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# Current applications of machine learning for causal inference in healthcare research using observational data

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## Background

**Machine learning (ML): a broad concept with many applications.**

- ML refers to a family of statistical methods that generally focus on classification, ranking, and prediction with minimal human supervision.[1]
- ML approaches have the potential to facilitate causal inference using large, multidimensional real-world data (RWD).
- However, the implementation of ML-based approaches in answering causal pharmacoepidemiology questions can be conceptually and computationally complex.
- Researchers often ask the following questions:
  - *What are the potential applications of ML to my project?*
  - *What kinds of barriers are there to using RWD for causal inference in my study? How can ML help?*

## Objective

To visually illustrate the relationships between different types of barriers to causal inference in healthcare research and selected ML applications targeted at addressing these barriers, using an applied pharmacoepidemiological perspective.

## Methods

- We conducted a targeted review of published literature to identify RWD studies with ML applications for causal research.
- We classified the applications into three broad domains (presented via an infographic) and generated a list of illustrative case studies.

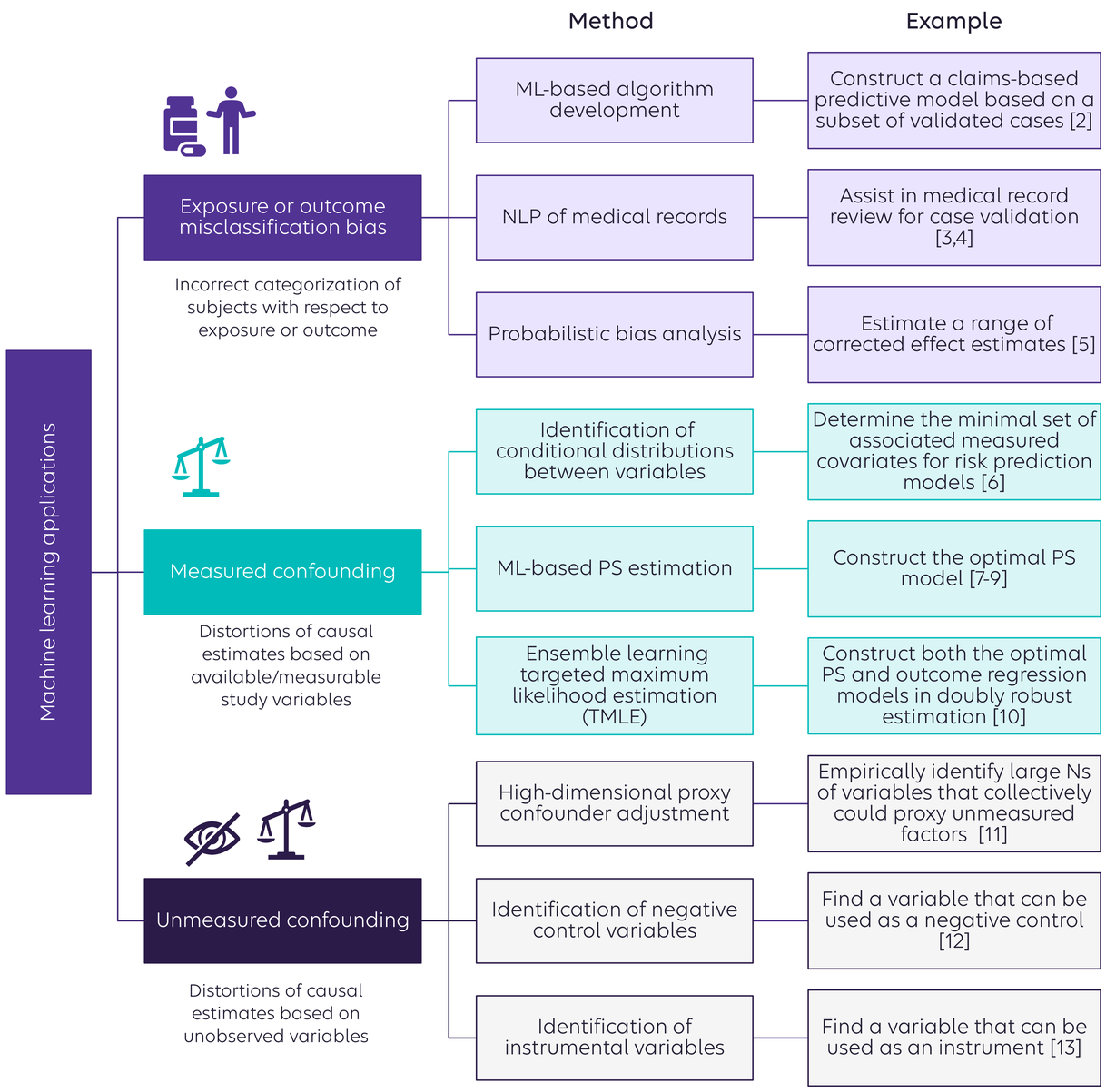
## Results

The identified ML applications were classified into three domains based on their potential to strengthen causal inference in pharmacoepidemiology studies.

## Funding and disclosures

No funding was received for the conduct of this study. All authors are employees of Carelon Research, which conducts health outcomes research with both internal and external funding, including a variety of private and public entities.

## Results (continued)




List of acronyms and terms:
High-dimensional proxy confounder adjustment: using large numbers of empirically identified features that collectively serve as proxies for unspecified or unmeasured confounders
Instrumental variable: a variable that affects the outcome of interest only through its effect on the exposure
Negative control variable: an alternative exposure (or outcome) variable whose relationship to the original outcome (or exposure) of interest does not use the same hypothesized causal pathway but is likely to involve the same sources of bias
NLP: natural language processing; a branch of AI concerned with the ability to support and manipulate human language
Probabilistic bias analysis: quantitative sensitivity analysis to assess the magnitude, direction, and uncertainty of bias using Monte Carlo techniques to repeatedly sample from bias parameter distributions
PS: propensity score; the conditional probability of being exposed given a set of covariates
Targeted maximum likelihood estimation: a doubly robust estimation method that includes a secondary targeting step that optimizes the bias-variance tradeoff for the parameter of interest

## Conclusions

- ML applications can strengthen causal research using real-world healthcare data. However, the range and complexity of applications limits wider use.
- To overcome this limitation, we provide a visual roadmap to relevant ML applications to help researchers quickly identify the appropriate tools given their specific research question.
- Note: The ML applications included in this poster are only a small fraction of all the potential utilities of ML for RWD research. This list can be expanded as new applications emerge and are developed.

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Poster presented at ISPOR 2024, May 5-8, Atlanta, GA.

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