", such as non-peer-reviewed reports from governments, companies, and non-governmental organizations, working papers, media coverages, and other web-based resources.

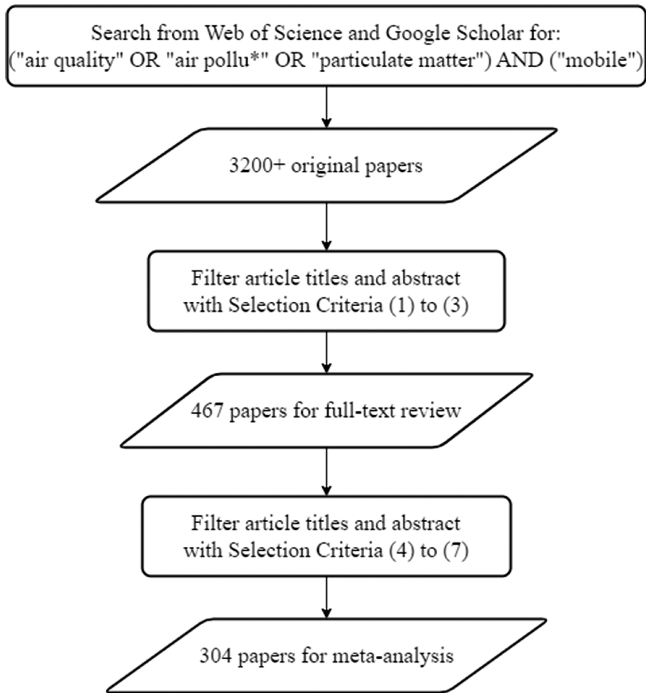

Figure 2. Literature search and filter flowchart; the selection criteria numbering corresponds to the text preceding the figure.

As shown in Figure 2, we screened the abstracts of the papers in the initial group according to the following seven selection criteria:

(1) The study is a full-length original research article from an indexed, peer-reviewed journal publication. We exclude publications in conference proceedings. We are aware that this will lead to an under-representation of papers published in the form of conference proceedings in domains like electrical engineering. The exclusion is intended as this study mainly focuses on the method of mobile monitoring and its applications rather than the development of mobile monitoring instruments. The target audience of this review is end-users of air sensors and instruments, such as environmental scientists, engineers, and practitioners. To the authors' knowledge, the quality of conference publications can vary in a much larger range than journal publications in the environmental science field. This selection criterion also contributes to our standardized information extraction, as conference publications can be in several forms, such as abstract, extended draft, or full-length articles.
(2) The study is presented in English.
(3) The study is published between January 2012 and December 2021, inclusive.
(4) The study should have a significant element of air quality data collection and analysis through mobile monitoring/sampling rather than using secondary data products.
(5) The study collects and analyzes ground-level air quality and air pollution.
(6) The study is not focused on closed microenvironments or indoor air quality.
(7) The study is not focused on firmware development or a conceptual data collection framework.

Of the 3263 initial papers, 304 were carried through to the final review stage. Not all 304 papers are cited and discussed in

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

Table 1. Definitions of Codes Used in Literature Delineation

Theme	Final Code	Standardized Response	Definition
Current landscape and prominent research gaps	Low-cost sensor used	Yes/ No/ Partially	This code considers if low-cost sensors are used in the study. The definition of the low-cost sensor in current literature is ambiguous, as the price gap can be huge for different pollutants and in different regions. This review defines that a low-cost sensor should cost no more than \$2500 or be listed as low-cost in papers or both, considering US EPA's guidance[28]. Specifically, the "Partially" response refers to a study that used both low-cost and non-low-cost sensors.
	Emission source	Stationary/ Mobile/ Multiple	Emission source denotes the target emission sources in the paper.
	Location	Specify city/ region, country	Location refers to where mobile monitoring is carried out at the level of city, region, or country.
	Target pollutant	Specify pollutant names	The target pollutant is the pollutant being monitored and analyzed in the study. PM refers to all studies examining the mass concentration of particulate matter with a range of sizes, excluding black carbon (BC). PN includes all studies examining particulate matter number concentrations. UFP refers to particles with less than 0.1 um diameter, mostly concerning only counts or number concentrations. NOx is tagged separately with NO and NO2.
Key factors in mobile monitoring experiment design	Architecture	Integrated/ Non-integrated	Architecture refers to the organization of instrumentation. An integrated architecture is a collection of sensors measuring at least two types of pollutants with at least one of the following features: a common power source, a common air inlet, or a common data storage/ communication system.
	Carrier	On-road vehicle/ Off-road vehicle/ Person/ Bike/ UAV/ Multiple	Carrier is the moving object that carries the instruments.
	Sensor model	Specify sensor make and model	The sensor model provides detailed information on the instrumentation.
	Collection spatial coverage	Neighborhood/ City/ Multi-city/ Country/ Multi-country	Data collection spatial coverage is the area in which the experiment occurred. A neighborhood is defined as a small portion of a city, usually less than 20% of the area. City and Country follow the natural definitions of a city and a country, despite their vastly different sizes.
	Collection spatial resolution	Hyperlocal/ Neighborhood/ City/ Region/ Country	Data collection spatial resolution denotes the spatial detailedness of the experiment. It should be compatible with the temporal resolution, where second-level data have a hyperlocal spatial resolution, minute-level data have a neighborhood spatial resolution, etc.
	Collection temporal coverage	Days/ Weeks/ Months/ Over a year/ Routine sampling	Data collection temporal coverage is the period during which the experiment occurred. Days: 1-7 days; Weeks: 1-4 weeks; Months: 1-12 months; Over a year: 1-2 years; Routine sampling: 3 years or over.
	Collection temporal resolution	Second/ Minute/ Hour/ Multi-hour/ Day	Data collection temporal resolution is the frequency at which the instruments record air quality data. Second: 1-60 seconds; Minute: 1-60 minutes; Hour: 1-2 hours; Multi-hour: 2-24 hours; Day: at least 24 hours.
	Personnel	Specialized crew/ Citizen	Personnel defines who conducts the mobile monitoring study. The specialized crew is trained, with a priori knowledge of the instruments and mobile monitoring, and dedicated to data collection.
	Sampling strategy	Pre-defined/ Opportunistic	The sampling strategy defines how data is collected. Opportunistic monitoring refers to campaigns where data collection is not the main purpose of movement.

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

Table 1. continued

Theme	Final Code	Standardized Response	Definition
Analysis tools and use cases	Analysis method/ research purpose	Descriptive/ Spatial regression/ Personal exposure assessment/ Epidemiology/ Source apportionment/ Emission rate analysis/ Protocols validation	The analysis method taxonomy used in our tagging system speaks a lot for the research purpose at a high-level, such as spatial regression methods used for spatial regression of air pollution concentrations. The analysis method/research purpose tag refers to how researchers make use of mobile monitoring data and what they are used for. Descriptive includes all studies that only summarize observations, such as data-only mapping, hotspot analysis, and species/chemical composition analysis using instruments. Spatial regression refers to all types and variants of land use regression, with or without temporal regression. Personal exposure assessment refers to the quantification of the inhalation dose of air pollution, excluding those that only evaluate concentrations. Epidemiology quantifies the health impacts of different air pollution concentrations or exposure levels. Source apportionment attributes air pollution to individual sources quantitatively, based on positive matrix factorization and species/chemical composition results. Emission rate analysis estimates fuel-based or facility-based emission rates. Protocol validation includes the evaluation of novel measurement schemes, methods, or dispersion models using mobile monitoring data as a reference.
	Complementary data sources	Reference station/Reference-grade stationary (self)/ Reference-grade mobile (self)/ Remote sensing/ Modeled results/ Specify other	Complementary data is data collected from sources other than the mobile monitoring campaign described in the study that are used in data analysis, excluding instrument calibration and background correction. Reference-grade stationary (self) is differentiated from reference station, as the former one is usually run by research conductors, but the latter one is not. Modeled results include physical experiments in controlled environments, mathematical dispersion models, and empirical statistical models.
	Data analysis temporal resolution	Aggregated/ Disaggregated/ Same as in data collection	Data analysis temporal resolution evaluates how data are aggregated in time in analysis. Aggregated refers to data's temporal aggregation, such as in land use regression studies. Disaggregated refers to data's interpolation in analysis.
	Instrument calibration	Reference station/ Reference instruments (self)/ Lab instruments (self)/ Remote sensing/ Specify other	Instrument calibration reports the reference that raw air quality data are calibrated against. Similar to the definition in complementary data sources, reference-grade instruments (self) are differentiated from reference stations, as the former one is usually run by research conductors, but the latter one is not. Factory calibration by the manufacturer is not considered reference-grade calibration.
	Machine learning	Traditional/ Specify machine learning algorithms if used	Machine learning distinguishes the empirical modeling tools used in data analysis only, acknowledging the versatility of machine learning in studies. That is to say, machine learning tools used in data collection are not considered. While linear regression is considered machine learning in the broadest sense, we classify all statistical models that are variants or spin-offs of linear regression as traditional.
	Repetition	Specify the number of repetitions	Repetition refers to repeated sampling over the same location (e.g., spots, road segments, sites of interest).

detail in the main body of this review. A complete bibliography for the 304 final reviewed papers is provided in a separate BibTex file, along with a bibliometric map with interactive resources for the audience to explore more related literature in the Supporting Information, Figure S1. We acknowledge that some relevant literature might be unintentionally excluded, especially when applying selection criteria (4) to (7). However, given the current extent of work in the field and the variety of papers we reviewed, we believe that our bibliography is representative of the current mobile monitoring literature.

2.2. The Literature Coding System and Meta-Analysis. A series of codes was developed iteratively before, during, and after multiple rounds of reviewing all papers in the final pool. The responses to each code were standardized to yield uniform and comparable information. The only exception was the research question code, where each study's main research question was reported; thus, no standardized responses exist. It is important to mention that all authors of this paper were trained on the review methodology before the coding process and constantly exchanged thoughts in the process to guarantee the same understanding and interpretation of all code responses. Final coding and labeling results for all included papers are presented in section 1 of the Supporting Information. Definitions of all 19 codes are detailed in Table 1.

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

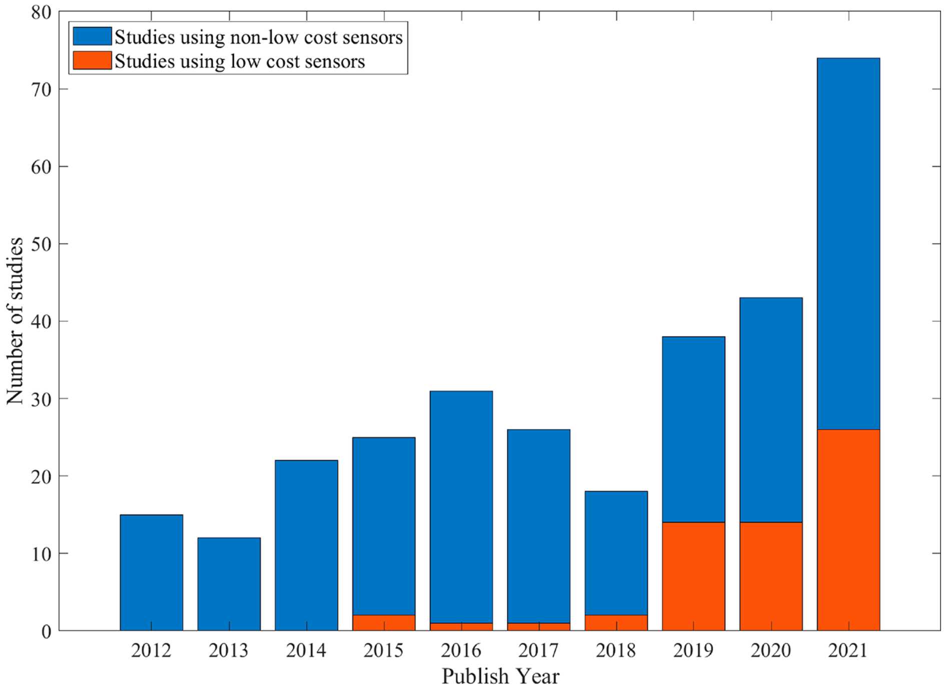

Figure 3. Number of mobile monitoring studies in the last ten years.

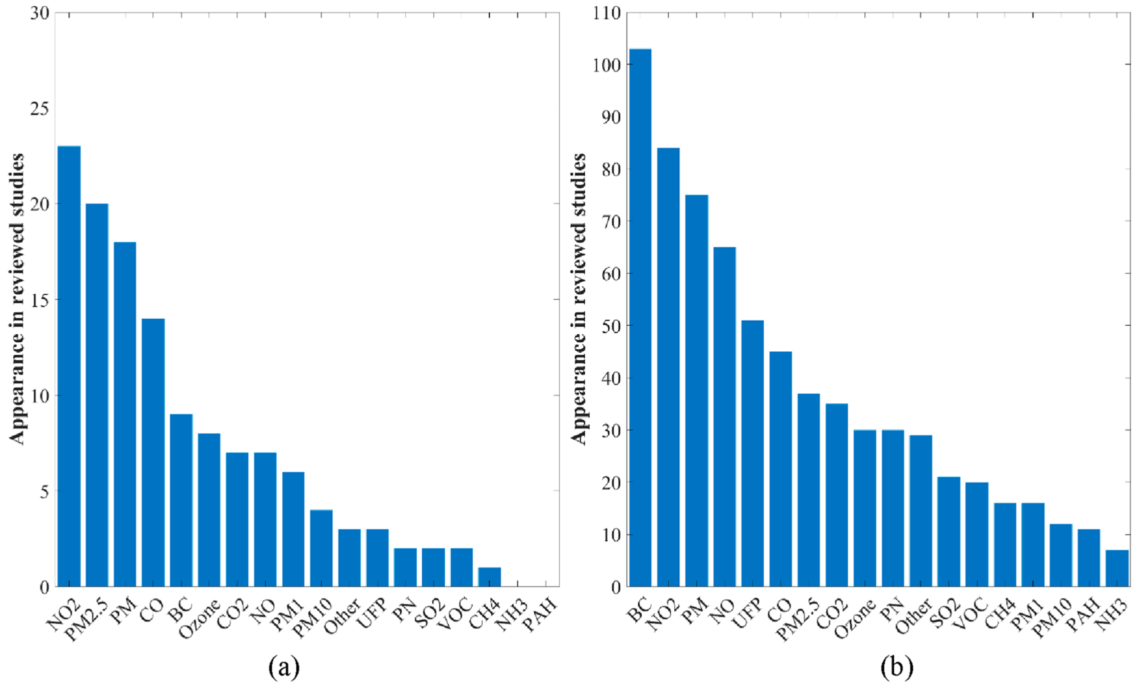

Figure 4. Target pollutants examined by studies done with (a) and without (b) low-cost sensors.

3. RESULTS AND DISCUSSION

3.1. Current Landscape and Prominent Research Gaps in Mobile Monitoring Studies. *3.1.1. Descriptive Analysis of Mobile Monitoring Studies.* The total number of mobile monitoring studies has significantly increased in the past decade, as shown in Figure 3, indicating the scientific community's wider adoption of mobile monitoring. Since 2019, the number of low-cost monitoring studies has grown substantially, where one-third of those are published in the later years. The proportion of studies using low-cost sensors (<2500 USD[28]) is also rising. From our study, it is hard to draw a conclusion about the efficacy of mobile monitoring and low-cost sensors in meeting researchers' study objectives. There is usually a screening process to find the instrumentation that best serves the study objectives. Moreover, the established paper reviewing and publishing system increases the bias in such an analysis. Positive results are much more likely to be published than negative results, leading to potential biases in concluding that one method is more effective than another. However, given the exponentially growing number of mobile monitoring and low-cost sensing studies (mostly with positive results), we can infer the growing trend of mobile monitoring

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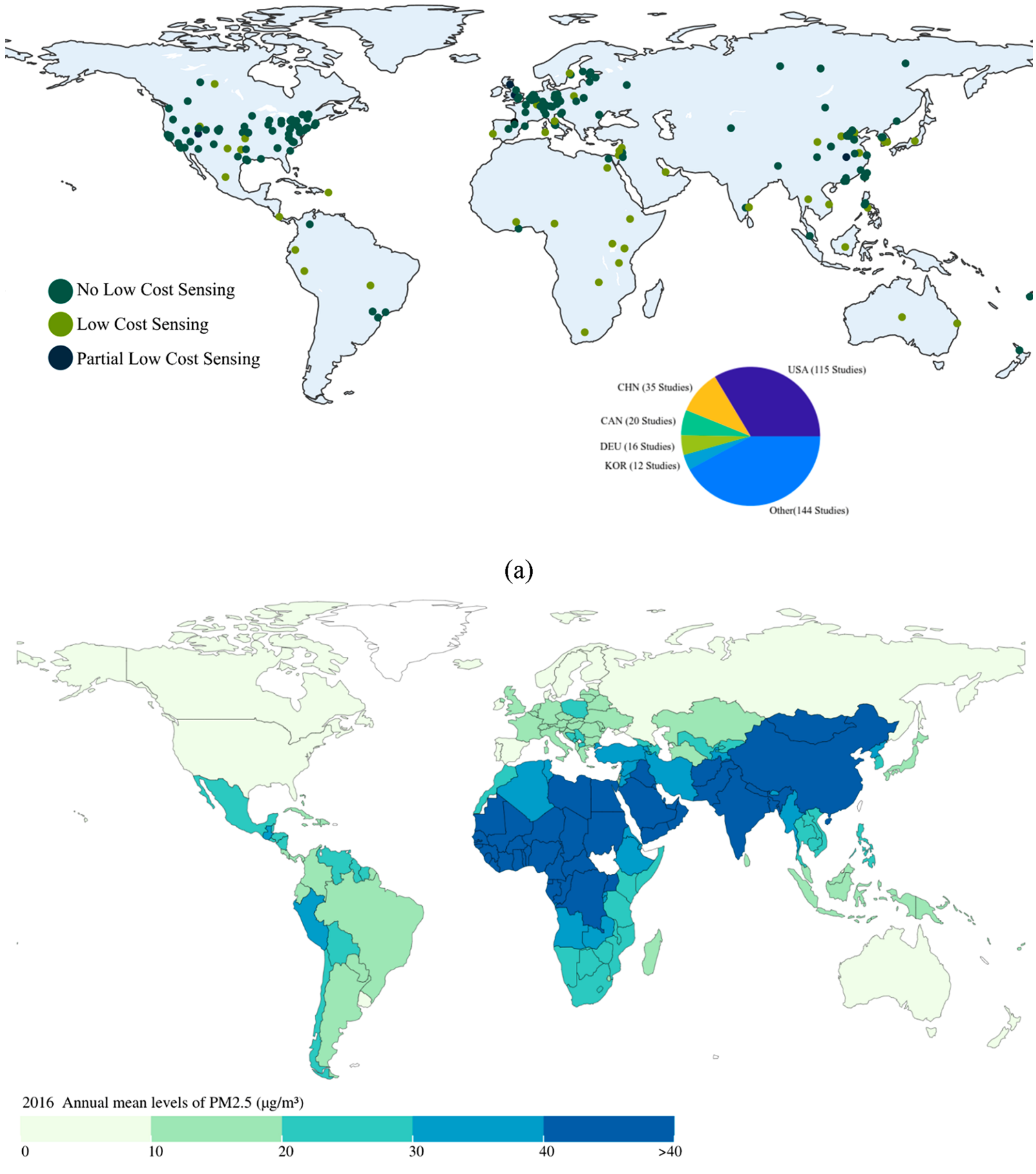

Figure 5. Global distribution of review studies (a) and annual average of $PM_{2.5}$ in 2016[38] (b).

and low-cost sensing's efficacy. It is worth noting that a "low-cost monitoring" study indicates a study that either completely or partially makes use of low-cost sensors in our context. If no low-cost sensors are involved in the study, it is classified as "non-low-cost monitoring".

We summarize the most studied pollutants in non-low-cost and low-cost sensing studies in Figure 4. Most studies measure more than one pollutant. The top pollutants measured in non-low-cost monitoring studies include black carbon, NOx, and particulate matter. In contrast, particulate matter, carbon monoxide, and NOx remain the most studied pollutants by low-cost sensors. In recent literature, ultrafine particles (UFPs) are increasingly being studied,[29−32] as there are mounting questions about their negative health effects. However, there are very few low-cost choices for UFP measurement in the market. None has been evaluated or proven effective in the current literature, presenting a significant gap in their capability. Similarly, while black carbon poses direct threats to human health and climate change, related low-cost monitoring studies involve both non-low-cost and low-cost sensors, necessitating the use of costly sensors for accurate measurements of these pollutants.

We further examined what types of emission sources were investigated in the literature. Recall that we specify the types of emission sources as "stationary", "mobile", and "multiple". More than 60% of all studies do not specify a targeted emission source type, which is coded as "multiple". More than a quarter of studies specifically investigate emissions from mobile sources, such as road and air traffic. Few studies are dedicated to stationary emission sources, which are typically large-area sources, such as wildfire, farmland, or burning field.[9,33,34] While mobile monitoring can greatly improve the spatiotemporal resolution and scope of air quality studies, it cannot continuously sample the same location in the long run, limiting its application in assessing stationary emission sources. Moreover, the confounding factors in uncontrolled environ-

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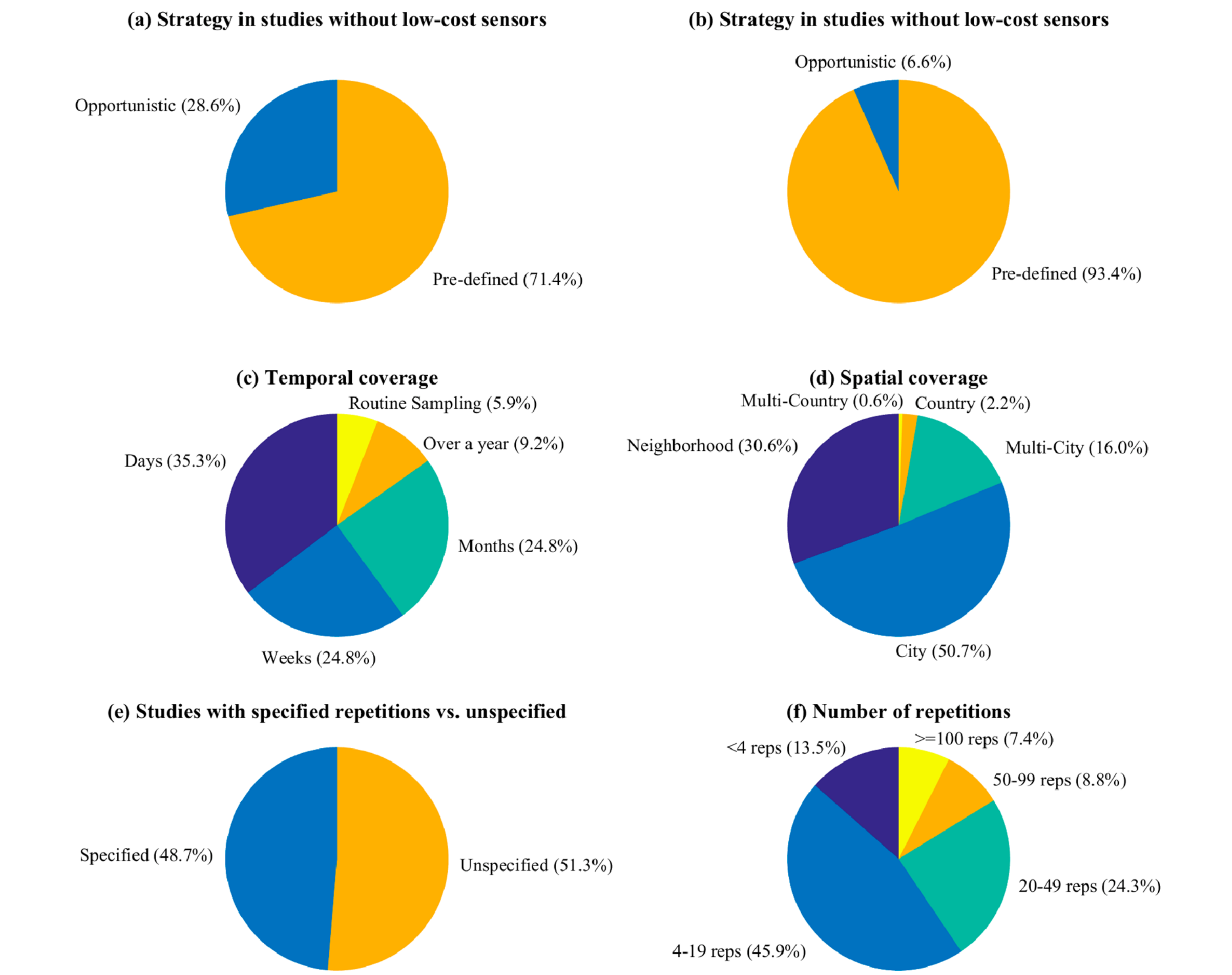

Figure 6. Sampling strategy of non-low-cost and low-cost sensor studies (a, b), spatial and temporal coverage (c, d), and repetition (e, f) of all reviewed studies

ments grow exponentially. Thus, it may be difficult to distinguish a single type of emission source without proper methods and tools for source apportionment.

3.1.2. Disparities in the Geographic Distribution of Mobile Monitoring Studies. Low- and middle-income regions face a double burden of poor air quality and insufficient air pollution monitoring and management resources. Despite the increasing ubiquity of mobile monitoring studies and the availability of low-cost sensors, there is a notable lack of air quality monitoring infrastructure, and many areas remain severely understudied.[35,36] It poses a projecting environmental justice problem across the globe.

Figure 5 shows North America, Europe, and East Asia have the highest numbers of mobile air quality monitoring studies. The top countries with the most studies are the United States (115), China (35), Canada (20), Germany (16), and South Korea (12), among which China is the only middle-income country. The United States is by far the most studied country by mobile monitoring researchers. While the studies in the United States are mostly spread throughout the continent, a few clusters emerged in California, the Midwest (especially in Colorado), the Gulf Coast, and the Northeast Corridor. South Asia has the highest levels of ambient $PM_{2.5}$ levels regionally, followed by the Middle East, North Africa, and Sub-Saharan Africa.[37,38] However, these regions do not have a significant body of peer-reviewed research within the scope of our interview. Of the 52 countries with studies included in this review, only 2 were low income, 11 were lower middle income, 16 were upper middle income, and 23 were high income.

Low-cost sensors have the potential to change the current paradigm of air quality monitoring and bridge the gap in air pollution management in developing regions.[24] Nonetheless, the spatial disparity in low-cost monitoring studies is as prominent as in mobile monitoring studies. Most low-cost monitoring studies are conducted in high- and upper-middle-income countries. The unequal distribution of air quality burden and the ability to monitor them between developed and developing countries highlights a critical environmental justice consideration. Gradually, global researchers are beginning to fill this research gap. Multiple initial studies in low-income countries are paving the road toward an equitable future in air quality measurement and management. In Jordan, Hussein et al.[39] conducted a preliminary mobile monitoring study on particulate matter that covered more than three-quarters of the country. One of the only studies from a Pacific Island nation, focused on Suva, Fiji, detailed the first attempt

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

to map and study airborne ultrafine particles in the region,[40] and other work examined fine particulate matter levels in multiple African countries with low-cost sensors.[7,36,41]

3.2. Key Factors to Consider in Mobile Monitoring Study Design. *3.2.1. Mobile Monitoring Strategies and Schemes.* Currently, there are three types of operational mobile monitoring sampling strategies that are complementary to the others. The first is the predefined strategy, which involves almost all independent mobile laboratories operated by research groups, governments, and local communities. This strategy is the most commonly seen in our literature, usually with research-grade instruments operated by trained personnel on predefined routes. It serves the purposes of a wide range of ad hoc mobile monitoring projects but is hard to coordinate for long-term, large-scale deployments. Second, the City Scanner initiative at MIT Senseable City Lab represents a complete opportunistic mobile monitoring strategy with low-cost monitoring and Internet of Things (IoT) technologies,[42] along with the practices in Hagemann et al.[43] and Mueller et al.[44] Existing fleets are used as sensing platforms, including public transit fleets, municipal service vehicles, and on-demand mobility service fleets. While having the potential to bridge the global air quality data gap, there is a strong need to balance such sensor network's cost, reliability, and longevity. Lastly, Google employs a hybrid data collection strategy with sampling campaigns carried out worldwide,[45] which combines the predefined and opportunistic strategies. The research-grade sensors are mounted on Google Street View vehicles that circulate in the city, which have been successfully implemented in multiple cities across the globe, including Hamburg, Dublin, Amsterdam, Copenhagen, London, Houston, and Oakland, for periods ranging from months to years. Since air quality data collected by Google is potentially a for-profit product, this might exacerbate data poverty in less developed regions. In Figure 6a and b, we observed that more opportunistic mobile monitoring used low-cost sensors, where data collection is not the main purpose of the carrier's movement. It allows mobile monitoring campaigns to collect data at unprecedented temporal resolution and spatial coverage that complement the current stationary monitoring networks.

In terms of the temporal and spatial coverage of mobile monitoring experiments, Figure 6c and d illustrates that more than 35% of studies only last for days, while only about 15% of studies last longer than a year. Compared to stationary measurements, mobile monitoring campaigns are subject to many sources of uncertainty in an uncontrolled environment that grows exponentially as the temporal coverage increases, such as instrument malfunction, disruption caused by weather, and traffic accidents. The sunk time cost spent in coordinating and managing both the carrier fleet and the instruments is also not negligible. The disparities in temporal coverage highlight that most mobile monitoring campaigns are currently ad hoc data collection projects capturing snapshots of air quality and have yet to become an environmental sensing infrastructure like stationary air quality sites. There are a few exploratory studies that are exceptions. Hagemann et al.[43] piloted a long-term deployment of an air quality monitoring system on the tram system in Karlsruhe, Germany. Mueller et al.[44] have deployed a network of particle number counters on the tram system in Zurich, Switzerland, for more than 1.5 years, where the sensor network operates as the tram system operates. Both studies demonstrate the possibility of operating mobile monitoring sensors on the existing public transit systems in the long run and eventually as a new type of municipal infrastructure. A conceptual study by O'Keeffe et al.[46] also confirms the potential of using on-demand mobility services, such as taxis and ride-hailing services, as mobile monitoring platforms in urban environments. The majority (81.3%) of mobile monitoring studies have a spatial scope no bigger than a city. Mobile monitoring is helpful in enhancing spatial coverage when the number of sensors is limited. Nonetheless, the complexity of mobile monitoring measurements with predefined sampling routes and frequency grows exponentially as the sensing nodes and spatial coverage increase, which can be seen as a traveling salesman problem essentially. Given the same temporal coverage and amount of sensing nodes, the spatial coverage of opportunistic measurements is even more limited than in predefined studies.

A vital element of mobile monitoring experiment design is the number of repeated measurements at the same location, especially for studies aiming at generating representative air quality profiles. Repetition reduces uncertainty in mobile monitoring data and helps extract information on interest from numerous confounding factors. Apte et al.[47] observed that 10 to 20 repetitions on different days over the course of a year are able to reproduce key spatial air quality patterns with low variability in Oakland, CA. Messier et al.[48] concluded that 50 times of drive-by sensing over two years on the same road segment generates robust long-term land use regression maps in the same study area, but only 4 to 8 repetitions are sufficient for data-only maps. Similarly, Hatzopoulou et al.[49] found that model uncertainty and performance gains diminish after ten repetitions while arguing that the "optimal" number of segments and visits identified in a specific city might not be transferable to others due to the complexity of local emission sources, urban form, and street topology. Figure 6e and f summarizes the information on repetition from reviewed studies. Surprisingly, over 50% of all studies did not specify repetitions, while 13.5% of studies have less than four repetitions among those specified with this information. We acknowledge that mobile monitoring studies can be subject to a variety of research purposes that require different levels of repetitions and temporal aggregation. Therefore, we analyzed 89 studies more closely that last from weeks to months, serving for emission rate analysis, spatial regression, source apportionment, personal exposure, and model validation. Table 2 presents the min, median, and max values of the number of repetitions in these studies. Descriptive studies are not included as they cover a wide range of study scopes and purposes and do not have universally adopted methods. The count column adds up to more than 89, as some studies adopted multiple methods. Study methods are ranked in median values of repetitions. Given the smaller number of studies evaluated for emission rate analysis, source apportionment, personal exposure, and protocol validation, one should

Table 2. Number of Repetitions Statistics for Different Mobile Monitoring Study Methods

Study Method	Min	Median	Max	Count
emission rate analysis	1	5	33	12
spatial regression	1	10	600	41
source apportionment	2	20	91	13
personal exposure	6	32	96	10
protocol validation	1	36	1600	17

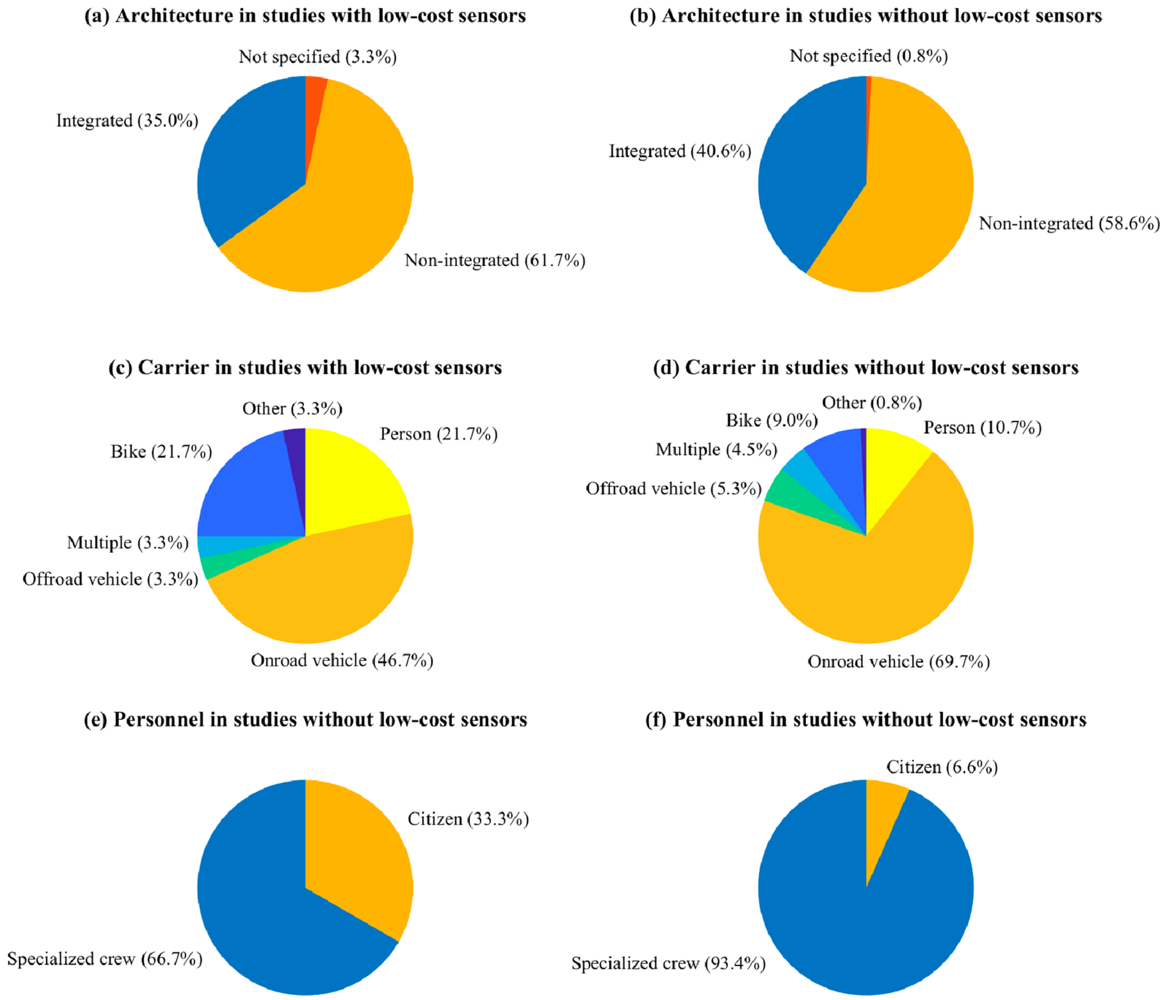

Figure 7. Architecture, carrier, and personnel for studies with (a, c, e) and without (b, d, f) low-cost sensors.

be cautious when referring to this table to determine suitable repetitions for a specific study method. For spatial regression studies, the median value of repetitions is 10, which can be safely used as a rule-of-thumb for future studies lasting up to a year. Four repetitions should be considered the bottom line for any type of analysis. This observation aligns well with findings from the above-mentioned studies and demonstrates the current consensus on mobile monitoring repetition.

3.2.2. Sensing Platform Design. In Figure 7, we summarize three major considerations that are ubiquitous in mobile monitoring platform design: instrument architecture, carrier, and personnel. Their respective definitions are detailed in Table 1. We observe that about 60% of studies employed nonintegrated instrumentation, where each sensor runs independently instead of being part of the same system. An integrated design has many edges over a nonintegrated one. A shared air inlet is important to guarantee consistent airflow for all instruments. Unified data storage and communication components can better coordinate and synchronize data collected from various sensors. Specifically, we would expect a higher percentage of integrated architecture in studies using low-cost sensors, as low-cost sensors are considered with higher integration flexibility.[24] Contrary to our hypothesis, the strength of low-cost sensors in integration is not fully exerted in current mobile monitoring studies, while about half of the low-cost monitoring studies deploy a single model of a sensor for one target pollutant, focusing on establishing a larger monitoring network.

Mobile monitoring on various carriers provides great flexibility in collecting air quality data at unprecedented spatiotemporal resolutions, with 65% of all reviewed studies carried out by on-road vehicles. For low-cost studies, only 46.7% of studies were performed by on-road studies, while this percentage is much higher for non-low-cost studies as research-grade instruments are usually less portable and require regular maintenance by trained personnel. Studies involving low-cost sensors demonstrate more diversity in instrument carriers than those featuring non-low-cost sensors. This is greatly facilitated by the portability, ease to deploy, and low energy consumption of low-cost sensors, which offers great flexibility in the study design. Instrument miniaturization and cost reduction have allowed studies to comprehensively map air quality by deploying such devices on transport modes such as trash trucks, taxi fleets, and trams.[3,50,51] We notice a significant increase in studies carried out by bikes and persons,[52−55] which brings a unique opportunity to assess personal exposure at unprecedented temporal and spatial resolutions.

Furthermore, low-cost sensors have created opportunities for members of the public to become key players in mobile measurement campaigns, which help better disseminate air quality knowledge, raise awareness, foster behavioral changes, and advocate for environmental justice among a larger

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

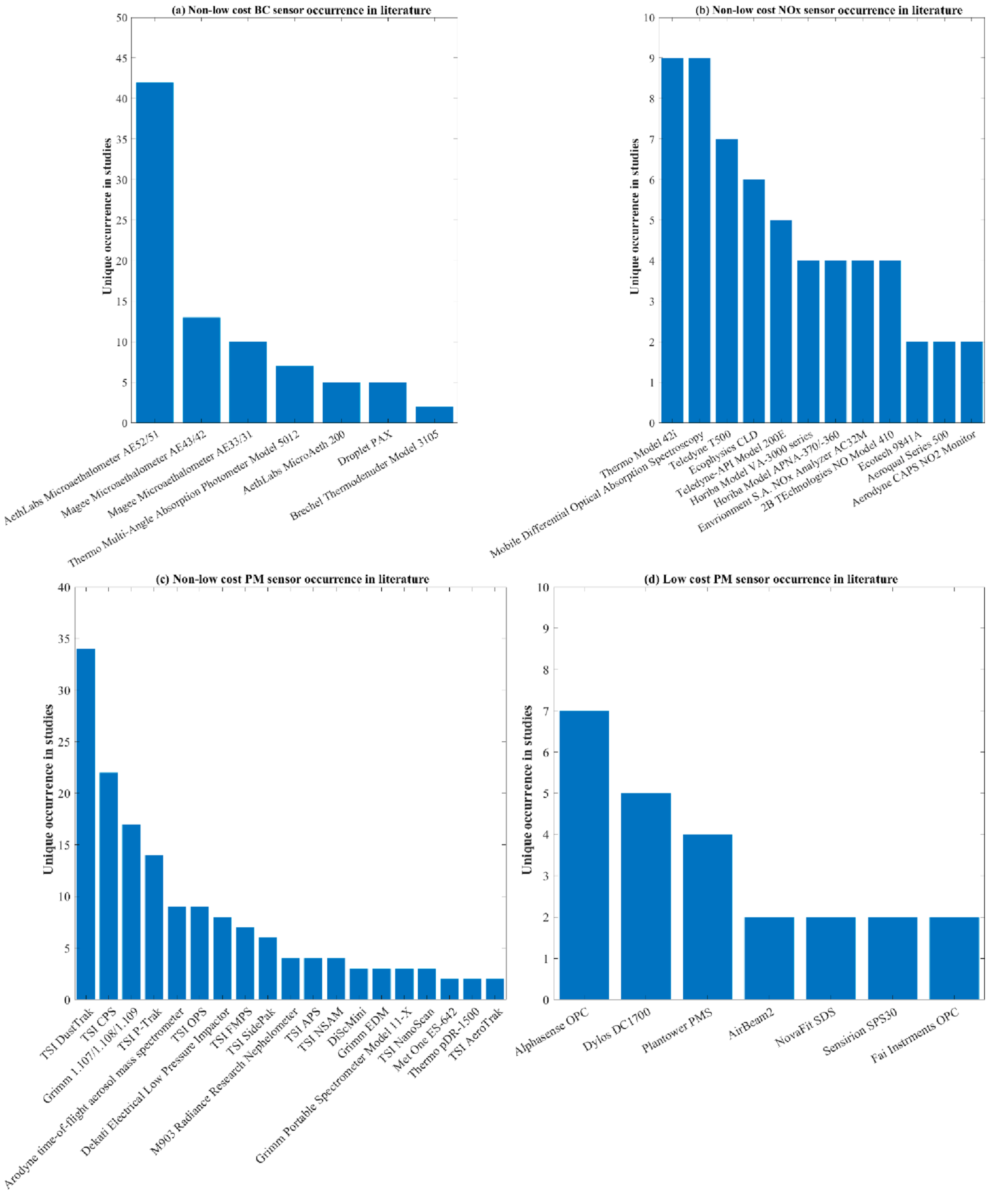

Figure 8. Sensors used in mobile monitoring of black carbon (a), nitrogen oxides (b), and PM (c, d).

audience. West et al.[56] engaged with a low-income community in Nairobi to use these sensors to better characterize the spatial distribution of pollution and potentially important sources in their neighborhood. Ellenburg et al.[57] used low-cost sensors to engage with school children to help them learn about pollution.

3.2.3. Sensing Instrumentation. Figure 8 summarizes the most used low-cost and non-low-cost sensors for the most studied air pollutants, including PM, NOx, and black carbon. It is worth noticing that, for PM sensors, we include particle number counters and mass concentration impactors for the whole spectrum of PM from UFP to PM10, excluding black carbon sensors. A detailed list of all accounted PM sensors is

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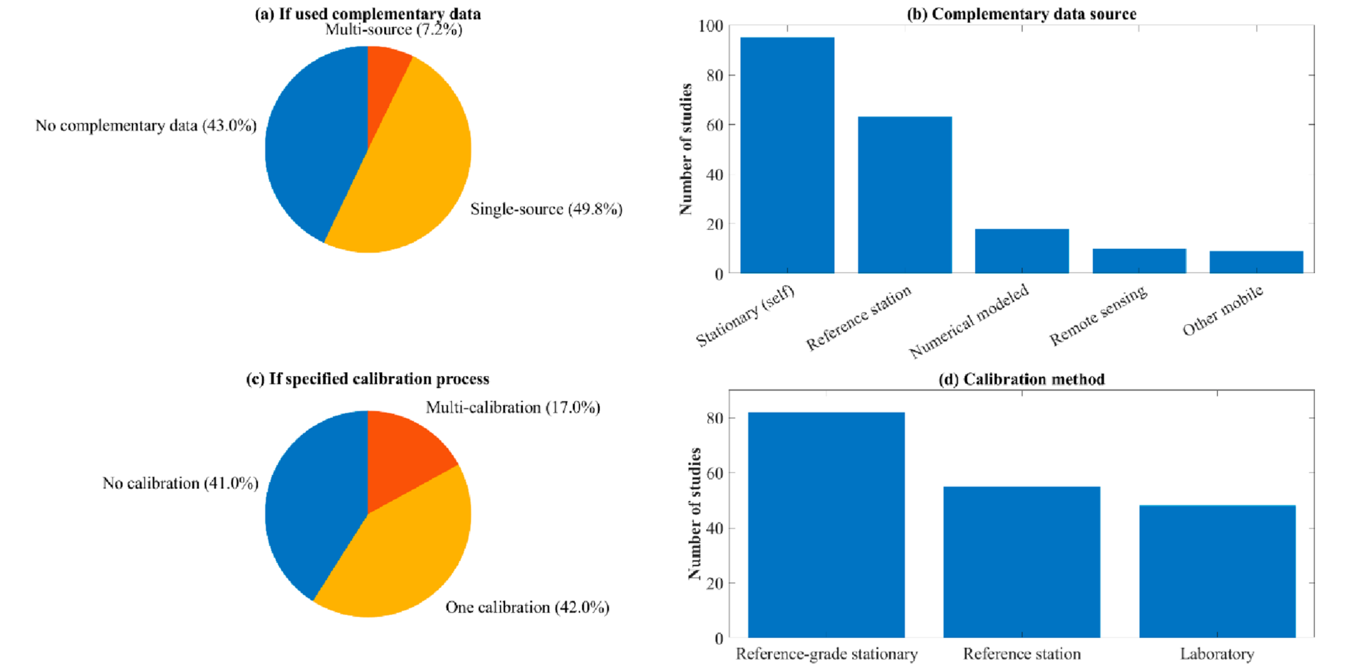

Figure 9. Complementary data (a, b) and calibration method (c, d).

documented in the Supporting Information, Table S1. Low-cost sensors for NOx are not included as their distribution among brands is scattered. While reference-grade NOx sensors are widely used in mobile monitoring (Thermo Model 42i, Teledyne T500, Horiba Model APNA-370/-360, etc.), mobile PM measurements are dominated by instruments not identified by the US EPA-regulated Federal Reference Methods (FRM) and Federal Equivalent Methods (FEM).[58] There is a wide spectrum of portable PM sensors on the market now that can cater to a variety of mobile monitoring applications, which are widely used as "research-grade instruments". The most notable ones are a series of PM impactors and PN counters manufactured by TSI, whose prices usually sit between low-cost and reference instruments. While their performances have been widely accepted by the scientific community,[59−62] they are currently not recognized as FRM/FEM. Rigorous calibration and data quality assurance procedures are necessary before and during their usage. We acknowledge that using EPA's definitions of reference-grade instruments might be biased toward studies done outside of the US and regions not accepting EPA's regulations, but we do not think this will significantly affect this observation.

3.3. Analysis Tools and Use Cases of Mobile Monitoring Air Quality Data.

3.3.1. Complementary Data Sources and Data Quality Assurance. Figure 9 presents complementary data sources and calibration methods used in mobile monitoring studies. Complementary data sources refer to those used in data analysis and modeling rather than in instrument calibration, data quality assurance, and background correction. Over half of the studies complement their mobile monitoring data with air quality data from other sources, most of which are stationary measurements by authors themselves or reference monitoring sites. Studies using more than one complementary data source are still scarce.

An unexpected finding is that about 41% of mobile monitoring studies do not explicitly explain how their instruments are calibrated or only claim their instruments are factory-calibrated, while most instruments used are not reference-level. Moreover, about half of the studies that reported detailed calibration processes use reference-grade monitors maintained by the researchers rather than at a reference station or in a laboratory with a controlled environment. Studies involving low-cost sensors should pay extra attention to delineating their calibration procedures due to the high uncertainty in their instruments. Specifically, it is crucial to validate low-cost sensors in a mobile setting. Crocchianti et al.[50] contrasted mobile low-cost sensors with high-quality optical instruments. Mui et al.[63] developed a performance evaluation protocol using a Google Street View vehicle equipped with both low-cost and research-grade instruments. They further test the effects of sensor siting, orientations, and vehicle speed on the accuracy of low-cost sensors. Few studies have systematically explored these factors, suggesting that important information that can illuminate uncertainties in mobile low-cost monitoring is missing in existing research.

We examined temporal resolution in data collection and analysis to provide insights into how studies are aggregating air quality data. A dominant portion (85.9%) of mobile monitoring campaigns collects highly time-resolved data in less than 1 min intervals. In this case, the response lag of sensors can lead to mismatched air quality and geographic observations and less effective spatial resolution of mobile measurements. Temporal data aggregation is essential to diminish this uncertainty, especially in spatial regression and epidemiological studies aiming to capture the representative air quality profile or its health effects, which is adopted by a majority of studies (73.8%). However, due diligence should be paid to sensor response lag calibration and coordination prior to the measurement in future studies.

However, incorporating temporal variations into spatial regression models remains understudied in the mobile monitoring literature. Current alternatives include developing periodical spatial regressions,[64] providing multiple snapshots instead of just one, and incorporating time-variant explanatory variables,[50] such as meteorology and traffic. These methods

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

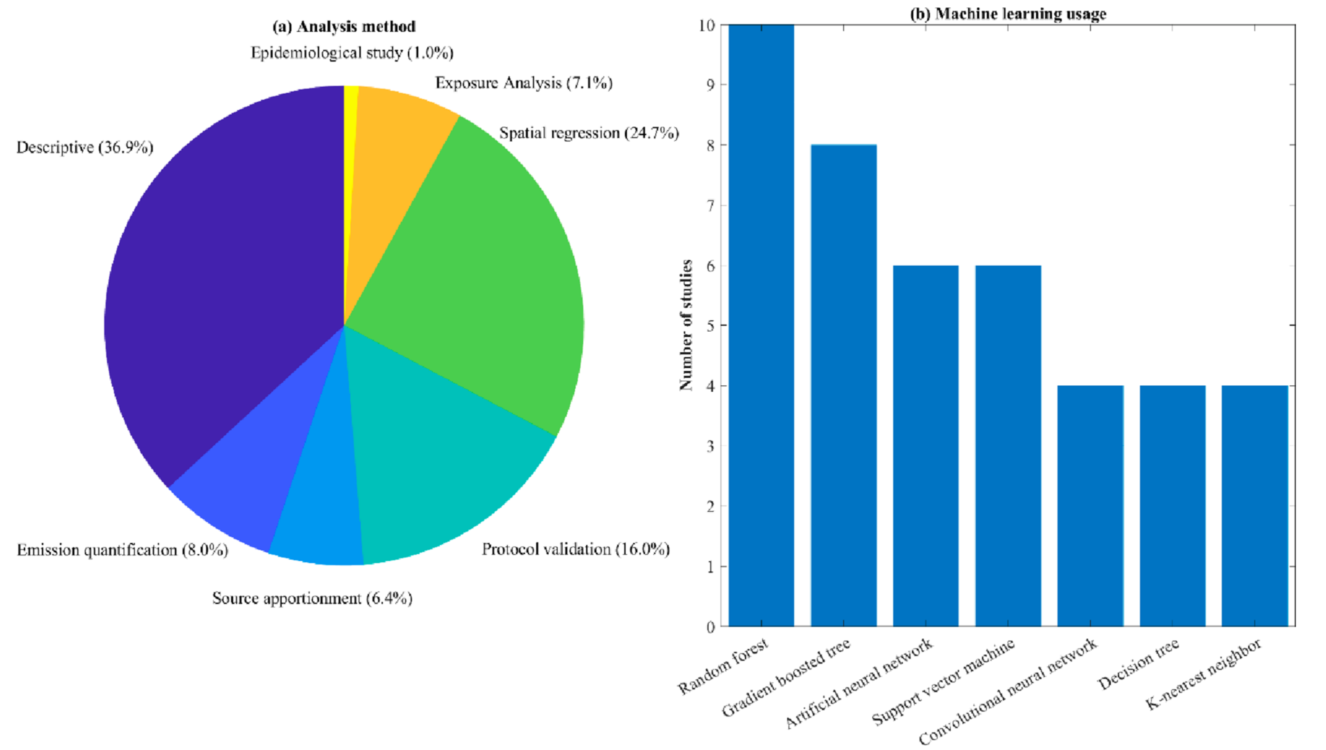

Figure 10. Analysis method (a) and machine learning (b).

treat observations in the temporal continuum as independent and neglect the effect of spatiotemporal autocorrelation.

3.3.2. The Role of Machine Learning in Mobile Monitoring Studies. Figure 10 summarizes the analysis methods used in all mobile monitoring studies. The most adopted analysis methods are descriptive analysis, spatial regression, and protocol validation. Limited studies are concentrating on exposure assessment and air pollution epidemiology. It is mainly attributable to our searching and exclusion criteria, which exclude studies that do not have a significant mobile monitoring data collection component or use only secondary mobile monitoring data products. Specifically, we are interested in the empirical modeling tools employed in spatial regression, exposure assessment, and epidemiological studies that aim to achieve better interpretation and prediction of air quality, recognizing the surging trend of machine learning and data mining algorithms in this area.

We filtered out 99 papers that focused on spatial regression, exposure assessment, and epidemiological impacts of air pollution with specified empirical models. Out of these, 24 employed machine learning and data-mining techniques, most of which were published within 5 years (from 2017 to 2021). Eighty-four studies involved traditional regression methods, as multiple studies have utilized more than one empirical model. The most used machine learning algorithms are tree-based ensemble models, including random forest and gradient boosting tree models. Artificial neural networks (ANNs) are also popular in air quality predictions that work with tabular data, focusing on real-time monitoring applications for health risk mapping. Given the lack of global interpretation tools, ANNs can hardly be adopted in air quality modeling for explanatory or causal inference purposes. Moreover, evidence states that ensemble models have better performance when dealing with tabular data.[65,66] However, given the increasing trend of machine learning techniques in the mobile air quality monitoring space, it is likely that we may see further improvements to these techniques or a wider range of applications. While a number of studies conclude that machine learning tools help improve our understanding of air pollution's spatial distribution, Kerckhoffs et al.[66] argue otherwise by contrasting over 20 prediction algorithms of all types side by side.

Tabular data, such as land use, traffic, points of interest, and other infrastructure information, are often taken for granted in developed countries yet extremely difficult to obtain in developing and remote regions. Crowd-sourced, nontabular data can greatly contribute to air quality information inference and extraction in these data-scarce regions. Several recent studies have explored these possibilities despite relatively low performance in prediction, most notably from street-view images using convolutional neural networks.[31,67,68] These studies provided valuable experience in deriving instantaneous air quality information from hyperlocal visual features. Zheng et al.[69] associated expressed happiness on social media with local air quality among Chinese urbanites, even though this is not a study using mobile monitoring data. Computer vision and natural language process techniques have already been widely adopted for various information extraction tasks in urban environments.[70−72]

3.4. Recommendations for Future Mobile Monitoring Studies. The continuous expansion of mobile monitoring in scientific research, engineering projects, and citizen science is very likely in the near future. The versatility of mobile monitoring methods brings more opportunities to enhance our understanding of hyperlocal air pollution and its impacts. However, a series of research gaps have yet to be filled in the current applications of mobile monitoring.

A glaring gap in mobile monitoring studies is the global geographic disparity of mobile monitoring studies. Studies are overwhelmingly concentrated in high-income countries,

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

despite the necessity of understanding air quality in regions worldwide. Given the notable lack of air quality monitoring infrastructure in many middle- and low-income countries, there is a strong need for the research community to focus efforts on filling these critical information gaps, emphasizing engaging local researchers' with the international scientific community. While there is an opportunity to carry out mobile air quality monitoring studies similar to those conducted elsewhere, it is also important to build upon existing methodology to adapt studies to the specific needs of these regions.

Robust instrument calibration and data quality assurance are at the core of developing valid results in mobile monitoring. We observe that many studies do not report their calibration process or simply state their instruments are factory-calibrated even though they are not using reference instruments. Given the popularity of low-cost sensors, there is an urgent need for the wider application of standard sensor calibration processes in the future. The European Metrology Research Programme of EURAMET[73] proposed a calibration and evaluation protocol for low-cost gas sensors. The US EPA recently published sensor performance target reports[74,75] for gaseous and particulate matter low-cost sensors, providing consistent testing protocols and metrics to evaluate low-cost sensor performance for nonregulatory uses. Both guidelines suggest a two-phase testing process, consisting of a laboratory and a field test, whereas the EPA guideline only recommends the laboratory test wherever it is available. However, few studies involving low-cost sensors followed regulated sensor performance evaluation protocols, while most studies adopted project-specific protocols. It limits the intercomparison between different air quality data products and the reproduction of observations and results. Moreover, instrument calibration and data quality assurance for mobile monitoring should go beyond reporting correct values. Researchers should pay due diligence to account for sensor response lag, sensor synchronization if there are multiple sensors involved, and geo-positioning data processing, which can all result in a mismatch of air quality data and geo-information. Specifically, transparency is especially called for in geo-positioning data collection, correction, and paring, as we noticed that this information is missing in a large number of studies.

Mobile monitoring brings an unprecedented opportunity for implementing big data and data mining tools in air quality studies. These tools help better understand air quality in two ways. On the one hand, data mining tools have broadened the channel to more relevant data, especially nontabular data. The development of computer vision and natural language processing empowers researchers to extract air quality information from satellite images, street view images, and social media postings. Still, more forms of nontabular data should be explored to complement tabular data to understand air quality better. On the other hand, data mining tools have great potential to improve performance with the help of big data. These tools can better capture complex nonlinearity relationships between emission sources and air quality. Future studies should better exploit the potential of data mining in time series analysis to reflect both temporal and spatial variations of air quality. Moreover, more attention should be paid to the transferability and interpretability of complex nonlinear models, especially those with a black-box nature.

Many countries and regions have established periodical air quality databases using data from reference monitors. The most notable ones include the US EPA's Air Quality System database and the European Environmental Agency's air quality database, both of which provide convenient data access via APIs. Unlike stationary monitoring and satellite remote sensing maintained by governmental agencies, mobile monitoring campaigns are mostly run by individual research groups, private companies, and nonprofit organizations receiving funding from various sponsors. Understanding the existence of various data disclosure restrictions in these studies, sharing and publishing mobile monitoring data products is tricky yet crucial for raising public awareness, knowledge dissemination, and promoting result reproducibility. Moreover, maintaining open access to air quality data, models, and results is also a key step in fighting for local, regional, and global environmental justice. Currently, there are relatively fewer open data platforms that provide public access to mobile monitoring data compared to stationary data. The South Coast Air Quality Management District is a leading regulatory agency in testing mobile air sensors, conducting mobile monitoring campaigns, and publishing mobile monitoring data focusing on air pollution in South California.[76] OpenAQ is a nonprofit organization that maintains an open-source platform[77] with a mobile monitoring database from multiple studies, including Apte[47] and Messier,[48] but the latest update was 2 years ago. A similar nonprofit HabitatMap operates the AirCasting Web site that shares mobile and stationary air quality monitoring data collected by their low-cost sensor network.[78] Google's Environmental Insights Explorer[79] analyzes and visualizes various urban environmental data collected by Google Street View cars, including air quality, tree canopy, and urban emissions. Hyperlocal mobile measurements, ranging from 1 to 2 years, are available via their Web site for London, Copenhagen, and Amsterdam.

4. CONCLUDING REMARKS

This paper presented a systematic review and meta-analysis of current literature on mobile ambient air quality monitoring, emphasizing the increasingly important roles of low-cost sensors and data mining techniques in the field. The unprecedented popularity of mobile monitoring and fast-evolving methodology in the field have made this work timely. Borrowing the concept of thematic analysis, we highlight the relevant themes, trends, and drivers of mobile monitoring that have important implications for its future deployment. This review examines three major stages in the life-cycle of a typical mobile monitoring study, including study proposal, experiment design, and data analysis. We summarize our insights into each of them as follows.

We first discussed the current landscapes and prominent research gaps in the field relevant to the study proposal. This study reveals a huge research gap in mobile monitoring applications, and in general insufficient ambient air quality measurements,[80] in the Global South, including Sub-Saharan Africa, Latin America, and South and Southeast Asia. It demonstrates an urgent but long-lasting environmental justice problem globally with a double burden of worse air quality and scarcer air pollution management and healthcare resources in these regions. Among other methods, mobile monitoring with low-cost sensors can bridge this research gap and advance the current situation in low- to middle-income counties. However, while capturing spatial variability continuously, mobile monitoring can only provide intermittent air quality snapshots for the same location. Thus, it is less useful for studies

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Environ. Sci. Technol. XXXX, XXX, XXX−XXX

emphasizing temporal air quality rather than spatial information.

We analyzed the key factors to consider in mobile monitoring experiment design. It is worth noting the unique opportunities brought by low-cost sensors in real-time personal exposure and acute health effect assessment due to their versatility in instrument carriers and operating personnel. We further highlighted three successful mobile monitoring programs that can serve as blueprints for future implementation of mobile monitoring, including predefined, opportunistic, and hybrid strategies. A critical element in mobile monitoring experiment design is repetition, which is under-reported in the current literature. We encourage future studies to provide this information to enable a better understanding of best practices for application-specific repetitions. Our meta-analysis demonstrates that spatial regression studies can use 10 unique repetitions at the same location as a rule-of-thumb in future studies lasting up to a year and four repetitions should be considered the bottom line for any type of analysis.

Regarding data analysis and modeling, our results revealed that an astoundingly large number of papers have reported sensor calibration and data quality assurance information poorly, despite the wide adoption of non-reference-grade instruments. Even fewer studies followed the recommended calibration guidelines by the regulating agencies. To complement the voluntary calibration efforts from the researcher's side, we further recommend that reviewers should ask authors to provide an appropriate description of calibration and data quality assurance to ensure more rigorous documentation of these processes in the scientific community. We further demonstrated the popularity of ensemble regression models in air quality prediction and interpretation. Meanwhile, there is much more to explore in extracting air quality information from nontabular data, such as text and images, and joint analysis of temporal-spatial patterns of air quality using data-mining techniques.

Finally, we acknowledge several limitations of this review. This study only includes publications in the English language, which can be biased for applications in non-English-speaking countries. Moreover, only peer-reviewed papers are included in the review. We recognize that local communities and environmental advocates, not-for-profit organizations, companies, and government-led projects do not prioritize scientific publication as an outcome, while such efforts also contribute to advancing mobile monitoring and global environmental justice. Lastly, our review excluded papers without a significant mobile monitoring data collection component or using only secondary mobile monitoring data products, which could lead to an under-represented number of personal exposure and epidemiological studies.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c06310.

Complete bibliography and related sources, landscape of mobile air quality monitoring literature in a word cloud, list of journals that publish most related studies, and list of non-low-cost particulate matter sensors (PDF)

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Notes

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