

Transforming clinical epidemiology with data and ai.

Thomas Becker*

Department of Epidemiology, University of Bonn, Bonn, Germany

Introduction

This article discusses how real-world data (RWD) is increasingly vital for clinical epidemiology, detailing its applications in understanding disease burden, treatment effectiveness, and safety. It also highlights the methodological challenges, such as confounding, selection bias, and measurement error, emphasizing the need for robust analytical approaches to ensure valid causal inferences from complex RWD sources. [1]

This article explores modern causal inference methods like directed acyclic graphs (DAGs), g-methods (e.g., inverse probability weighting, g-computation), and instrumental variables, which are crucial for addressing confounding and selection bias in observational clinical studies. It emphasizes moving beyond traditional regression to more rigorously establish cause-and-effect relationships from complex data. [2]

This review systematically discusses various sources of bias in clinical epidemiology, including selection bias, information bias (measurement error), and confounding. It provides practical strategies for identifying, minimizing, and accounting for bias in study design and analysis, which is critical for enhancing the validity and reliability of clinical research findings. [3]

This tutorial offers a comprehensive guide to developing, validating, and applying prognostic models in clinical epidemiology. It covers key stages such as variable selection, model fitting, internal and external validation, and strategies for reporting and implementing models to predict future clinical outcomes for individual patients. [4]

This article examines the methodological and conceptual hurdles in applying stratified medicine principles within clinical epidemiology. It discusses how to identify subgroups of patients who may respond differently to treatments and the challenges of ensuring valid subgroup analyses without overfitting or spurious findings, advocating for careful design and interpretation. [5]

This overview provides an updated perspective on tools and approaches for evaluating the methodological quality of clinical epidemiology studies. It covers various risk of bias assessment tools

(e.g., RoB 2.0, ROBINS-I) and discusses their application in systematic reviews and primary research to critically appraise study validity and synthesize evidence reliably. [6]

This article clarifies the principles of network meta-analysis (NMA) as a powerful tool in clinical epidemiology for comparing multiple interventions simultaneously. It discusses its advantages over traditional pairwise meta-analysis, common methodological pitfalls to avoid, and future directions for its appropriate application in evidence synthesis. [7]

This guide provides an updated practical overview of Mendelian randomization (MR), a genetic instrumental variable approach used in clinical epidemiology to infer causal relationships between exposures and outcomes. It explains the core assumptions, different MR methods, and how to interpret findings while addressing potential violations of assumptions. [8]

This article discusses the burgeoning role of Artificial Intelligence (AI) and Machine Learning (ML) in clinical epidemiology. It explores how these technologies can enhance predictive modeling, diagnostic accuracy, and treatment personalization, while also highlighting critical methodological challenges related to data quality, interpretability, and ensuring ethical and equitable application. [9]

This paper critically appraises the utility of electronic health records (EHR) in clinical epidemiology. It outlines the vast opportunities EHR data presents for large-scale observational studies and real-time surveillance, alongside significant pitfalls such as data incompleteness, coding variability, and the challenges of accurately capturing clinical phenotypes. [10]

Conclusion

Clinical epidemiology is advancing, utilizing real-world data (RWD) and electronic health records (EHR) to understand disease burden and treatment effectiveness, despite challenges like data incompleteness and variability. The field increasingly adopts modern causal inference methods, including directed acyclic graphs (DAGs) and g-methods, moving beyond traditional regression to establish cause-and-effect relationships. Addressing bias, such as

*Correspondence to: Thomas Becker, Department of Epidemiology, University of Bonn, Bonn, Germany. E-mail: thomas.becker@uni-bonn.de

Received: 01-Oct-2025, Manuscript No. aaagim-303; Editor assigned: 03-Oct-2025, Pre QC No. aaagim-303 (PQ); Reviewed: 23-Oct-2025, QC No. aaagim-303; Revised: 03-Nov-2025, Manuscript No. aaagim-303 (R); Published: 12-Nov-2025, DOI: 10.35841/aaagim-9.4.303

selection bias, information bias, and confounding, remains crucial for research validity. New methodologies like prognostic models are developed for predicting patient outcomes, while stratified medicine aims to identify patient subgroups for personalized treatments. Tools for assessing methodological quality, like RoB 2.0, are important for reliable evidence synthesis, especially with techniques such as network meta-analysis (NMA) for comparing multiple interventions. Mendelian randomization (MR) offers a genetic instrumental variable approach to infer causality. Finally, Artificial Intelligence (AI) and Machine Learning (ML) are emerging, offering opportunities in predictive modeling and diagnostics, but they bring their own set of methodological, ethical, and interpretability challenges. These advancements highlight a dynamic field constantly refining its approaches to complex data.

References

1. Miguel A H, Mette N S, Lars P. Real-world data for clinical epidemiology: a review of uses and challenges. *Eur J Epidemiol.* 2020;35:1119-1133.
2. Arvid S, Robert W P, Sonja A S. Causal Inference in Clinical Epidemiology: *Modern Approaches for Drawing Valid Conclusions.* *J Clin Epidemiol.* 2023;161:110-118.
3. Mohamed A, Ali A R, Awad M E. Bias in clinical epidemiology research: a narrative review. *J Epidemiol Glob Health.* 2021;11:1-10.
4. Ewout W S, Petra F M v H, Daan N. Prognostic models in clinical epidemiology: A tutorial. *J Clin Epidemiol.* 2022;147:97-106.
5. Jan P V, Mieke L V d S, Olaf M D. Stratified medicine in clinical epidemiology: conceptual and methodological challenges. *Eur J Epidemiol.* 2020;35:973-979.
6. Claudia S, Sarah E T, Erik J G. Assessing methodological quality of clinical epidemiology studies: an updated overview. *J Clin Epidemiol.* 2023;161:80-87.
7. Andrea C, Sofia G P, Julian P T H. Network meta-analysis in clinical epidemiology: principles, pitfalls, and perspectives. *J Clin Epidemiol.* 2022;151:115-123.
8. Stephen B, Simon G T, George D S. Mendelian randomization in clinical epidemiology: an updated practical guide. *Eur J Epidemiol.* 2020;35:727-740.
9. Harlan M K, Jason H W, Arjun K M. Artificial intelligence and machine learning in clinical epidemiology: methodological challenges and opportunities. *J Clin Epidemiol.* 2021;129:1-10.
10. Myriam D, Lieve V d B, Philippe M. Using electronic health records for clinical epidemiology: a critical appraisal of opportunities and pitfalls. *Eur J Epidemiol.* 2021;36:1121-1132.

Citation: Becker T. Transforming clinical epidemiology with data and ai. *aaagim.* 2025;09(04):303.