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Air pollution accountability research: Moving from a chain to a web

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A B S T R A C T

Air pollution accountability studies examine the relationship(s) between an intervention, regulation, or event and the resulting downstream impacts, if any, on emissions, exposure, and/or health. The sequence of events has been schematically described as an accountability chain. Here, we update the existing framework to capture real-life complexities and to highlight important factors that fall outside the linear chain. This new "accountability web" is intended to convey the intricacies associated with conducting an accountability study to various audiences, including researchers, policy makers, and stakeholders. We also identify data considerations for planning and completing a robust accountability study, including those relevant to novel and innovative air pollution and exposure data. Finally, we present a series of recommendations for the accountability research community that can serve as a guide for the next generation of accountability studies.

Introduction

Air pollution accountability studies examine the relationship(s) between an intervention whose intention (or consequence) is to change air pollution levels and downstream impacts on pollutant emissions, exposure, and/or health. These interventions include policy changes (e.g., London's congestion charging system), regulations (e.g., a lower air quality standard), and events (e.g., factory closure), and may be impacted by environmental justice issues. Accountability studies are useful for assessing the effectiveness of interventions and guiding plans for future actions. These studies are versatile and can focus on the impact of interventions that cover multiple spatial and temporal scales. For example, an accountability study could quantify the observed air quality changes and health benefits resulting from a national air quality standard, or it might focus on changes in emissions following a well-specified, immediate, local regulation (e.g., a regulated fuel retrofit at a power plant). The Health Effects Institute [1] described the steps that connect an air pollution intervention or a policy change with a downstream effect on health. These steps, called the accountability chain, include: Regulatory or Other Action → Emissions → Ambient Air Quality → Exposure and Dose → Human Health Response (Fig. 1).

The accountability chain has provided a framework for guiding accountability studies over the past two decades. In the same period, knowledge has increased about challenges associated with estimating

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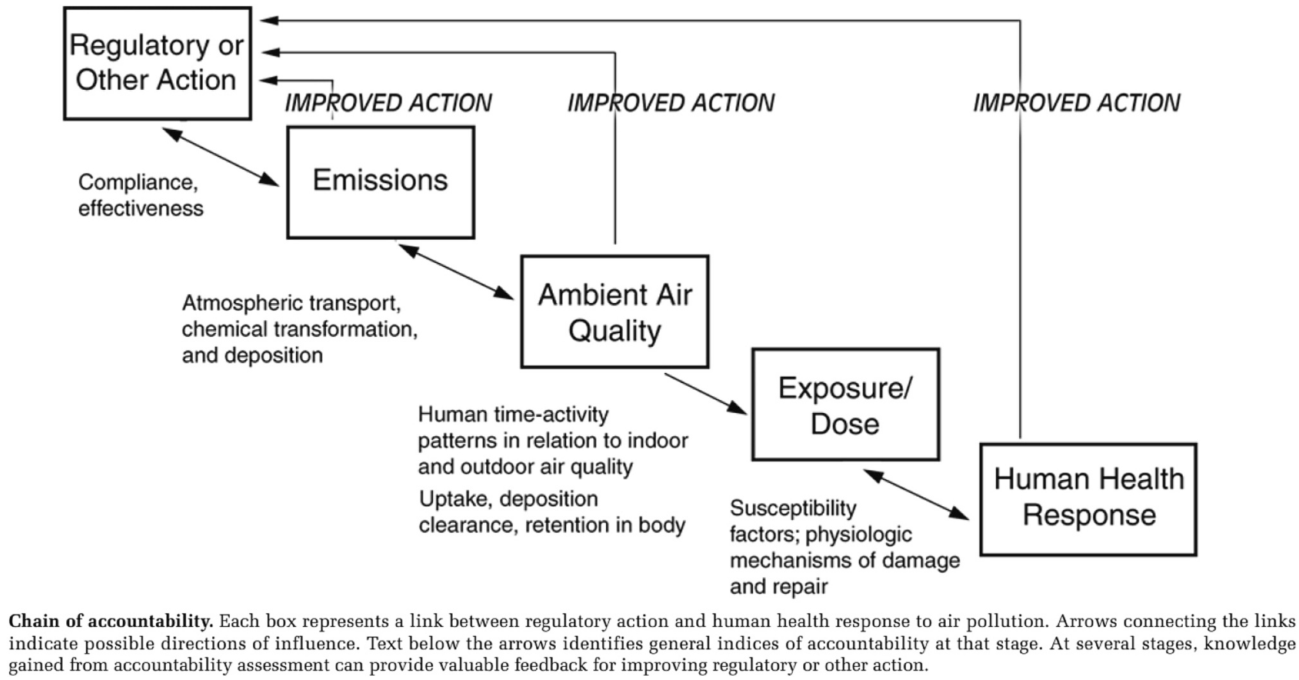

Fig. 1. Chain of accountability. Source: HEI Accountability Working Group, 2003 [1].

impacts resulting from the intervention on changes to emissions, exposures, and/or health effects. In particular, downstream impacts, if any, from a national standard may be more difficult to identify and/or quantify than a well-specified local regulation because many more factors can impact the potential cause-and-effect relationship between the policy and downstream impacts. Hypothetical counterfactual emissions and air pollution exposure fields, along with literature-based concentration-response functions, are often used to quantify air quality and health benefits of interventions [2,3]; however, these methods rarely assess regulatory implications on the areas and populations directly impacted by the intervention. Due to potentially significant costs associated with interventions, an understanding of the benefits they do or do not deliver is critical feedback for policy makers.

As an example of accountability study complexities, implementation of some interventions, such as the US Environmental Protection Agency's (US EPA) National Ambient Air Quality Standards (NAAQS), can take years and occur concurrently with local and regional actions that also result in changes in air pollution concentrations and/or population health. This makes it difficult to disentangle their respective effects. An additional complication relates to understanding the impact of population changes that occur as an intervention is implemented, including behavior fluctuations that impact exposure or health, which may or may not be related to the intervention of interest. Broader socioeconomic shifts, including economic or social opportunities and new medical facilities, may induce differential population migration [4,5].

Accountability studies rely upon an evidence base that has already integrated and synthesized data which may be incomplete or a mix of modeled, observational, and interventional data at personal and ecological scales. Still, epidemiologists, risk assessors, and other scientists conducting accountability studies should acknowledge and account for imperfect data, and carefully and thoughtfully select and utilize the most valid exposure and outcome data available. As a result, there are opportunities to improve the status quo. Some of the potential opportunities are included in the recent National Academies report, Advancing the Framework for Assessing Causality of Health and Welfare Effects to Inform National Ambient Air Quality Standard Reviews [6]. In 2010, the Health Effects Institute [7] called for "a concerted effort to assemble and make widely available longitudinal data on major health outcomes, air pollution concentrations, and, critically, factors that may confound or modify estimates of the effects of air quality regulations." In the interim, researchers have endeavored to better quantify emissions, air quality, and health changes associated with interventions. However, limitations and complications in accountability research remain. Today's increased availability of methods and large datasets provides an opportunity for renewed exploration of air pollution accountability methods in general, and approaches to handle temporally or spatially co-varying factors outside the accountability chain in particular.

Here, we describe the outcome of a workshop (*Workshop on Accountability in Air Pollution Regulations and Research: Advancing the Science on Temporality Issues;* Baltimore, Maryland; April 2023) in which an interdisciplinary group of scientists was convened with the goals of examining key factors in air pollution accountability research and developing recommendations for obtaining and incorporating information on those factors into future accountability research. The objectives of this workshop were to: 1) offer a modified accountability chain framework for evaluating the relationships between an air pollution policy change and potential downstream impacts on population health outcomes; 2) identify research gaps and challenges; and 3) recommend research to improve the design and conduct of accountability studies.

Results and discussion

Framework: from a chain to a web

The accountability chain relating an air pollution intervention to emissions, air quality, exposure/dose, and a human health response is shown in Fig. 1. While elegant in its simplicity, this chain does not fully capture the complexities of the steps from a policy to a change in a health outcome. A more detailed description of the path from beginning to end would help to identify key research needs and assist in communicating the difficulties in performing this kind of research. Fig. 2 shows the adaptation of the accountability chain to an accountability web by highlighting the complex factors both inside and outside of the linear chain when linking policies and actions (blue circles) to downstream

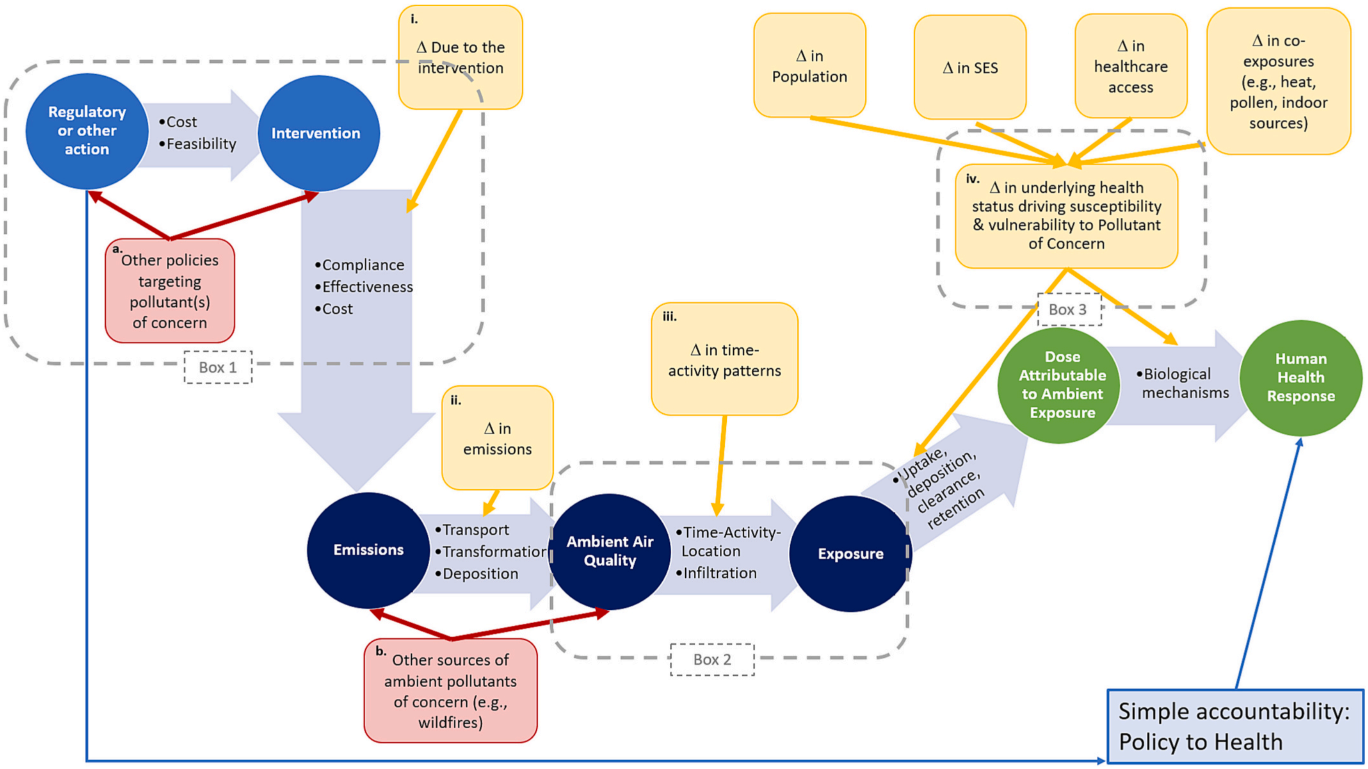

Fig. 2. Adapted web of accountability. The web of accountability highlights the complex factors outside the accountability chain when linking **policies and resulting actions** (*light* blue circles) to **emissions and exposures** (*dark blue circles*) and eventually to **downstream impacts** (*green circles*). The light blue arrows connecting each circle to the next are examples of information (i.e., mediators) necessary to inform or predict the next circle in the chain. Temporal changes in these mediators, driven by external factors (*yellow boxes*), can introduce error in estimating downstream impacts. The *red boxes* are factors that may be correlated with the policy or action of interest that have the potential to confound the impact of the policy or action on the downstream steps. The *gray dashed boxes* outline broad areas where potential knowledge and/or data gaps exist, specifically when considering temporal complexities, and the parts of the accountability chain most affected by such complexities. Δ – change. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

impacts (green circles).[1] The light blue arrows connecting each circle provide examples of information (i.e., mediators) necessary to inform or predict the next circle in the central chain. Temporal changes in these mediators, driven by external factors (yellow boxes), can introduce error in estimating downstream impacts. The red boxes are factors that may be correlated with the policy or action of interest and have the potential to confound the relationship between the impact of the policy or action and the downstream steps. The gray dashed boxes outline broad areas where potential knowledge and/or data gaps exist in the accountability chain, specifically when considering temporal complexities [8], and the parts of the accountability chain most affected by such complexities. As shown in Fig. 2, these include 1) moving from policy to intervention; 2) the accurate estimation of changes in personal exposure; and 3) adequately characterizing the health status of the population. Failure to adequately understand and evaluate these factors can impact our ability to effectively and precisely identify and quantify the impacts, if any, of policy changes on emissions, exposure, and health outcomes. We explore these three areas as examples to highlight the intricacies of accountability studies.

From regulation to intervention (Fig. 2, Box 1)

While the original accountability *chain* (Fig. 1) shows *regulations* acting directly on *emissions*, the accountability *web* (Fig. 2) introduces an intermediate step – the active intervention taken to reduce emissions (e.g., installation of a pollution control device on a power plant) – that is both necessary and difficult to quantify. The relationship between a specific policy, the intervention taken, and an emissions change is confounded by, for example, multiple policies acting on the source of interest (e.g., separate federal and state rules that also apply to power plants); multiple organizations contributing to actions taken on the pollution source (such as companies, environmental regulators, utility commissions); varying implementation effectiveness; and costs of environmental control decisions (Fig. 2, a.). Further, interventions taken to comply with regulations are not always transparent [5,9]. Some interventions – for example, vehicle software modifications used to adjust automotive emissions controls – are not readily observable. While other interventions are observable (e.g., a scrubber installation or newer vehicles with lower-emitting engines replace older vehicles), their relationship with a particular regulatory action may be influenced by various factors, including regulatory policy at multiple governmental levels, as well as societal and market-based drivers.

It is also difficult to account for and quantify changes in factors impacting the effectiveness of the intervention on emissions (Fig. 2, i.). Controls on emissions are generally not directly measured (large point sources in the United States are an exception). They also may not work as efficiently as planned and can degrade. Improved quantification of emissions using models (as opposed to measurements) are potentially useful in this step. Accountability studies quantifying emissions changes over time could utilize satellite data and large-scale analyses of emissions estimates that are then compared to observations using chemically-detailed observations. For example, satellite-derived emissions estimation methods, which have challenges such as uncertainty associated with measurements and attributions, are increasingly being used to assess emissions changes from point and non-point sources [10–18].

[1] We note that neither the chain nor the web addresses all aspects of risk management decision-making.

If one is to assess the effectiveness of a policy, it is crucial to accurately characterize and quantify the regulatory impacts on both relevant *intervention(s)* and *emissions*. While it may not be possible to provide a simple answer as to why a specific control or operational framework was implemented to conform to air quality regulations, case studies and system wide analyses can help quantify changes in the first three steps in the accountability web.

Estimation of personal exposure (Fig. 2, Box 2)

Ambient concentrations of a specific pollutant naturally impact individuals' personal exposures to that ambient pollutant. Personal exposures may lead to inhaled doses that may ultimately impact downstream health outcomes, which are of key interest for public health (Fig. 2). The accurate assessment of personal exposure is a well-documented limitation in environmental epidemiology studies, and it persists in air pollution accountability studies. Data from ambient air quality monitors – assumed to represent the population average personal exposures – are often used as the measure of exposure in epidemiology studies on air pollution and health [19,20]. While measurements from such monitors can provide accurate location-specific information on ambient pollutant concentrations, the degree to which these data represent *personal* exposures to ambient pollution varies due to time-activity-location patterns and outdoor-to-indoor pollutant infiltration (Fig. 2). It is important to note that the framework of accountability studies is less focused on the magnitude of the relationship or the absolute differences between ambient concentrations and personal exposures to a specific pollutant of interest, and more on whether these relationships change over time and/or are different between populations, which may obscure the impact of an intervention of interest (Fig. 2 (iii)).

Accountability researchers often lack access to empirical data on factors changing over time that may impact how individuals are exposed to ambient concentrations. For example, personal exposures vary in space and time due to the combination of individuals' activities and emission sources impacting air pollutant levels in the different locations where their activities occur [21–23]. In addition, people spend much of their time indoors [24], and as such the fraction of ambient air infiltrating a building (i.e., the infiltration rate) is an important factor in the degree of personal exposure to ambient source pollution. Some pollutants, like fine particles with small size and low volatility and reactivity, have relatively high infiltration, while others like PM_{10} or ozone have relatively low infiltration [25–27]. Characteristics such as the air exchange rate can also affect how outdoor air infiltrates indoors, and in turn, the amount of outdoor air to which an individual is exposed [27,28]. In particular, air conditioning (A/C) is promoted as an effective climate adaptation measure, thus, the prevalence of tighter buildings is increasing along with, the presence of A/C in homes and indoor workplaces [29] among those who can afford it. However, existing data sources for these factors do not have the resolution needed for assessing trends over time or across geographic regions. Behaviors related to how and where people spend their time also change over time in relation to season, age, and socioeconomic patterns [30]. In recent years in particular, employment and labor patterns related to telecommuting and employment types have changed [31]. Environmental health awareness may have also changed over time, with more people having access to and being interested in air quality alerts, which may alter their behavior regarding time spent outdoors on high pollution days [32]. Historical time-activity data [24] that are often accessed for personal exposure estimation may no longer be accurate. While some acknowledge the lack of relevant data (e.g., CARB, 2021 [33]), more work is needed to characterize current time-activity-location patterns. More fully assessing variability in personal air pollution exposure to ambient pollutants of concern across time, space, and populations has clear potential to inform epidemiological research in general and will illuminate how changes in ambient concentrations from policies or interventions influence health in accountability studies.

Population health status (Fig. 2, Box 3)

When estimating the downstream health impacts in an accountability study, it is important to consider the underlying health status of the study population (Fig. 2, (iv)), especially those factors that may drive susceptibility or vulnerability to the pollutants of concern. In particular, changes in the underlying health status of a population can directly confound the assessment of health impacts attributable to a policy-related change in air pollution exposure. Changes in underlying health status may be driven by complex sets of factors, as indicated by Fig. 2. For example, socioeconomic position (SEP) can impact both air pollution exposure and health status. While challenging, properly characterizing SEP, and temporal and spatial changes in SEP, is critical [34]. Accountability studies often include measures of SEP as a proxy because it is highly correlated with underlying population health status and underlying population health status is not readily observable. However, as suggested by Fig. 2, numerous additional factors can impact health status of a population and changes in health status over time.

Given the recent advances in data availability, accountability studies might be improved by direct observations and controlling for factors that may affect or predict underlying health status as an approach for reducing confounding concerns. These may include: changes in the population structure (e.g., immigration or emigration in or out of the study area over time); changes in socioeconomic status occurring over time (e.g., due to gentrification); temporal changes in health care access such as changes in health insurance, and opening/closing of health care facilities; or differences in co-occurring exposures including heat, pollen, and indoor air pollutants.

Research recommendations

Future successful accountability research will need to rely on improved data, appropriate designs and statistical methods, and enhanced collaboration with experts. We present here eight recommendations as guides to design, conduct, and interpret future accountability studies.

1. Increase multidisciplinary collaboration: Due to the multidisciplinary breadth of accountability studies that address the linkages described by the accountability web, collaboration among air pollution and exposure scientists, epidemiologists, statisticians, toxicologists, and policymakers would facilitate the development of robust study designs, data analysis techniques, and policy-relevant interpretations. In addition, we recommend that future research addressing the complexities and challenges in accountability studies integrate scientific disciplines not typically included in such research, for example, social and behavioral researchers (to inform areas iii and iv from Fig. 2) and exposure scientists (to inform area ii from Fig. 2).

2. Invest in methods for studying local-scale policy impacts: As regulations to reduce emissions evolve, two major anthropogenic source categories – electricity-generating units and mobile sources – contribute less and less to overall emissions (Fig. 2 (i)). Future policies targeting emissions sources are expected to have increasingly smaller impacts to health outcomes and will likely focus more on local-scale effects [5]. This shift necessitates greater attention to studying specific characteristics of local areas and populations to assess the effectiveness of these policies. We recommend investing in expanded and improved local monitoring networks that provide comprehensive spatial and temporal coverage in order to improve exposure measurements at increasingly local scales [35]. Leveraging emerging technologies like satellite remote sensing, sensor networks, and wearable sensors can address gaps in air quality monitoring network data to improve exposure assessment.

3. Improve estimates of personal exposure: Accurately estimating personal exposure to ambient air pollutants of concern is a key challenge in accountability studies (Fig. 2 (Box 2)). Estimating personal exposure is complex and costly, as it requires combining ambient monitoring data with an understanding of pollutant infiltration into buildings (where people spend most of their time) and information on individual activities. Accounting for variations in exposure over time and space poses further difficulties [36]. As air quality can vary substantially over small geographic areas and over short periods, we recommend incorporating high spatial and temporal resolution data to accurately measure ambient air concentrations [9]. Further, we recommend integrating machine learning to develop updated and targeted time-activity profiles, as well as air exchange rate models based on realistic housing conditions and consideration of indoor pollutant sources. Together, these data may be used to improve estimates of personal exposure to ambient pollutants of concern in the context of an accountability study.

4.Harmonize and improve access to data resources: Data access, collection, and manipulation can be challenging aspects of any research project, including accountability research. Relevant data sources must be identified, and then harmonized to appropriate spatial or temporal scales.

Innovative data sources are becoming more widely available for deployment in accountability research. Data gathered from satellites, sensors, and wearable technologies have brought significant advances in the scale, resolution, and quality of air pollution data available. In particular, satellite remote observations [11,37–41] and space-based observations (e.g., new missions such as TEMPO [https://tempo.si.edu/] and MAIA [https://maia.jpl.nasa.gov/]) provide data to inform top-down estimates of air emissions [10,17]. In addition, low-cost sensors (such as PurpleAir) provide readily available, crowd-sourced data (https://www2.purpleair.com/ [42]). Intelligent ("smart") wearable sensors can acquire, process, store, and transmit electrical signals generated by physical and/or chemical changes occurring in the environment, making them potential tools for measuring personal exposures [43,44].

These new data along with a myriad of other data sources (demographic, energy, land use, traffic) bring exciting possibilities for accountability research. Some of these entail developing air pollutant exposure fields [45–51]; allow for linking of location- and time-specific emissions estimates to resulting air quality; or produce estimated exposures based on enhanced air quality data that can be linked to health outcomes (see Kim, 2020 [52]; Li et al., 2022 [53]; Xia et al., 2022 [54]). However, these data also bring challenges related to accuracy and usability as well as ethical and privacy considerations in occupational and community settings. As an example, advantages and disadvantages of wearable sensors are provided in Supplemental Table 1. Furthermore, with advances in the resolution of air pollution data, attention must be paid to the granularity of confounder and effect modifier data because biased risk estimates may result from a relatively higher degree of misclassification in the specification of these covariates [55].

We recommend the development of publicly available repositories for information and datasets useful in accountability research. Supplemental Table 2 contains a library of selected data sources that could be incorporated into accountability studies, including air pollution data, health statistics, other regulatory/non-regulatory events (e.g., changes in motor vehicle use), population changes, SEP changes, information about lifestyle, health, medical practice, personal activity data, and changes in exposure to other sources such as indoor air pollution. Additionally, the research community would benefit from readily available data science tools for harmonizing datasets to the scales of interest for any given accountability study.

5. Focus on health outcomes causally related to the ambient pollutant of concern: Determining health outcomes causally related to changes in ambient air pollution exposure can be challenging due to the latency period between exposure and manifestation of the health outcome, and general limitations of epidemiological methods. Additionally, confounding variables such as socioeconomic factors, lifestyle behaviors, population demographics, pre-existing health conditions, and co-pollutant exposures can influence both pollutant exposures and health outcomes [56–58]. We recommend that accountability studies focus on health outcomes for which there is adequate certainty in the causal nature of the relationship between the pollutant(s) of concern and the health outcome(s) examined. Researchers may refer to the US EPA Integrated Science Assessments for detailed syntheses and evaluations of the existing literature on criteria pollutants and health outcomes (https://www.epa.gov/isa).

6. Incorporate appropriate study designs and statistical tools: The statistical analysis and modeling techniques used in air quality accountability studies vary considerably depending on the particular focus of the study. We see the accountability web as agnostic in term of time scales (i.e., it is applicable to both long-term and short-term studies). The specific methods would be chosen based on the time scales involved. Accountability research can be (and has been) applied at multiple time scales, including from rapid interventions over a short time scale (e.g., for the Olympic Games) to longer term studies (e.g., impacts of the Clean Air Act Amendments and regulations), and the chosen methods should reflect this for each step. Defining a "structural" approach that attempts to understand the series of steps in the accountability web is complex due to the multifaceted nature of the issues, such as differentiating the effects of a policy change from larger underlying background trends in air pollution emissions, and the difficulty in obtaining the data required to carry out the approach. Air quality is influenced by complex meteorological, chemical, and physical processes, making it challenging to model and predict pollutant concentrations accurately. In addition, for epidemiological modeling, handling spatial and temporal correlations, accounting for confounding factors, and addressing uncertainties require advanced study design, statistical methods, and modeling approaches [59,60].

Studies that focus on understanding the relationship between one particular step in the accountability web and downstream health impacts can utilize varied approaches. Methods to help disentangle intervention effects from background trends, for example, include robust time-series analysis methods such as interrupted time series, regression discontinuity design, difference-in-differences analyses, and instrumental variables [61]. These approaches attempt to mimic the properties of randomized experiments by identifying treatment and control groups, such that they limit the concern for confounding when properly applied. Recent methodological advances have enhanced the options for selecting control groups to minimize potential bias, such as propensity score matching [62] and synthetic control methods [63]. With these approaches, an important step involves assessing the sensitivity of estimates to potential confounding variables. With an appropriate control group and adequate inclusion of confounding variables, adding further control variables to the statistical model should have minimal impacts on parameter estimates (see Altonji et al., 2005 [64] and Oster, 2019 [65] for suggestions on implementation and interpretation).

7. Distinguish between effects of simultaneous policy interventions: Specific air pollutants may be targeted by several interventions (and in response to multiple policies) at the same time, making it difficult to attribute changes to a particular policy or intervention. This is further complicated when interventions occur at multiple temporal and regional scales; for example, the impact of short-term, localized interventions on air quality and health outcomes may be overshadowed by long-term and/or larger-scale interventions [5]. Additionally, the effects of temporary interventions may not be sustained over time. This underscores the importance of working to ascribe changes in emissions to particular interventions and in response to particular policy changes (Fig. 2 (Box 1)). To address these challenges, we recommend researchers conduct sensitivity analyses and evaluate the differential impacts of multiple interventions affecting the same location to help disentangle their individual contributions. Alternatively, researchers may consider the cumulative effects of multiple interventions when evaluating long-term trends in air quality and health outcomes.

8. Improve generalizability of accountability studies: All populations are not impacted equally by a particular policy, making it challenging to accurately isolate the specific effects of a given intervention and attribute a specific health outcome to a specific change in air pollutant concentration. We recommend improved techniques for identifying appropriate control populations, and that accountability studies explicitly state the population(s) or sub-population(s) to which their results are most relevant, as well as identify those to which their results may not be generalizable (or generalized with less certainty).

Conclusions

At the April 2023 workshop, the authors of this paper discussed the accountability chain that describes the relationship between the following steps: the intervention, followed by changes in emissions levels, air quality, exposure/dose, and human health responses. While it is impossible to not appreciate the simplicity and elegance of the linear chain, it does not adequately capture the real-life complexities of each step. We re-envisioned the chain as an accountability web, clearly highlighting (i) the factors outside the chain that impact accountability research, and (ii) the connections these factors have to each step along the path from policy to health response. The accountability web is designed to better convey the difficulties and nuances associated with conducting accountability studies to various audiences, including scientists and researchers, policy makers, stakeholders, and others, and to highlight factors that should be considered when designing these studies.

In developing the accountability web, we identified a number of data considerations for planning and completing a robust accountability study. First among these are the recent advances (within the last decade) in the scale, resolution, and quality of air pollution data available for accountability research. Incorporation of high-quality and well-validated modeled air quality data, in addition to or in place of measured air quality data, can greatly enhance accountability studies. Novel and innovative sources of exposure data can augment measured and modeled air quality data to provide person-level air pollutant exposure and health data. We note the need to test the accuracy and usability of wearable technology and to evaluate performance and cross-validations of these technologies before they are relied upon. Finally, we stress the importance of compiling, harmonizing, and openly sharing sources of air pollution data, health statistics, data describing regulatory/non-regulatory events (e.g., changes in motor vehicle use), population changes, SEP changes, information about lifestyle, health, and medical practices, personal activity data, and changes in exposure to other stressors (e.g., indoor air pollution) with the accountability research community.

While we recognize that no single set of recommendations could realistically address all aspects of the accountability web, we hope those provided here will serve as guides for the next generation of accountability studies.

Author contributions

All authors participated in person in the workshop on *Accountability in Air Pollution Regulations and Research: Advancing the Science on Temporality Issues* held in Baltimore, Maryland, in April 2023. The Steering Committee and CJB, JSL, and JEG conceived the concept and charge questions, with CJB, JSL, and JEG facilitating the workshop discussion. All authors contributed to the text of the manuscript.

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Declaration of Competing Interest

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Appendix A. Supplementary data

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