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Editor-in-Chief  
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Dear Editor,

We are pleased to submit our manuscript, “When Algorithms Mirror Inequality: Structural Encoding of Fairness Disparities in Early Childhood Risk Prediction,” for consideration as a regular article in *AERA Open*.

**Summary.** School districts increasingly deploy machine learning algorithms to identify students at risk of academic failure, yet whether these tools work equitably across demographic groups—and why they may not—remains understudied. Using the nationally representative ECLS-K:2011 ( $N = 9,104$ ; sensitivity analyses on  $N = 18,151$ ), we audited seven algorithms spanning classical regression and state-of-the-art gradient boosting, evaluating group fairness, calibration fairness, intersectional fairness, and temporal generalization simultaneously.

**Key findings.** Three results are especially noteworthy:

1. *Structural encoding, not algorithmic bias.* All seven algorithms converged on nearly identical performance ( $AUC = 0.837\text{--}0.848$ ) and the same pattern of racial disparities—Hispanic students flagged at 2.4 times the rate of White students, Black students experiencing 3.7 times higher calibration error. Counterfactual decomposition traced these disparities to differences in children’s baseline characteristics: the gap attributable to distributional differences exceeded the observed disparity (152%), meaning the algorithms partially *compressed* rather than amplified inequality. The source of inequity lies in the data, not the model.
2. *The poverty detector problem.* Removing socioeconomic status from the model changed almost nothing ( $\Delta AUC = 0.003$ ), because cognitive scores already encode the same disadvantage. Exploratory intersectional analysis (race  $\times$  SES) suggested the model identifies risk primarily through socioeconomic signals, potentially missing minority students whose difficulties arise from non-poverty-related factors.
3. *Irreducibility within the predictive paradigm.* Additional longitudinal data improved accuracy without resolving fairness gaps. Fairness compliance held at only one of four tested thresholds. Both post-processing and in-processing mitigation reduced disparities but at substantial accuracy cost ( $AUC$  penalty = 0.21–0.23), consistent with known impossibility results.

**Significance for AERA Open’s readership.** This manuscript reframes the policy conversation from “which algorithm?” to “what data and institutional practices produce

these disparities?” It provides both a methodological framework for comprehensive fairness auditing—spanning uncertainty quantification, calibration analysis, intersectional assessment, and temporal stability—and empirical evidence that fairness failures in early childhood prediction are properties of the institutional conditions that generate the data, not fixable by algorithmic selection alone. As predictive analytics become standard in K–12 settings, this evidence base is essential for responsible deployment.

**Fit with AERA Open.** This manuscript addresses a timely intersection of educational equity, quantitative methods, and algorithmic governance—core concerns for AERA’s readership. The work is empirical, uses rigorous methods on nationally representative data, and yields actionable implications for researchers, practitioners, and policymakers considering algorithmic tools in education.

**Manuscript details.** The manuscript is approximately 10,000 words with 6 figures and 14 tables in the main text, plus Supplementary Materials with 9 additional figures and 8 tables. All analyses use freely available public-use data and fully reproducible open-source code. This manuscript has not been published or submitted elsewhere. All authors have approved the submitted version.

We appreciate your consideration and look forward to your response.

Sincerely,

Kismat Raj Vishwakarma  
(on behalf of all authors)