GECC

GATEWAY EXPOSOME COORDINATING CENTER

Guidance Documentation

Exposure Measurement Error A Short Methodological Primer and Playlist

Authors
Emma Nichols
Erik Meijer
Yao-Yi Chiang
Alden L. Gross
Eleanor Hayes-Larson
Sindana D. Ilango
Kayleigh Keller
Regina A. Shih
Adam A. Szpiro
Jennifer Weuve
Sara D. Adar

Version: 1.0 (November 2026)

SUGGESTED CITATION

Emma Nichols, Erik Meijer, Yao-Yi Chiang, Alden L. Gross, Eleanor Hayes-Larson, Sindana D. Ilango, Kayleigh Keller, Regina A. Shih, Adam A. Szpiro, Jennifer Weuve, and Sara D. Adar. 2026. *Exposure Measurement Error: A Short Methodological Primer and Playlist.* GECC Guidance Series. Version 1.0 (November 2026). Funded by the US National Institute on Aging, grant U24 AG088894. Los Angeles: University of Southern California, November. https://doi.org/10.25553/gecc.101

Download citation: BibTeX • RIS • EndNote

Preface

This guidance document is intended to make exposome data easy to access and to provide support on how best to use it for aging and exposome research and policy evaluation. The document provides concise and reusable instructions for researchers on available data in the document's topical areas, recommendations for how to use and interpret that data, common pitfalls, and examples of use cases and effective methodologies. We encourage all researchers to complete their own review of the literature in these areas depending on the research questions they have in mind.

If you have feedback or questions or identify an error, please message contact@gatewayexposome.org.

Background — *Gateway Exposome Coordinating Center*

The *Gateway Exposome Coordinating Center (GECC)* (https://gatewayexposome.org/) is an NIA-funded initiative that advances open-science research on environmental exposures over the life course – known as the exposome – that affect health, with a focus on Alzheimer's Disease (AD) and AD-Related Dementias (ADRD) risk and resilience. The GECC brings together experts across the social, behavioral, natural, and health sciences to identify exposome research priorities, develop harmonized exposome measures, and establish guidance for their use. By bringing together expertise across broad domains of exposures, ranging from extreme weather and policy environments to physical, social, and community services environments and life experiences, the GECC facilitates interdisciplinary research to achieve a better understanding of how different components of the exposome relate to each other and interact to influence health, principally AD/ADRD. Through an inclusive and transparent curation of exposome data for research, the GECC aims to lower the effort required by individual researchers to capture diverse exposomes over the life course and make high-quality harmonized measures, data, and guidance freely and publicly available, maximizing benefits to the research community.

Acknowledgements

We greatly appreciate support from the National Institute on Aging (U24AG088894).

Exposure Measurement Error
A Short Methodological Primer and Playlist *

Contents

1 Introduction 4

2 Simple additive measurement error structures 4

2.1 Classical vs. Berkson error . . . 4

2.1.1 Classical measurement error . . . 5

2.1.2 Berkson measurement error . . . 5

3 More complex measurement error structures 5

3.1 Differential measurement error . . . 6

3.2 Dependent measurement error . . . 6

3.3 Measurement error in categorical variables . . . 7

4 Quantifying and adjusting for more complex measurement error structures 8

4.1 Regression calibration . . . 8

4.2 Multiple imputation for measurement error correction (MIME) . . . 8

4.3 Simulation extrapolation (SIMEX) . . . 8

4.4 Simulation analysis . . . 9

4.5 Joint modeling . . . 9

4.6 Measurement error in geospatial exposures based on prediction models . . . 9

4.7 Latent variable modeling . . . 10

5 Conclusion 10

References 11

Version information 11

* If you have questions or suggestions, please message contact@gatewayexposome.org.

1 Introduction

Studying the exposome, or the totality of exposures that individuals experience across the life course, requires measuring features of the exposome. Although researchers seek to optimize measurement, some measurement error is unavoidable. Understanding, quantifying, and accounting for error in exposome measurement is an important methodological consideration in exposome research.

While error in an outcome value is handled directly by many modeling approaches (with exceptions), most traditional methods assume no measurement error in the exposure. Error in measuring the exposome can have different impacts on the estimation of health effects depending on multiple factors, including:

- The type of measurement error
- The relationship between measurement error and other variables in the model (e.g., differential measurement error[1])
- The modeling framework used

This primer and publication playlist seeks to briefly explain key concepts in defining, quantifying, and accounting for measurement error, while embedding and summarizing key citations that cover these concepts in substantial depth.

2 Simple additive measurement error structures

We first focus on the two most common structures of simple additive measurement error: classical and Berkson.

2.1 Classical vs. Berkson error

Classical measurement error. This form of measurement error occurs when the observed value varies randomly around the true value. This often arises when a measurement tool is noisy.

> **Example:** Using a slightly imprecise scale to measure weight. Sometimes weight is overestimated and sometimes underestimated, with an average measurement error of 0. Error is independent of the true value and other variables.
>
> **In equation form:**

$$X_{\text{observed}} = X_{\text{true}} + \text{random error} \tag{1}$$

Berkson measurement error. This form of measurement error occurs when the true value varies randomly around the observed value. This often arises when a single value is assigned to a group of individuals, but the true value randomly fluctuates around the assignment.

> **Example:** Values from central monitors for environmental conditions (e.g., air pollution concentrations) in a community may be assigned to everyone in that community. Though the assigned exposure is assumed to capture the condition of interest for everyone, the actual exposure varies randomly around that common level from person to person. Error is independent of the observed value and other variables.
>
> **In equation form:**

$$X_{\text{true}} = X_{\text{observed}} + \text{random error} \tag{2}$$

When the mean measurement error is 0 and measurement error is unrelated to the true value (for classical error) or observed value (for Berkson error), in addition to being unrelated to other variables in the model, bias from either form of error is well understood in linear regression models. In these settings, with a single continuous exposure variable, the results are as follows:

1. Measurement error that is associated with another variable in the model, such as the outcome.

2.1.1 Classical measurement error

Expected result: Regression coefficients from linear models will be **biased towards the null** (i.e., towards zero).

There is a large body of research within psychology, epidemiology, and other fields that focuses on this form of bias, typically called "attenuation bias."[2] A number of procedures have been proposed to use estimates of reliability (a ratio that depends on the magnitude of exposure variation and measurement error variation) to correct for attenuation, given a set of assumptions.

SUGGESTED READING

Paul M. Muchinsky. 1996. "The Correction for Attenuation." *Educational and Psychological Measurement* 56 (1): 63–75. https://doi.org/10.1177/0013164496056001004

Brief summary: This paper provides historical context and discusses controversies around the correction for attenuation within the psychology literature. The psychology literature focuses on corrections for the correlation between two variables (rather than adjustments for coefficients estimated within a regression framework, as is typical in other literature). The paper can help readers understand the historical foundations of scholarly investigation of the impact of measurement error on measures of association between two variables.

Additional approaches in the econometrics literature to adjust for classical measurement error include:

- Estimating bounds on coefficients. No additional information or assumptions are necessary (Schennach 2020, Section 3.9).
- When a variable is available that is correlated with the true measure but not with measurement error, and is not included in the model, this can be used as an instrumental variable (IV)[3] (Schennach 2020, Section 3.10.2).

SUGGESTED READING

Susanne M. Schennach. 2020. "Chapter 6 - Mismeasured and unobserved variables." In *Handbook of Econometrics, Volume 7A*, edited by Steven N. Durlauf et al., 7:487–565. Handbook of Econometrics. Elsevier. https://doi.org/10.1016/bs.hoe.2020.07.001

Brief summary: This chapter is a technical reference on econometric concepts and approaches for handling measurement error. It includes the two econometric approaches highlighted above along with a variety of approaches to deal with more complex measurement error structures, and it includes details on the identification of available estimators.

2.1.2 Berkson measurement error

Expected result: Regression coefficients from linear models will be **unbiased**. Variance will be inflated, but no correction is required for valid inference.

3 More complex measurement error structures

When models are nonlinear, or when measurement error structures are more complex (e.g., associated with the outcome or errors in other variables), other approaches are needed. Given the common occurrence of complex measurement error patterns, existing literature cautions researchers against the use of the simple heuristics described above, which apply only to non-differential, independent classical measurement error of continuous variables and do not apply to more complex situations.

We review a few of the most common complex forms of measurement error below and use directed acyclic graphs (DAGs)[4] to illustrate these structures.

2. Bias of regression coefficients towards the null (zero) caused by classical measurement error.
3. A variable correlated with the true measure but not with measurement error, and not included in the model.
4. Diagrams used in causal inference to represent relationships among variables, including measurement error.

Representing error with DAGs. The DAGs in this section are adapted from Hernán and Robins (2020), which covers a variety of topics in causal inference, including measurement error.

SUGGESTED READING

Miguel A. Hernán and James M. Robins. 2020. "What If." Chap. Measurement Bias and "Noncausal" Diagrams, 125–131. Boca Raton: Chapman & Hall/CRC. https://static1.squarespace.com/static/675db8b0dd37046447128f5f/t/6a86cf7ecfcb6b4ca8eea5cb/1787219838424/hernanrobins_WhatIf_19aug26.pdf

Brief summary: This section of the book by Hernán and Robins (2020) on causal inference focuses on measurement error and the representation of measurement error in DAGs. The authors review different types of measurement error, map them to DAGs, and provide examples of how that measurement error could appear in practice.

In all of the following DAGs, we consider an exposure (X) and an outcome (Y). We use a $*$ to denote a mismeasured variable and U to denote measurement error. In one DAG, we also include a second exposure (W). For example, classical measurement error in the exposure is encoded as:

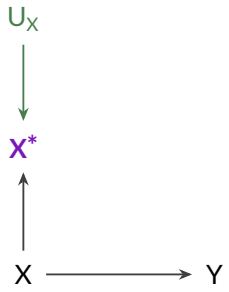


Figure 1: Classical measurement error in the exposure

3.1 Differential measurement error

Differential measurement error is an error structure in which the measurement error is associated with another variable in the model, such as the outcome.

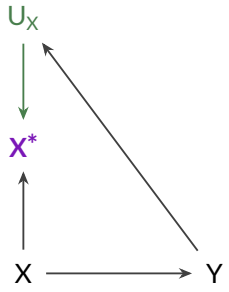
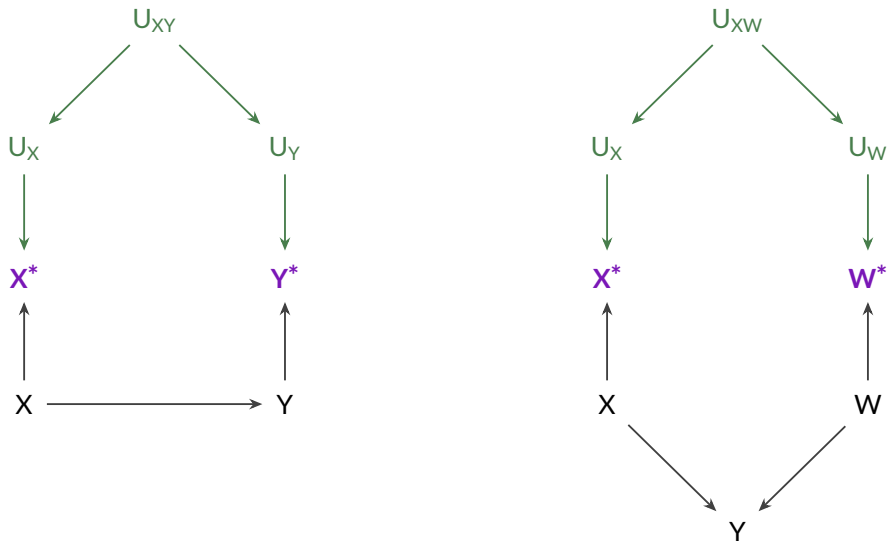


Figure 2: Differential measurement error

3.2 Dependent measurement error

Dependent measurement error is an error structure in which measurement errors in multiple variables are associated with each other. Measurement error in the exposure and outcome can be dependent (Panel A, below). In exposome research with multiple exposures of interest, measurement error can also be dependent across the exposure variables (Panel B, below).



A. Exposure and outcome

B. Multiple exposures

Figure 3: Dependent measurement error

SUGGESTED READING

Scott L. Zeger et al. 2000. "Exposure measurement error in time-series studies of air pollution: concepts and consequences." *Environmental Health Perspectives* 108, no. 5 (May): 419–426. https://doi.org/10.1289/ehp.00108419

Brief summary: This paper creates a framework for understanding measurement error in models focused on air pollution, including the case of multipollutant models with dependent measurement error between the exposures. The authors present a series of simulation results, with succinct summaries of findings that can be used as rules of thumb, and also implement analyses to quantify measurement error in a realistic analysis of real-world data.

These forms of error can also occur in combination. For instance, it is possible to have differential, dependent measurement error.

3.3 Measurement error in categorical variables

If the error-prone variable is categorical, the error is often referred to as misclassification, which can lead to bias even in the case of classical measurement error.

SUGGESTED READING

Anne M. Jurek, Sander Greenland, and George Maldonado. 2008. "Brief Report: How far from non-differential does exposure or disease misclassification have to be to bias measures of association away from the null?" *International Journal of Epidemiology* 37, no. 2 (April): 382–385. https://doi.org/10.1093/ije/dym291

Brief summary: This brief paper presents multiple scenarios based on published data showing the sensitivity of measures of association to small changes in measurement error parameters related to misclassification that may be common in epidemiologic research. Findings illustrate the importance of considering complex measurement error patterns.

4 Quantifying and adjusting for more complex measurement error structures

Validation data[5] or repeated measurements can often be useful in estimating bias or adjusting findings in the presence of complex measurement error structures. We highlight key topic areas and papers related to various types of measurement error structures and approaches to adjusting for measurement error.

4.1 Regression calibration

Regression calibration uses validation data to predict the true value (i.e., the value without measurement error) based on the potentially mismeasured value and a set of covariates. Alternatively, regression calibration can leverage information about error variance from other sources, such as from repeated noisy measurements. Information from the calibration model is then used to adjust the biased regression coefficient. Standard errors can be estimated using a bootstrap or an asymptotic variance estimator.

SUGGESTED READING

Gabriel K. Innes et al. 2021. "The Measurement Error Elephant in the Room: Challenges and Solutions to Measurement Error in Epidemiology." *Epidemiologic Reviews* 43, no. 1 (January): 94–105. https://doi.org/10.1093/epirev/mxab011

Brief summary: This easy-to-digest guide reviews conceptual topics in measurement error and summarizes common approaches to address measurement error in epidemiologic studies, including regression calibration, MIME, and SIMEX. For each approach, the review summarizes the type of mismeasured data the approach can be applied to, requirements around validation data, and available software packages to facilitate use. The citations highlight both foundational papers and examples of applications from the literature.

4.2 Multiple imputation for measurement error correction (MIME)

MIME treats measurement error as a missing data problem. Internal validation data are needed, and these data are used to derive an imputation model that leverages covariate and outcome data as well as the mismeasured variable.

SUGGESTED READING

Gabriel K. Innes et al. 2021. "The Measurement Error Elephant in the Room: Challenges and Solutions to Measurement Error in Epidemiology." *Epidemiologic Reviews* 43, no. 1 (January): 94–105. https://doi.org/10.1093/epirev/mxab011

Brief summary: This easy-to-digest guide reviews conceptual topics in measurement error and summarizes common approaches to address measurement error in epidemiologic studies, including regression calibration, MIME, and SIMEX. For each approach, the review summarizes the type of mismeasured data the approach can be applied to, requirements around validation data, and available software packages to facilitate use. The citations highlight both foundational papers and examples of applications from the literature.

4.3 Simulation extrapolation (SIMEX)

SIMEX relies on a good estimate of error variance, which, as in the case of regression calibration, can come from validation data or repeated noisy measurements. The SIMEX procedure involves repeatedly simulating additional error in the mismeasured variable and re-estimating the association of interest. These simulations enable the estimation of a smooth curve describing the relationship between the magnitude of error and the estimated coefficient, which can then be extrapolated to estimate what the coefficient would be without measurement error (i.e., under the condition where the measurement error variance is 0). This procedure is a generalization of bootstrap-based measurement error bias correction.

5. External data or a subset of internal data containing both mismeasured and true measurements.

SUGGESTED READING

Gabriel K. Innes et al. 2021. "The Measurement Error Elephant in the Room: Challenges and Solutions to Measurement Error in Epidemiology." *Epidemiologic Reviews* 43, no. 1 (January): 94–105. https://doi.org/10.1093/epirev/mxab011

Brief summary: This easy-to-digest guide reviews conceptual topics in measurement error and summarizes common approaches to address measurement error in epidemiologic studies, including regression calibration, MIME, and SIMEX. For each approach, the review summarizes the type of mismeasured data the approach can be applied to, requirements around validation data, and available software packages to facilitate use. The citations highlight both foundational papers and examples of applications from the literature.

4.4 Simulation analysis

Simulations are a flexible tool that can be used to ask questions about the impact of measurement error on findings in scenarios where the truth is known. Simulation analysis to probe the effects of measurement error is often discussed in the context of literature on quantitative bias analysis, though this umbrella term describes a broader suite of methods and approaches, including approaches to quantify the impacts of other forms of bias.

SUGGESTED READING

Matthew P. Fox, Richard F. MacLehose, and Timothy L. Lash. 2023. "SAS and R code for probabilistic quantitative bias analysis for misclassified binary variables and binary unmeasured confounders." *International Journal of Epidemiology* 52, no. 5 (October): 1624–1633. https://doi.org/10.1093/ije/dyad053

Brief summary: This tutorial describes how simulation-based quantitative bias analysis can be used in the setting of a misclassified binary variable. The authors include example code in both SAS and R and walk readers through the process of conducting a simulation-based quantitative bias analysis and interpreting the results.

4.5 Joint modeling

Joint models for the exposure-outcome relationship and the measurement error process can also be used to directly account for exposure measurement error, with or without validation data. These models typically estimate two models simultaneously: one for the relationship between the outcome and the observed (with error) exposure, and one for the relationship between the true exposure and the observed (with error) exposure. The two models are linked by a latent variable representing the true exposure. Estimation is possible by bringing in additional information about the magnitude of the measurement error (typically the error variance). Hierarchical Bayesian estimation approaches are well suited for estimating these joint models and are often used in this setting.

SUGGESTED READING

Sylvia Richardson and Walter R. Gilks. 1993. "A Bayesian Approach to Measurement Error Problems in Epidemiology Using Conditional Independence Models." *American Journal of Epidemiology* 138, no. 6 (September): 430–442. https://doi.org/10.1093/oxfordjournals.aje.a116875

Brief summary: This paper describes how hierarchical Bayesian models can be used to correct for measurement error in epidemiologic research. It explains how ancillary data from validation studies or repeated measures can be used to estimate the models and confirms their performance in a simple simulation analysis.

4.6 Measurement error in geospatial exposures based on prediction models

Measurement error in spatial exposures resulting from prediction models (e.g., air pollution, heat) is complex, as the prediction process typically results in highly correlated measurement error with features of classical and Berkson errors. Existing approaches to adjust for this form of measurement error typically require re-estimation of the exposure model, which may not be feasible for researchers due to data availability restrictions.

SUGGESTED READING

Lianne Sheppard et al. 2012. "Confounding and exposure measurement error in air pollution epidemiology." *Air Quality, Atmosphere & Health* 5, no. 2 (June): 203–216. https://doi.org/10.1007/s11869-011-0140-9

Brief summary: This approachable review discusses both confounding and exposure measurement error in the context of air pollution research, though the concepts are relevant to other spatially predicted exposures as well. The discussion of exposure measurement provides both a conceptual framework for why exposure measurement error matters and is complex in this setting and a review of existing literature on available approaches to adjust for measurement error, with key references providing more technical information.

4.7 Latent variable modeling

Latent variable models can be used when the construct of interest is not directly observed but can be inferred from a larger number of variables hypothesized to be caused by the latent variable. For example, cognitive functioning can be conceptualized as a latent variable, and modeled using observed responses to a battery of cognitive tests.

In addition to estimating the measurement structure of cognition or other latent variables, latent variable models can be embedded in a broader structural equation modeling framework. By simultaneously estimating a measurement model for the potentially mismeasured variable and the health effects model in the same modeling framework, this approach can explicitly consider and account for measurement error.

5 Conclusion

Measurement error in capturing features of the exposome is an underappreciated aspect of exposome research that can have important impacts on research findings. We note that measurement error in other components of health outcome models, including in covariates and in outcomes, is beyond the scope of this primer, but can have important (and different) impacts. We also do not consider the impacts of measurement error on more complex model structures, including machine learning models or mixture models that consider many potentially mismeasured exposures simultaneously, which are important areas for future research investment.

Nonetheless, this primer can serve to increase awareness and understanding of both basic concepts in measurement error and available approaches that can help researchers quantify the impacts of measurement error and correct findings for the resulting bias.

References

Fox, Matthew P., Richard F. MacLehose, and Timothy L. Lash. 2023. "SAS and R code for probabilistic quantitative bias analysis for misclassified binary variables and binary unmeasured confounders." *International Journal of Epidemiology* 52, no. 5 (October): 1624–1633. https://doi.org/10.1093/ije/dyad053.

Hernán, Miguel A., and James M. Robins. 2020. "What If." Chap. Measurement Bias and "Noncausal" Diagrams, 125–131. Boca Raton: Chapman & Hall/CRC. https : / / static1 . squarespace . com / static / 675db8b0dd37046447128f5f / t / 6a86cf7ecfcb6b4ca8eea5cb/1787219838424/hernanrobins_WhatIf_19aug26.pdf.

Innes, Gabriel K., Fiona Bhondoekhan, Bryan Lau, Alden L. Gross, Derek K. Ng, and Alison G. Abraham. 2021. "The Measurement Error Elephant in the Room: Challenges and Solutions to Measurement Error in Epidemiology." *Epidemiologic Reviews* 43, no. 1 (January): 94–105. https://doi.org/10.1093/epirev/mxab011.

Jurek, Anne M., Sander Greenland, and George Maldonado. 2008. "Brief Report: How far from non-differential does exposure or disease misclassification have to be to bias measures of association away from the null?" *International Journal of Epidemiology* 37, no. 2 (April): 382–385. https://doi.org/10.1093/ije/dym291.

Muchinsky, Paul M. 1996. "The Correction for Attenuation." *Educational and Psychological Measurement* 56 (1): 63–75. https://doi.org/10.1177/0013164496056001004.

Richardson, Sylvia, and Walter R. Gilks. 1993. "A Bayesian Approach to Measurement Error Problems in Epidemiology Using Conditional Independence Models." *American Journal of Epidemiology* 138, no. 6 (September): 430–442. https://doi.org/10.1093/oxfordjournals.aje.a116875.

Schennach, Susanne M. 2020. "Chapter 6 - Mismeasured and unobserved variables." In *Handbook of Econometrics, Volume 7A*, edited by Steven N. Durlauf, Lars Peter Hansen, James J. Heckman, and Rosa L. Matzkin, 7:487–565. Handbook of Econometrics. Elsevier. https://doi.org/10.1016/bs.hoe.2020.07.001.

Sheppard, Lianne, Richard T. Burnett, Adam A. Szpiro, Sun-Young Kim, Michael Jerrett, C. Arden Pope III, and Bert Brunekreef. 2012. "Confounding and exposure measurement error in air pollution epidemiology." *Air Quality, Atmosphere & Health* 5, no. 2 (June): 203–216. https://doi.org/10.1007/s11869-011-0140-9.

Zeger, Scott L., Duncan C. Thomas, Francesca Dominici, Jonathan M. Samet, Joel D. Schwartz, Douglas W. Dockery, and Aaron J. Cohen. 2000. "Exposure measurement error in time-series studies of air pollution: concepts and consequences." *Environmental Health Perspectives* 108, no. 5 (May): 419–426. https://doi.org/10.1289/ehp.00108419.

Version information

Current Version: 1.0 (November 2026)

Version history

- 1.0 (November 2026): First version.