Decision support based on AI in medical imaging

AI in medical imaging (AIBIA) parallel session

Wouter van Amsterdam

University Medical Center Utrecht

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1. different uses of AI in medical imaging

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- 2. using AI for treatment effect estimation

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- 2. using AI for treatment effect estimation
- 3. warning: harmful self-fulfilling prophecies

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- 5. treatment effect (*X* determines effect of a treatment)

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- for example, whether tamoxifen increases survival for breast cancer patients depends on whether their tumor is hormone sensitive
- some characteristics may be well captured in medical imaging:
 - T-cell distributions around tumors related to effect of immunotherapy in cancer

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What if you cannot do a (big enough) RCT?

Emulate / approximate the ideal trial in observational data you do have, using causal inference techniques

(which rely on untestable assumptions)

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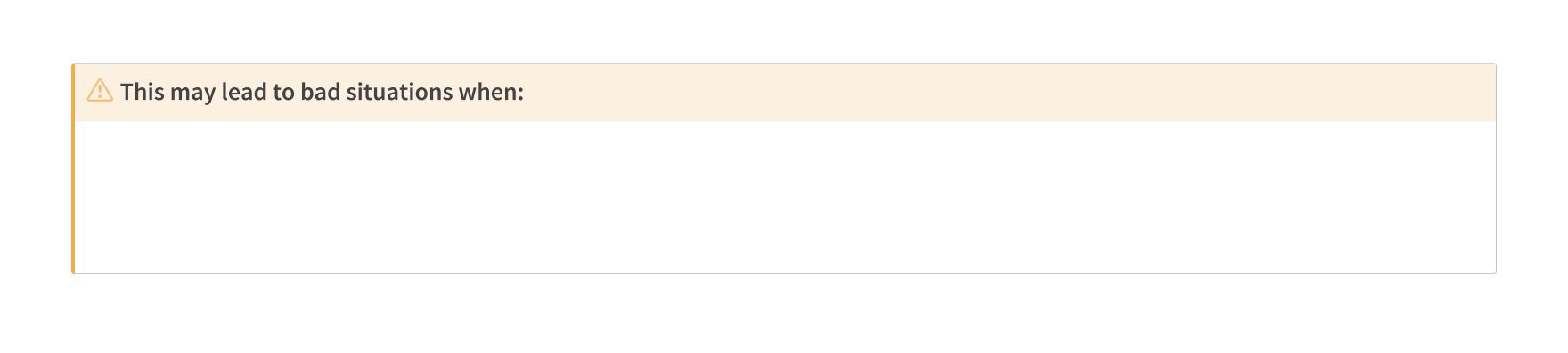
- 1. give chemotherapy to cancer patients with high predicted risk of recurrence
- 2. give statins to patients with a high risk of a heart attack

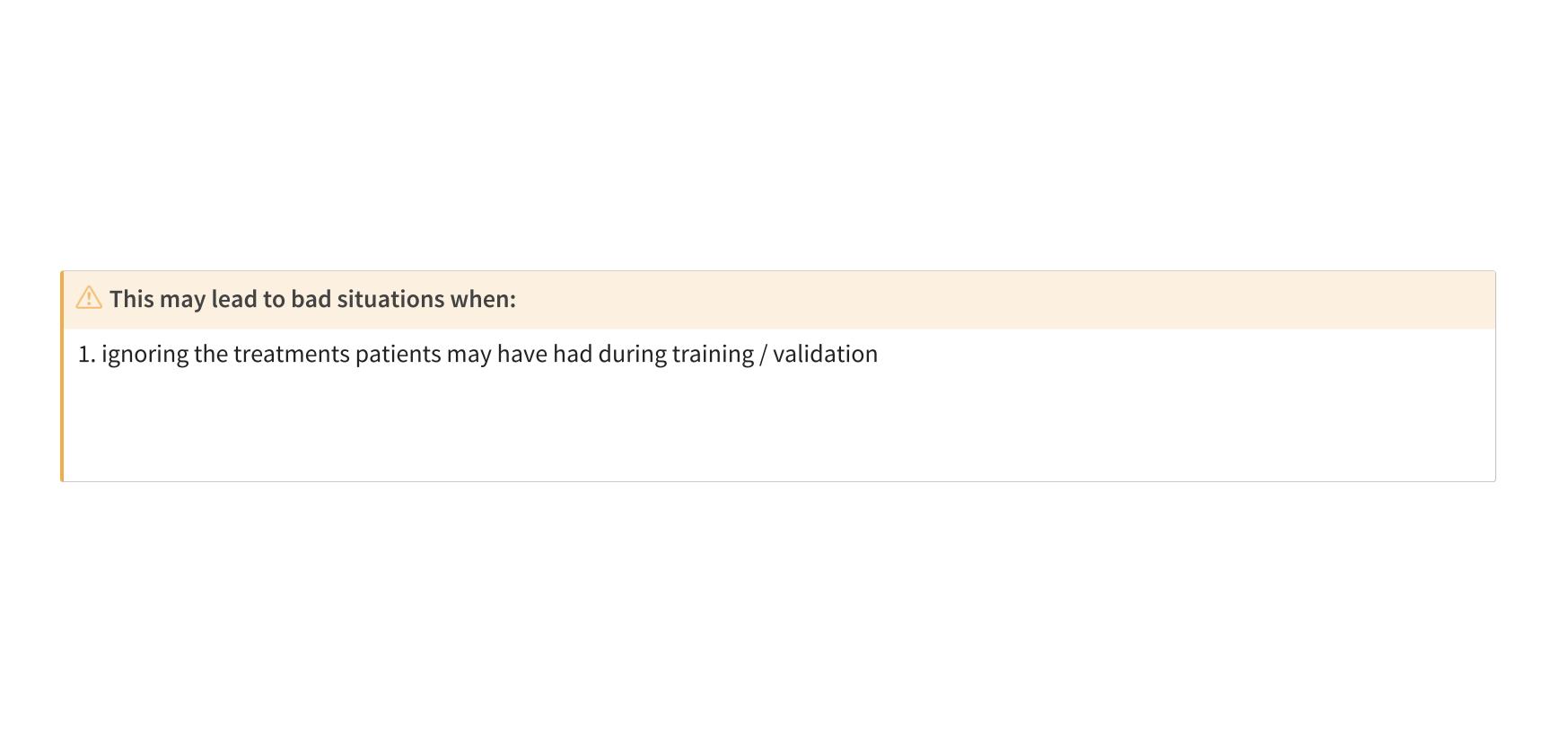
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TRIPOD+AI on prediction models (Collins et al. 2024)

"Their primary use is to support clinical decision making, such as ... initiate treatment or lifestyle changes."





⚠ This may lead to bad situations when:

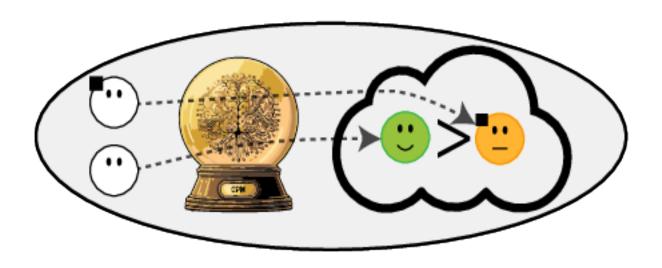
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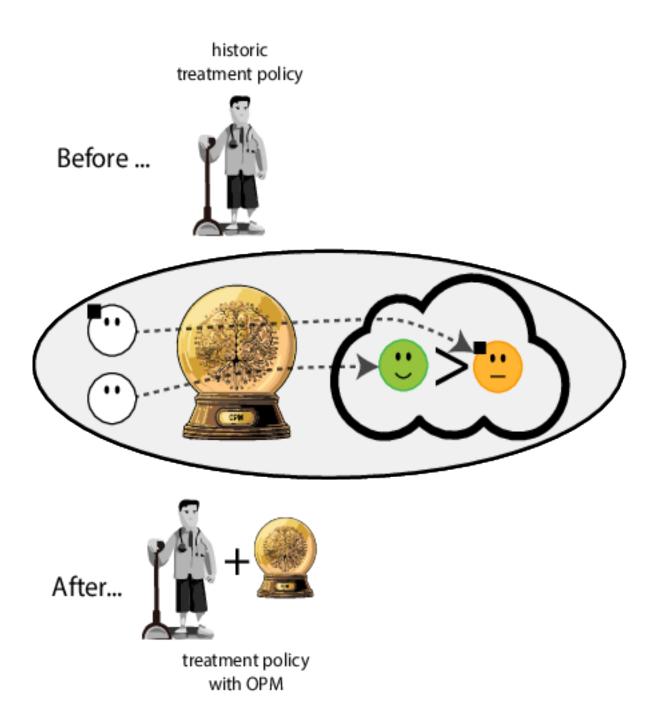
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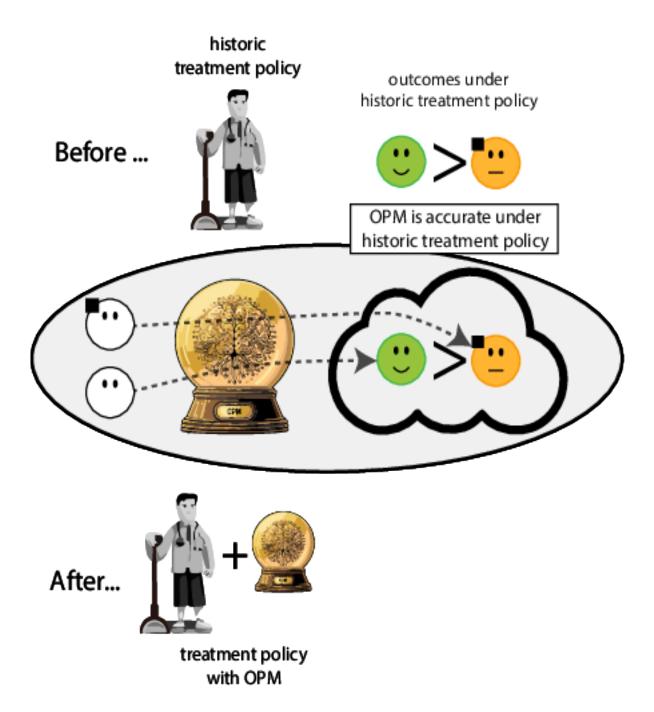
- 1. ignoring the treatments patients may have had during training / validation
- 2. only considering measures of predictive accuracy as sufficient evidence for safe deployment
- 3. predictive accuracy (AUC) may be measured pre- or post-deployment of the model

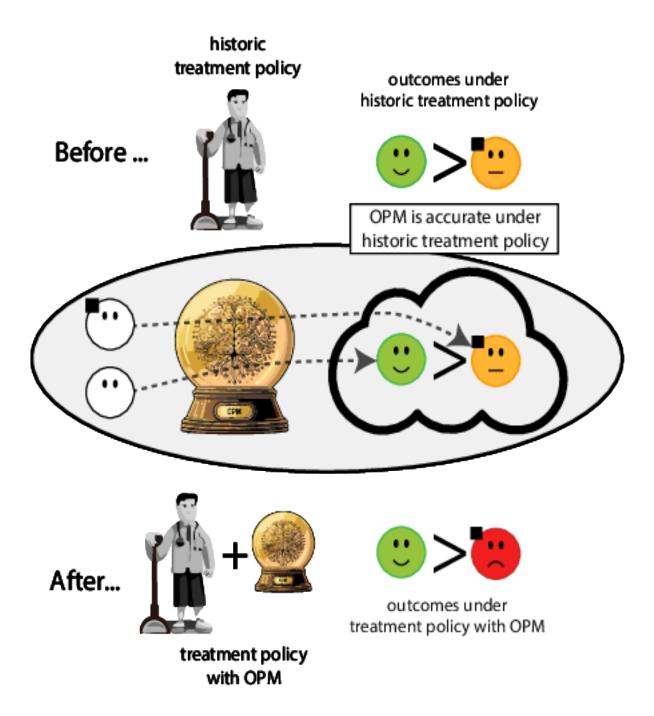
When accurate prediction models yield harmful self-fulfilling prophecies

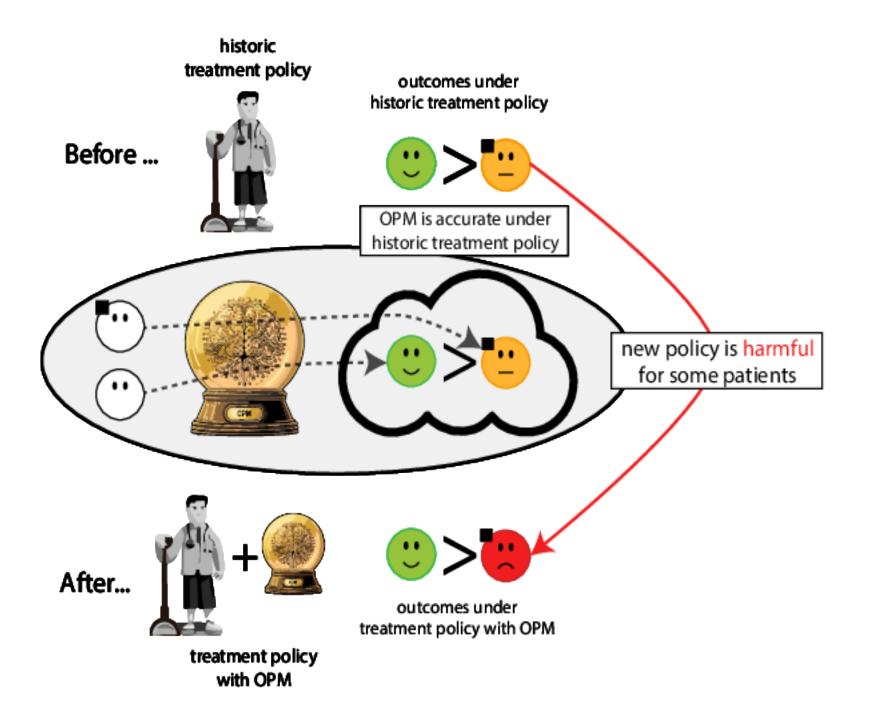


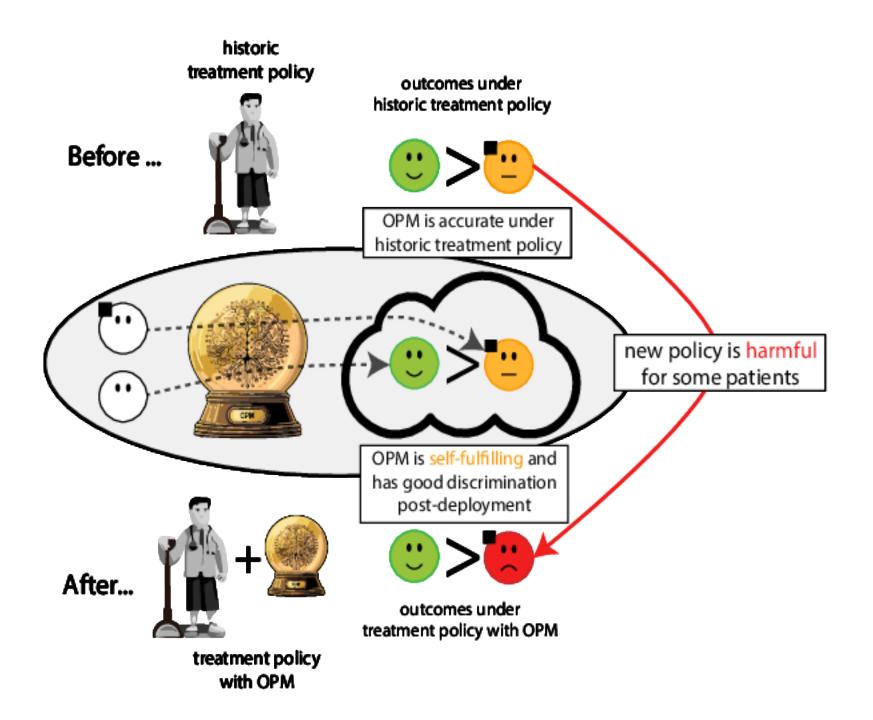












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From algorithms to action: improving patient care requires causality (W. A. C. van Amsterdam et al. 2024b)

When accurate prediction models yield harmful sel-fulfilling prophecies (W. A. C. van Amsterdam et al. 2024a)

References

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