Reducing Bias in AKI
Artificial Intelligence
Algorithms: Does a Machine Have an Unconscious Bias?

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Organized by the ASN AKI!Now
Artificial Intelligence Workgroup
Welcome and Introductions

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This webinar is being recorded.

Following today’s webinar, the recording, slides, and speaker bio handout will be posted on the ASN AKI website at:

https://www.asn-online.org/aki!now/
This webinar, **Reducing Bias in AKI Artificial Intelligence Algorithms: Does a Machine have an Unconscious Bias?** is provided as information and education and should not be construed as medical advice or recommendations for patient care.

The information expressed is that of the speaker(s) and contributor(s) only. Clinicians are to use their own training, clinical observations, and judgment to make all diagnostic and treatment decisions. The ASN Alliance (including ASN) does not offer medical advice.
Artificial Intelligence (AI) Effort for Quality Improvement in Acute Kidney Injury

**Gaps**
- Many desired tools do not exist.
- AI tools may not be broadly validated.
- Current efforts are uncoordinated.
- AI tools can carry implicit bias if not carefully designed and evaluated.
- AI tools may not consistently provide evidence on improvements in care or cost savings.

**Patients**
- Design fair and equitable AI models
- Identify scenarios based on personal and caregiver experience that could be improved with AI
- Improve patient centered outcomes in AKI survivors

**Clinicians**
- Design fair and equitable AI models
- Identify areas of clinical uncertainty that may benefit from new AI tools
- Guide appropriate follow-up for AKI survivors

**Researchers**
- Evaluate current AI tools, with a focus on removing implicit bias
- Develop new AI tools to address gaps identified by patients and clinicians
- Develop AI methods to advance the science of AKI

**Improve the quality, accessibility, affordability, and equity of care.**

Visit [https://www.asn-online.org/akiNow/ai](https://www.asn-online.org/akiNow/ai) to learn more.
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American Society of Nephrology
"Uncovering the Ways in which AI Captures and Propagates Bias"

Today’s Moderator
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Disclosures

I receive grant support from Blue Cross Blue Shield of Michigan and Teva Pharmaceuticals.

I serve on a scientific advisory board for Flatiron Health.
Why AI in AKI?

Alerting clinicians to intervene on patients after the onset of AKI appears to be an ineffective strategy.¹

Artificial intelligence (AI) — specifically prediction models — appear capable of predicting the onset of acute kidney injury (AKI).

**An open question in the field:** Do we need to target our interventions to patients at high risk of AKI before its onset?

What can AI do for us?

AI can distill a patient’s record at a given moment in time down to a probability of experiencing AKI.

We can then use that probability to guide clinical actions.

But AI can learn biases

What is bias?

Bias means that an AI model isn’t working equally well for all people who are subject to its use.

We can think of this in mathematical terms (e.g., “false positives”)

We can also think of this in terms of fairness.
Biases start in world, enter into the data, are embedded in model evaluations, and affect people’s health through actions we take in response to models.

Kidney function has often been estimated based on non-diverse populations.

But even if the model population is representative of the US population (e.g., 12% Black), we may need to oversample minorities to build good models.

Black. The Cockcroft and Gault creatinine clearance equation was originally developed in only White men, and the majority of GFR-estimating equations derived in European cohorts did not specify whether Black individuals were included, or specifically excluded Black participants, in equation development or internal validation (approaches CG_Clcr, FAScr, EKFCcr, LMcr, FAScr-cys, FAScys, and CAPAcys). Other racial and ethnic minority groups (e.g., Asian, Hispanic/Latinx, Native American, and Pacific Islander groups) are also under-represented in eGFR research. Similar considerations may be needed to identify suitable approaches for non-US populations.
When you change the equation, you change people’s lives.

Changes affect kidney transplant eligibility and donor eligibility.

Exciting work is underway to help us better predict—and hopefully prevent—AKI.

A clinically applicable approach to continuous prediction of future acute kidney injury

Nenad Tomašev, Xavier Glorot, ... Shakir Mohamed

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A clinically applicable approach to continuous prediction of future acute kidney injury

context and enough time to act. Here we develop a deep learning approach for the continuous risk prediction of future deterioration in patients, building on recent work that models adverse events from electronic health records and using acute kidney injury—a common and potentially life-threatening condition—as an exemplar. Our model was developed on a large, longitudinal dataset of electronic health records that cover diverse clinical environments, comprising 703,782 adult patients across 172 inpatient and 1,062 outpatient sites. Our model predicts 55.8% of all inpatient episodes of acute kidney injury, and 90.2% of all acute kidney injuries that required subsequent administration of dialysis, with a lead time of up to 48 h and a ratio of 2 false alerts for every true alert. In addition to predicting future acute kidney injury, our model provides confidence assessments and a list of the clinical features that are most salient to each prediction, alongside predicted future trajectories for clinically relevant blood tests. Although the recognition and prompt treatment of acute kidney injury is known to be challenging, our approach may offer opportunities for identifying patients at risk within a time window that enables early treatment.
AI systems are worse at diagnosing disease when training data is skewed by sex.

The artificial intelligence model showed great promise in predicting which patients treated in U.S. Veterans Affairs hospitals would experience a sudden decline in kidney function. But it also came with a crucial caveat: Women represented only about 6% of the patients whose data were used to train the algorithm, and it performed worse when tested on women.

The shortcomings of that high-profile algorithm, built by the Google sister company DeepMind, highlight a problem that machine learning researchers working in medicine are increasingly worried about. And it’s an issue that may be more pervasive — and more insidious — than experts previously realized, new research suggests.

Fairness is not a simple thing to define.

This is because fairness is a multidimensional concept.
What patients and providers want may not always align.

Bias in Artificial Intelligence for Acute Kidney Injury

Non-polar predictions:
e.g. Clinical decision making for the use of cholesterol-lowering medications based on cardiovascular disease risk

Polar predictions:

Positively polar predictions
e.g. micro-allocation for organ transplantation, care management programs

Negatively polar predictions
e.g. Screening for child abuse risk, involuntary commitment
Should we just remove “protected variables” from models?

Removing a variable from an AI model **does not** always remove the effect of that variable from the model.
Protected variables are often correlated with other factors (like income and health care utilization).

The effects of race may be captured in a model even if race is not directly in the model.
What should we do to prevent bias from entering algorithms?

1. Assess and correct bias in the data:
   - Representation bias
   - Measurement bias

2. Assess and correct bias in existing algorithms
   - i.e. “Algorithmic auditing”

ALGORITHMIC BIAS PLAYBOOK

Is your organization using biased algorithms? How would you know? What would you do if so?
This playbook describes 4 steps your organization can take to answer these questions. It distills insights from our years of applied work helping others diagnose and mitigate bias in live algorithms.

Algorithmic bias is everywhere. Our work with dozens of organizations—healthcare providers, insurers, technology companies, and regulators—has taught us that biased algorithms are deployed throughout the healthcare system, influencing clinical care, operational workflows, and policy.

This playbook will teach you how to define, measure, and mitigate racial bias in live algorithms. By working through concrete examples—cautionary tales—you’ll learn what bias looks like. You’ll also see reasons for optimism—success stories—that demonstrate how bias can be mitigated, transforming flawed algorithms into tools that fight injustice.

Bias in Artificial Intelligence for Acute Kidney Injury

Thank you!

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Panel Discussion

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