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Leveraging Machine Learning to Reconcile Missing Demographic Data in IISs

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National Meeting

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The IIS of the Past, Present, and Future

Connected Intelligence

Predictive Insights

Improved Outcomes

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The Challenge

IIS data plays a critical role in guiding public health interventions and program development

Missing data is a widespread issue, compromising the validity of findings

If not properly handled, missing data can introduce bias, distort analysis outcomes, and misinform decisions

Traditional Methods

Omit or “Unknown”

Traditional analyses will omit records with missing data or label them as “unknown”

Computationally Expensive

In large, public health datasets, MICE utilizes a lot of time and computing resources

Multiple Imputation using Chained Equations (MICE)

Creates multiple complete datasets to reflect missing value ambiguity

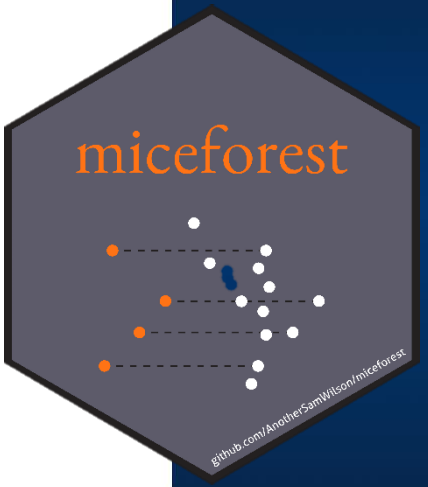
Managing Missing Data with Machine Learning

Machine learning (ML) offers robust methods for missing data reconciliation

Like MICE, ML depends on the type and pattern of missingness

Studies show that MICE has less bias and comparable standard errors compared to ML techniques

Combining MICE with ML can further reduce bias in imputed datasets



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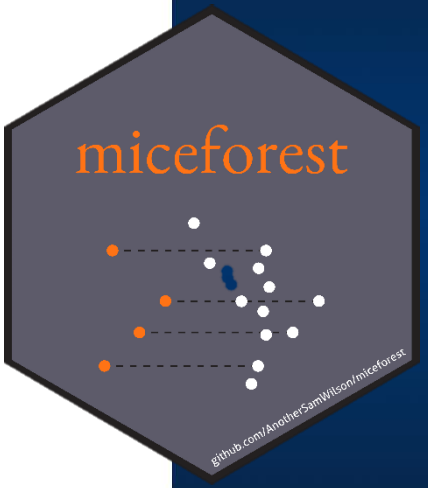
Miceforest

Blends classical epidemiological methods with ML

Uses MICE and LightGBM, a gradient-boosted decision tree



Purpose

1. To evaluate the use of the ML technique Miceforest, in combination with cloud-based computing, for reconciling missing demographic data – compared to traditional MICE

2. Determine whether these methods impact flu vaccination coverage estimates

Materials & Methods

Data was obtained from a synthetic dataset based on census data, representing approximate IIS data distributions (N=4,472,365)

Variable	Missing (%)	Missing (n)
Gender	0.09%	4,154
Ethnicity	0.03%	1,299
Age	0.17%	7,650

Materials & Methods

Multiple Imputation Using Chained Equations (MICE)

STATA 17

Informing variables: race, city, county, & previous flu vaccine activity

15 imputations, 20 iterations

Miceforest

Python package, tree-based algorithm

Databricks platform

Informing variables: race, city, county, & previous flu vaccine activity

15 imputations, 20 iterations

Results

Through MICE and Miceforest, we obtained an additional 12,557 observations compared to the complete case analysis.

Flu coverage went from 49% to 24%

Computational time:

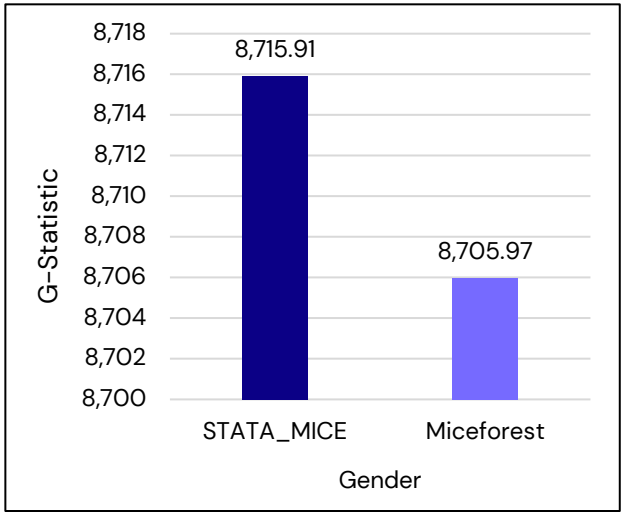
MICE = 8 hours

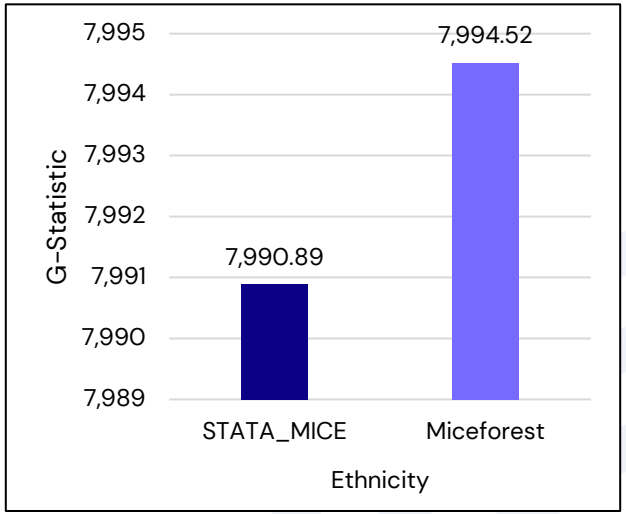
Miceforest = 10 minutes

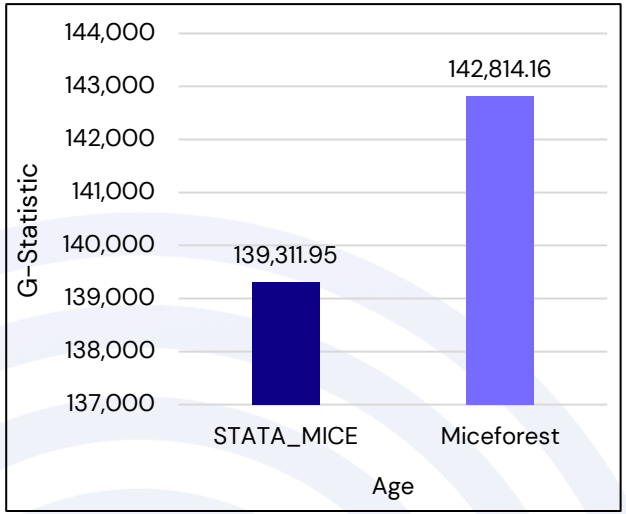
Likelihood Ratio Test Results

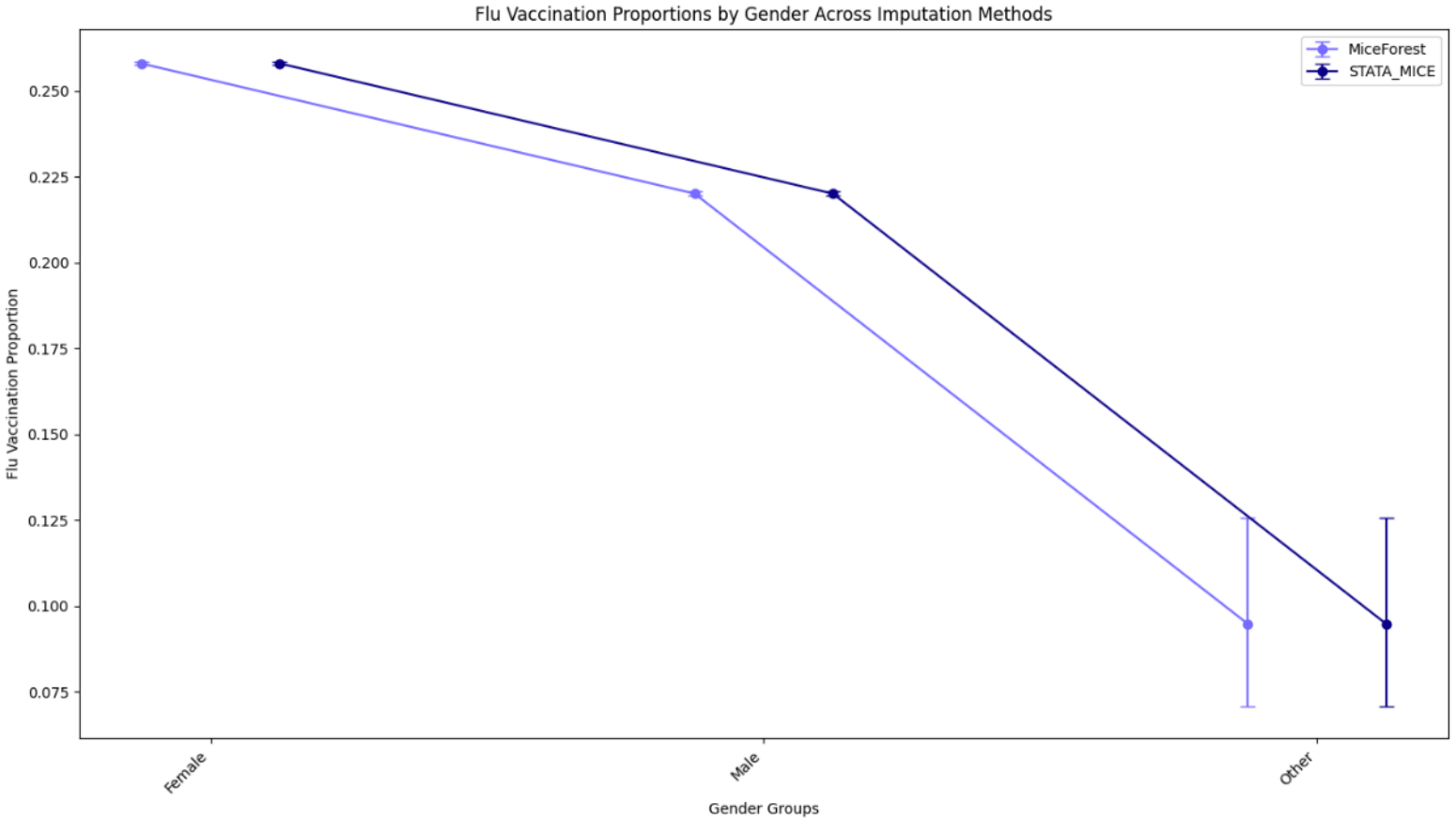
Variable	Method	G-Statistic	P-value	Degrees of Freedom	Between-Imputation Variance
Gender	STATA MICE	8715.905	<0.001	-	16.6847
	Miceforest	8705.9659	<0.001	2	-
Ethnicity	STATA MICE	7990.888	<0.001	-	4.1832
	Miceforest	7994.5242	<0.001	1	-
Age	STATA MICE	139311.949	<0.001	-	9588.596
	Miceforest	142814.1625	<0.001	5	-

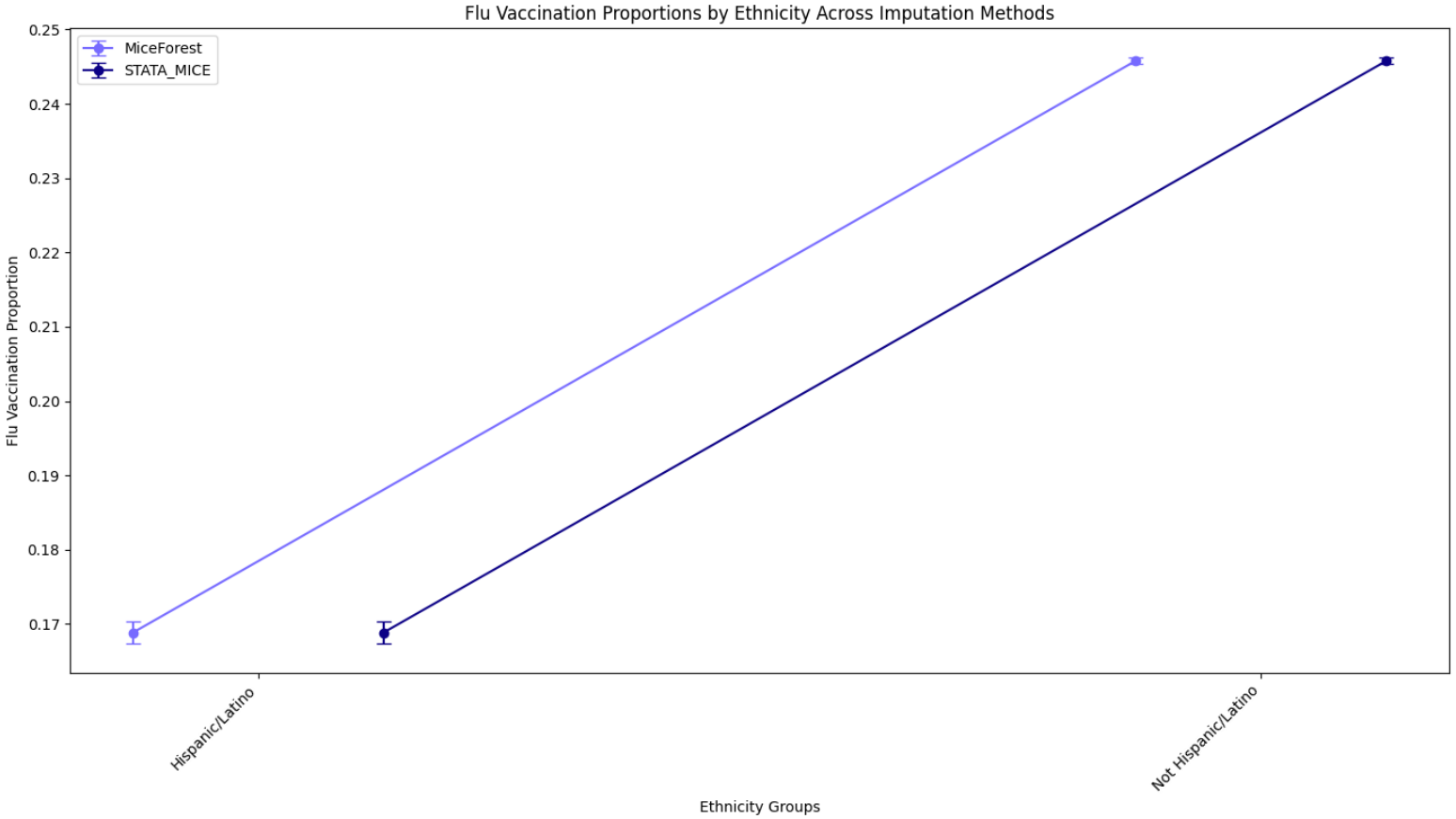
Likelihood Ratio Test Results

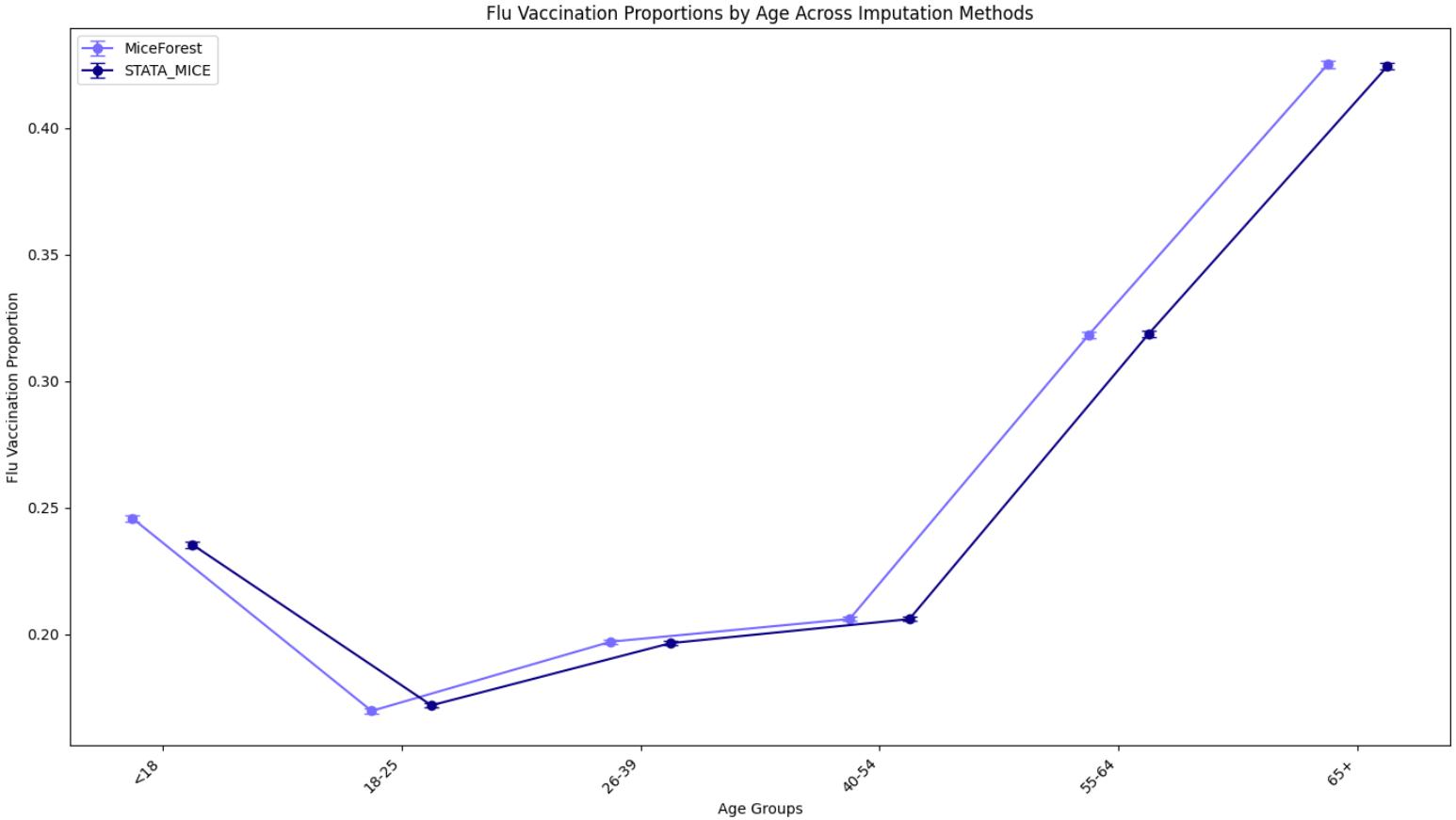




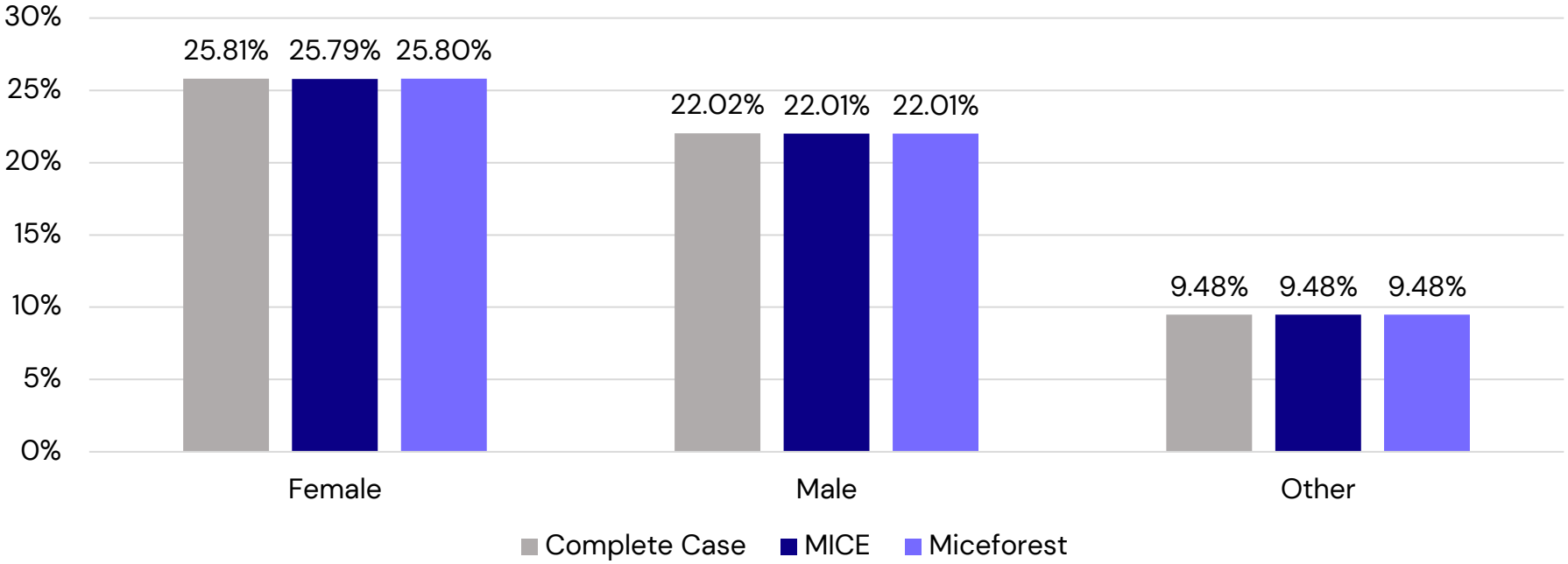



Flu Vaccination Proportions by Gender Across Imputation Methods
MiceForest
STATA_MICE
Flu Vaccination Proportion
0.250
0.225
0.200
0.175
0.150
0.125
0.100
0.075
Female
Male
Other
Gender Groups

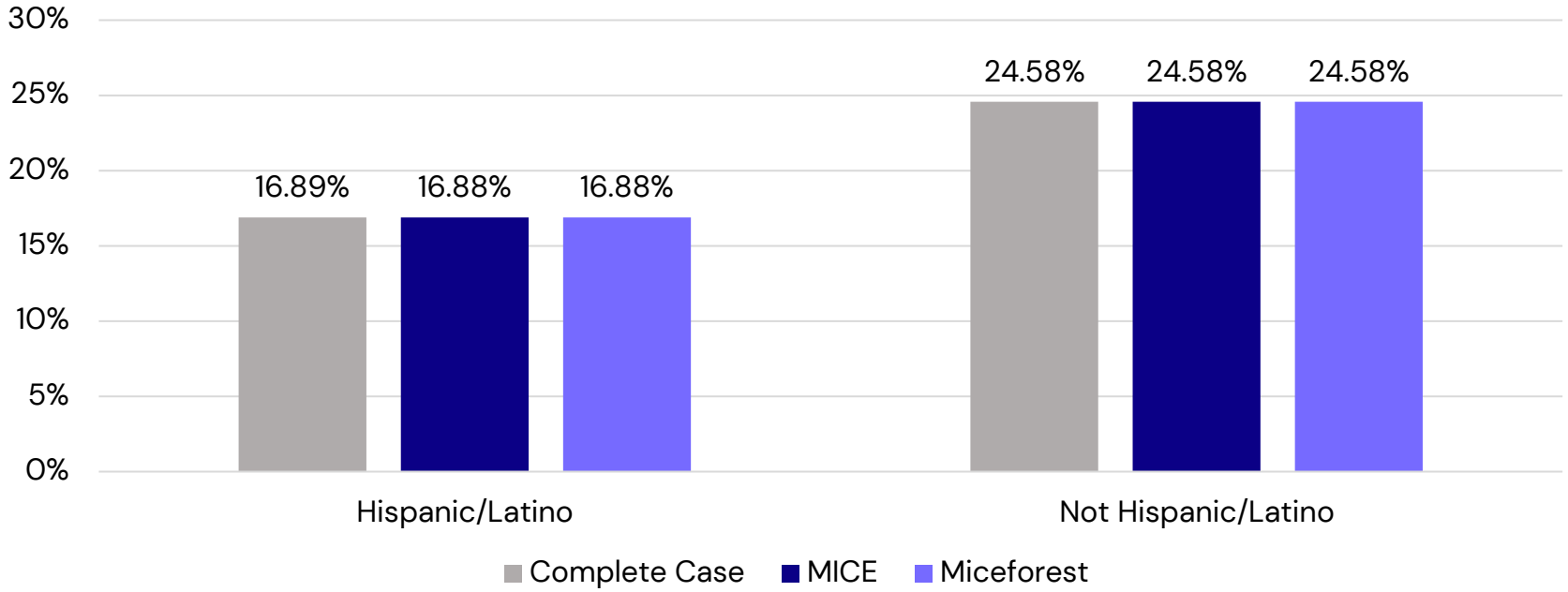

Flu Vaccination Proportions by Ethnicity Across Imputation Methods
MiceForest
STATA_MICE
Flu Vaccination Proportion
0.25
0.24
0.23
0.22
0.21
0.20
0.19
0.18
0.17
Hispanic/Latino
Not Hispanic/Latino
Ethnicity Groups


Flu Vaccination Proportions by Age Across Imputation Methods
MiceForest
STATA_MICE
Flu Vaccination Proportion
0.40
0.35
0.30
0.25
0.20
<18
18-25
26-39
40-54
55-64
65+
Age Groups

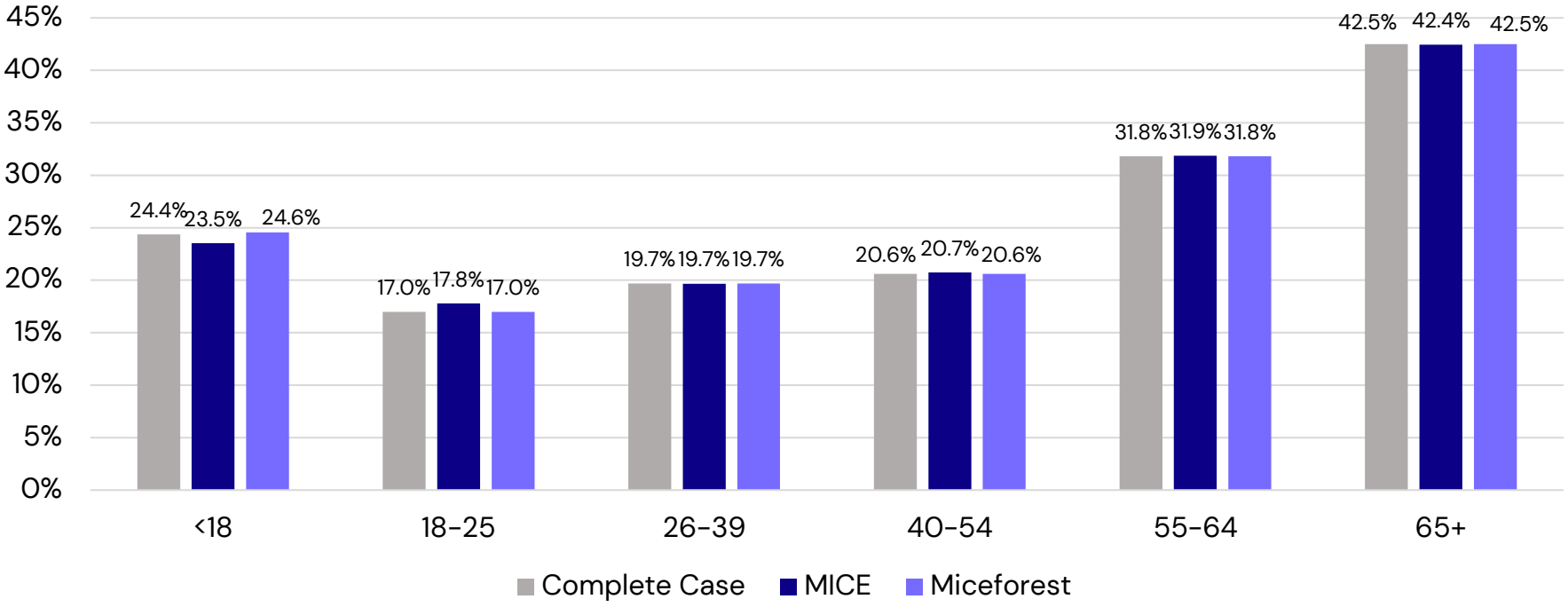
Flu Vaccination Coverage Rates by Gender Across MICE & Miceforest



Flu Vaccination Coverage Rates by Ethnicity Across MICE & Miceforest



Flu Vaccination Coverage Rates by Age Across MICE & Miceforest



Discussion

Imputation method alters initial findings.

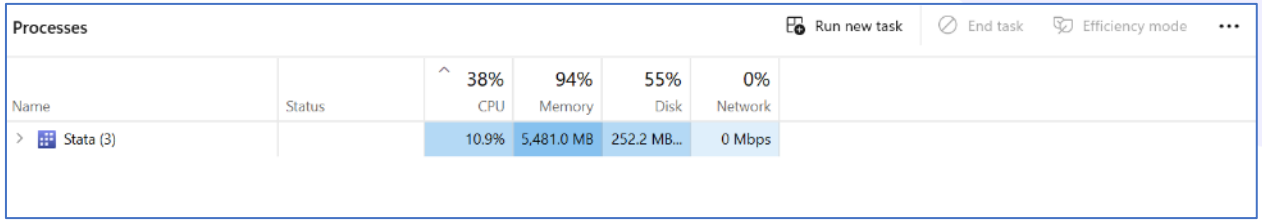
Ethnicity, gender, and age disparities in flu vaccination were consistently significant across all methods ($p\text{-}value < 0.001$).

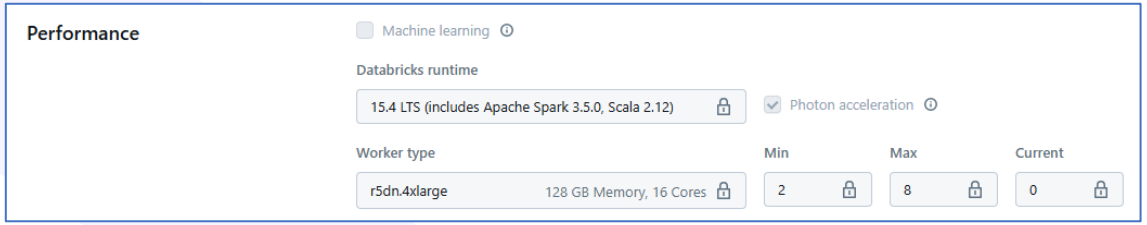
MICE and Miceforest performed similarly across all imputed variables (G-statistic).

Discussion

MICE (STATA 17): 8 hours, high CPU usage

Miceforest (Cloud): < 10 minutes, scalable





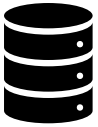
Implications

Imputation inflated dataset by 0.28%, reducing estimated flu coverage from 49% to 24%.

Stratified rates declined across all groups post-imputation, revealing potential hidden disparities.

Cloud-based tools offer speed and scalability for large datasets.

Conclusions



Accurate Data = Better Public Health Decisions

Even small amounts of missing data can obscure critical health disparities

Imputation is Essential

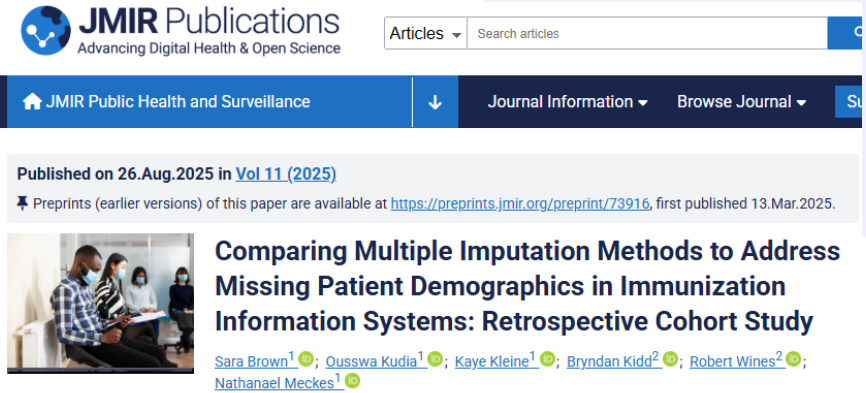
Proper imputation reveals hidden inequities and supports culturally responsible interventions

Cloud-Based Machine Learning = Scalable Solutions

Offloading to the cloud enables:

- Faster processing
- Reduced downtime
- Parallel task execution
- Greater productivity

Check us out!



Thank you

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