

# **Hospital AI/ML Adoption by Neighborhood Deprivation**

## BACKGROUND

 AI/ML-assisted care coordination has the potential to reduce health disparities, but there is a lack of empirical evidence on Al's impact on health equity.

### OBJECTIVE

- The objective of our study is to assess the adoption of AI/ML technologies among hospitals, with a focus on the use of ML and predictive models in electronic health records (EHR).
- We aim to understand the variation in AI/ML adoption based on different hospital characteristics and neighborhood social determinants of health.
- We hypothesize that hospitals serving areas with higher levels of underserved populations and more significant neighborhood deprivation and those in rural locations may lack the necessary information technology (IT) infrastructure and personnel, limiting their capacity to adopt these advanced technologies.
- We are interested in understanding whether hospitals enrolled in value-based performance models are more incentivized to adopt AI/ML.

### DATA AND MEASURES

- Our primary dataset was linked datasets from the 2022 American Hospital Association (AHA) Annual Survey and the 2023 AHA Information Technology (IT) Supplement
- Using hospital service area codes, we matched each hospital with the average 2021 Area Deprivation Index (ADI) of its service area
- The ADI is derived from 17 indicators encompassing education, employment, housing quality, and poverty levels. It has been validated and widely used to assess various health outcomes and disease domains at the neighborhood level
- We mapped ZIP codes to hospital service areas using a crosswalk from the Dartmouth Atlas and averaged the ZIP code-level ADI national percentiles to obtain a measure of ADI at the hospital service area level.

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		RE	SUL
e 1: Hospital Application of Machine Learning (ML) Other Predictive Modeling and Adoption of AI/ML in kforce Development	Mean 100%	Std Dev	Fig De
ator of whether hospital uses ML or other predictive models 285)	0.73	0.44	
number of ML and other predictive modules adopted ranged 1 to 8 (n=1,670) (unit: count)	4.02	1.74	
edicting health trajectories or risks for inpatients	0.93	0.26	
entify high risk outpatients to inform follow-up care	0.82	0.38	
onitor health	0.35	0.48	
commend treatments	0.46	0.50	
nplify or automate billing procedures	0.38	0.48	ļ
cilitate scheduling	0.50	0.50	
her (operational process optimization)	0.26	0.44	
her (clinical use cases)	0.32	0.47	Та
number of domains in which EHR was used ranged from 1 to 6 390) (unit: count)	4.93	1.57	Ma in
eate an approach for clinicians to query the data	0.76	0.43	In
sess adherence to clinical practice guidelines	0.73	0.44	le
entify care gaps for specific patient populations	0.83	0.38	A
pport a continuous quality improvement process	0.90	0.30	A
onitor patient safety (e.g. adverse drug events)	0.85	0.36	
ntify high risk patients for follow-up care using algorithm or r tools	0.84	0.37	
number of areas in which Al/ML was used in workforce cations ranged from 1 to 5 (n=1,703) (unit: count)	1.39	1.81	
edicting staffing needs	0.25	0.44	Α
edicting patient demand	0.26	0.44	A
aff scheduling	0.24	0.43	
Itomating routine tasks	0.31	0.46	
otimizing administrative and clinical workflows	0.33	0.47	A

a. Create an approach for clinicians to query the data		0.76	0.43	Indicator of whether hospital uses machine	Margins						
b. Assess adherence to clinical practice guidelines		0.73	0.44	learning or other predictive models (n=2,286)	100%	95%	CI	P value			
c Identify care gans for specific natient populations		0.83	0.38	ADI quantile 1	reference						
		0.00	0.00								
d. Support a continuous	quality imp	provement	process		0.90	0.30	ADI quantile 2	-0.04	-0.10	0.01	0.12
e. Monitor patient safety (e.g. adverse drug events)		0.85	0.36	ADI quantile 3	-0.09	-0.15	-0.02	0.01			
f. Identify high risk patients for follow-up care using algorithm or other tools		0.84	0.37	ADI quantile 4 (the most vulnerable)	-0.10	-0.18	-0.03	0.01			
The number of areas in which AI/ML was used in workforce applications ranged from 1 to 5 (n=1,703) (unit: count)		1.39	1.81	The number of ML and other predictive modules adopted ranged from 1 to 8 (n=1,671)	Margins 100%	largins 100% 95% CI		P value			
a. Predicting staffing needs		0.25	0.44	ADI quantile 1		reference					
b. Predicting patient demand		0.26	0.44	ADI quantile 2	-0.02	-0.29	0.24	0.86			
c. Staff scheduling		0.24	0.43	ADI quantile 3	-0.19	-0.50	0.12	0.23			
d. Automating routine tasks		0.31	0.46	ADI quantile 4 (the most vulnerable)	0.02	-0.35	0.39	0.92			
Table 3: Decomposition results comparing hospital AI/ML adoption by ADI $O_{4}$ vs. ADI $O_{1} = O_{3}$					The number of domains in which EHR was used ranged from 1 to 6 (n=2,391)	Margins 100% 95% CI P value					
The number of MI The number of The number of areas					ADI quantile 1 reference						
	and other domains in which predictive EHR was used		in which as used	in which Al/ML was used in workforce		ADI quantile 2	0.01	-0.19	0.22	0.90	
	modules adopted ranged		appli	cations	ADI quantile 3	-0.40	-0.63	-0.17	0.001		
ADI Q1 – Q3	Coef 0.80	P value <0.001	Coef 5.18	P value <0.001	Coef 1.56	P value <0.001	ADI quantile 4 (the most vulnerable)	-0.26	-0.51	0.001	0.05
ADI Q4 (the most vulnerable areas) Difference	0.62 0.18 %	<0.001 <0.001 p	4.59 0.59 %	<0.001 <0.001 p	0.89 0.67 %	<0.001 <0.001 p	The number of areas in which Al/ML was used in workforce applications ranged from 1 to 5 (n=1704)	Margins 100%	ns 95% CI		P value
Explained by the model	78.94	<0.001	95.73	<0.001	65.94	< 0.001	% Deputation Block	0 51	0.40	1 1 1	0.00
Explained by the individual factor							ADI quantile 1	0.51	-U.42	1.44	0.28
Government owned	00.74	-0.004	44.00	-0.004	00.05	-0.001					
nospital Bed size large	22.74	< 0.001	14.28	< 0.001	28.35	<0.001	ADI quantile 2	-0.21	-0.46	0.03	0.09
Teaching hospital	-	-	-	-	21.39	< 0.001	ADI quantile 3	-0.16	-0 44	0 12	0.25
ACO affiliated	16.59	<0.001	12.41	<0.001	24.78	<0.001		-0.10	-0.44	0.12	0.20
Rural	22.72	<0.001	22.64	0.003	-	-	ADI quantile 4 (the most vulnerable)	-0.40	-0.70	-0.09	0.01





### ble 2: : State-Fixed Multivariate Regressions of Hospital Application of achine Learning (ML) and Other Predictive Modeling and Adoption of AI/ML **Workforce Development**

# RESULTS

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- The sample included general medical and surgical hospitals, with sample sizes varying by outcome from 1,671 to 2,286 hospitals.
- Hospitals serving the most vulnerable areas (ADI Q4) were significantly less likely to apply ML or other predictive models (coef = -0.10, p=0.01) and provided fewer AI/MLrelated workforce applications (coef=-0.40, p=0.01), compared to those in the least vulnerable areas.
- Decomposition results showed that our model specifications explained 79% of the variation in AI/ML adoption between hospitals in ADI Q4 versus ADI Q1 - Q3.
- Additionally, Accountable Care Organization affiliation accounted for 12% - 25% of differences in AI/ML utilization across various measures.

### CONCLUSION

- The underuse of AI/ML in economically disadvantaged and rural areas, particularly in workforce management and EHR implementation, suggests that these communities may not fully benefit from advancements in Al-enabled healthcare.
- Our results further indicate that value-based payment models could be strategically used to support AI integration

### **CONTACT INFORMATION**

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