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Hospital Artificial Intelligence/Machine Learning Adoption by Neighborhood Deprivation

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Objective: To understand the variation in artificial intelligence/machine learning (AI/ML) adoption across different hospital characteristics and explore how AI/ML is utilized, particularly in relation to neighborhood deprivation.

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

Methods: We used linked datasets from the 2022 American Hospital Association Annual Survey and the 2023 American Hospital Association Information Technology Supplement. The data were further linked to the 2022 Area Deprivation Index (ADI) for each hospital's service area. State fixed-effect regressions were employed. A decomposition model was also used to quantify predictors of AI/ML implementation, comparing hospitals in higher versus lower ADI areas.

Results: 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/ML-related workforce applications (coef = -0.40, P = 0.01), compared with 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. In addition, Accountable Care Organization affiliation accounted for 12%–25% of differences in AI/ML utilization across various measures.

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

Key Words: artificial intelligence and machine learning, neighborhood deprivation, accountable care organization, equity

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The integration of generative artificial intelligence (AI) and machine learning (ML) in health care is rising.[1,2] This technology can potentially revolutionize medical practice by enhancing care coordination, disease prevention, care management, and health outcomes through advanced analytical tools.[3] Studies have highlighted the potential of AI/ML to tackle health equity through promoting care coordination, particularly in managing chronic diseases.[4–6] However, studies reveal that care coordination strategies are not evenly distributed, with disadvantaged areas experiencing lower availability.[7] AI/ML-assisted care coordination could bridge these gaps. At the same time, using such tools for decision support carries risks, and inappropriate implementation could exacerbate health disparities.[8] Despite the potential and risk, research on the health equity implications of AI/ML remains limited.[9,10] As the FDA begins to recognize Software as a Medical Device and the CMS considers new procedural terminology codes for AI/ML, it becomes critical to examine the landscape of AI/ML adoption.[11,12]

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 (EHRs). We aim to understand the variation in AI/ML adoption based on different hospital characteristics and neighborhood social determinants of health. Macroeconomic and technological readiness can be factors influencing hospitals' adoption of AI/ML technologies.[13] 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. In addition, policies such as the 21st Century

Cures Act and state policies, like Virginia's initiative to provide access to intelligent personal assistants, may differently incentivize hospital adoption of AI/ML.[14,15] We are interested in understanding whether hospitals enrolled in value-based performance models are more incentivized to adopt AI/ML. Emerging evidence suggests that accountable care organization (ACO) models aimed at improving care coordination and population health could support the integration of AI in health care.[16,17] Hence, we hypothesize that hospitals affiliated with ACOs are more likely to adopt ML and predictive models to monitor patient health.

METHODS

Data

Our primary dataset was linked datasets from the 2022 American Hospital Association Annual Survey and the 2023 American Hospital Association IT Supplement.[18] The IT Supplement, particularly its Advanced Analytics section, gathered data on hospital use of ML and other predictive models. The Annual Survey assessed the application of AI and ML within the workforce. Using hospital service area codes, we matched each hospital with the average 2021 Area Deprivation Index (ADI) of its service area.[19,20] 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.[21] A higher ADI score indicates greater socioeconomic deprivation. We mapped ZIP codes to hospital service areas using a crosswalk from the Dartmouth Atlas. We averaged the ZIP code-level ADI national percentiles to obtain a measure of ADI at the hospital service area level.[22] The sample included general medical and surgical hospitals, with sample sizes varying by outcome from 1671 to 2286 hospitals.

Outcome Measures

Our analysis has four key AI/ML measures. First, we measured whether hospitals employed ML or other predictive models. Second, for those using these tools, we assessed the number of specific areas (out of 8) in which they were applied, including monitoring health, recommending treatments, and identifying high-risk outpatients. Third, we quantified the extent of ML usage in EHRs across six domains, such as data querying by clinicians, adherence to clinical guidelines, and identifying care gaps for specific patient populations. Finally, we evaluated the breadth of AI applications in workforce development, measuring their use in predicting staffing needs, patient demand, staff scheduling, automating routine tasks, and optimizing workflows.

Independent Variables

Covariates included hospital teaching status, ownership type, number of beds, urban/rural status, whether the hospital's county is considered a health professional shortage area, and percentage of the county population non-Hispanic Black. We also controlled for hospital participation in an ACO and examined AI/ML variation by ADI quartile. We specifically compared hospitals with hospital service areas with ADI below and above the 75th percentile.

Analysis

We presented summary statistics for AI/ML applications and applied state fixed-effect multivariable regressions. State fixed-effect models were selected, given the variation of state healthcare AI regulations in the United States.[15] We employed a decomposition model to quantify predictors of implementing ML models and AI in workforce development, comparing hospitals in higher versus lower ADI areas.[23,24] The Blinder-Oaxaca decomposition for linear regression models was used to identify and quantify specific predictors affecting location disparities in hospital-based AI/ML adoption. For example, to decompose the difference in the probability of adopting ML and advanced analytic tools, multivariable logistic regressions of ADI Q4 versus ADI Q1–Q3 were first estimated separately. Then the regression results were rearranged into differences due to observed population characteristics (ie, the controlled variables), and the difference due to unobserved factors. Among the observed population characteristics, disparities associated with each specific factor can also be quantified (e.g., ACO affiliation).

In addition, we conducted sensitivity analyses to test the robustness of our findings, exploring various model specifications with and without state-fixed effects (Supplement Table 1, Supplemental Digital Content 1, http://links.lww.com/MLR/C949) and various outcome measures (Supplement Table 2, Supplemental Digital Content 2, http://links.lww.com/MLR/C950). We used Stata 18 MP4 to conduct all the analyses. Two-tailed P value < 0.05 was considered statistically significant.

RESULTS

Table 1 presents the statistics of hospitals' applications of ML and other predictive modeling and adoptions of AI/ML in workforce development. Approximately 73% of hospitals (n = 1670) utilized ML or other predictive models. Among these, hospitals applied ML and other predictive modeling in an average of 4 out of 8 modules. Notably, 93% used ML to predict health trajectories or risks for inpatients and 82% to identify high-risk outpatients for follow-up care. However, fewer than half employed these tools for monitoring health, recommending treatments, simplifying billing procedures, or facilitating scheduling. Providers applied EHR technology in roughly 5 out of 6 areas, including supporting continuous quality improvement processes and monitoring patient safety (e.g., adverse drug events). On average, hospitals applied AI/ML to 1.4 out of 5 workforce-related areas, with less than one-third utilizing it to predict staffing needs or to optimize workflows.

Figure 1 further maps out hospital ML modeling and AI workforce adoption by the deprivation level in the hospital service area. On average, hospitals serving vulnerable areas were less likely to adopt AI/ML technology.

TABLE 1. Hospital Application of ML and Other Predictive Modeling and Adoption of AI/ML in Workforce Development

Characteristic	Mean 100%	SD
Indicator of whether the hospital uses ML or other predictive models (n = 2285)	0.73	0.44
No. ML and other predictive modules adopted ranged from 1 to 8 (n = 1670); unit: count	4.02	1.74
a. Predicting health trajectories or risks for inpatients	0.93	0.26
b. Identify high-risk outpatients to inform follow-up care	0.82	0.38
c. Monitor health	0.35	0.48
d. Recommend treatments	0.46	0.50
e. Simplify or automate billing procedures	0.38	0.48
f. Facilitate scheduling	0.50	0.50
g. Other (operational process optimization)	0.26	0.44
h. Other (clinical use cases)	0.32	0.47
No. domains in which EHR was used ranged from 1 to 6 (n = 2390); unit: count	4.93	1.57
a. Create an approach for clinicians to query the data	0.76	0.43
b. Assess adherence to clinical practice guidelines	0.73	0.44
c. Identify care gaps for specific patient populations	0.83	0.38
d. Support a continuous quality improvement process	0.90	0.30
e. Monitor patient safety (e.g., adverse drug events)	0.85	0.36
f. Identify high-risk patients for follow-up care using algorithms or other tools	0.84	0.37
No. areas in which AI/ML was used in workforce applications ranged from 1 to 5 (n = 1703); unit: count	1.39	1.81
a. Predicting staffing needs	0.25	0.44
b. Predicting patient demand	0.26	0.44
c. Staff scheduling	0.24	0.43
d. Automating routine tasks	0.31	0.46
e. Optimizing administrative and clinical workflows	0.33	0.47
f. None of the above		

Data source: 2022 AHA Annual Survey and the 2023 AHA IT Supplement. Unit is 100% unless indicated otherwise.
Specific AHA survey questions:
Indicator of whether the hospital uses ML or other predictive models: Does your hospital use any ML or other predictive models that display output or recommendations (e.g., risk scores or clinical support) in your EHR or an App embedded in or launched by your EHR? 1 = yes, 0 = no.
The number of ML and other predictive modules adopted: Which of the following uses has your hospital applied ML or other predictive models? Please check all that apply.
a. Predicting health trajectories or risks for inpatients.
b. Identify high-risk outpatients to inform follow-up care.
c. Monitor health.
d. Recommend treatments.
e. Simplify or automate billing procedures.
f. Facilitate scheduling.
g. Other (operational process optimization).
h. Other (clinical use cases).
The number of domains in which EHR was used: Please indicate whether you have used electronic clinical data from the EHR or other electronic system in your hospital to:
a. Create an approach for clinicians to query the data.
b. Assess adherence to clinical practice guidelines.
c. Identify care gaps for specific patient populations.
d. Support a continuous quality improvement process.
e. Monitor patient safety (e.g., adverse drug events).
f. Identify high-risk patients for follow-up care using algorithms or other tools.
The number of areas in which AI/ML was used in workforce applications: Does your hospital use AI or ML in the following?
a. Predicting staffing needs.
b. Predicting patient demand.
c. Staff scheduling.
d. Automating routine tasks.
e. Optimizing administrative and clinical workflows.
f. None of the above.
AHA indicates American Hospital Association; AI, artificial intelligence; EHR, electronic health record; IT, information technology; ML, machine learning.

State fixed-effect multivariate regressions (Table 2) showed that hospitals serving the most vulnerable areas (ADI Q4 and ADI Q3) were 10 and 9 percentage points (P = 0.01) less likely to apply ML or other predictive models compared with those in the least vulnerable areas (ADI Q1), respectively. Hospitals serving areas with ADI Q4 and Q3 applied EHR in significantly fewer domains (coef = −0.26, P = 0.05; coef = −0.40, P = 0.001). In addition, hospitals serving ADI Q4 areas adopted significantly fewer AI/ML tools in workforce management (coef = −0.40, P = 0.01). Results also showed that hospitals with smaller bed sizes and rural hospitals were less likely to use ML and EHR than urban hospitals. Hospitals affiliated with ACOs were more likely to adopt and apply AI/ML in more areas, including workforce development.

Decomposition approaches (Table 3) showed that our model specifications explained 79% of the differences in the number of ML and other predictive modules adopted in ADI Q4 versus ADI Q1–Q3, 96% of EHR domains, and 66% of AI/ML applications in workforce development. Among the observed factors, rural location

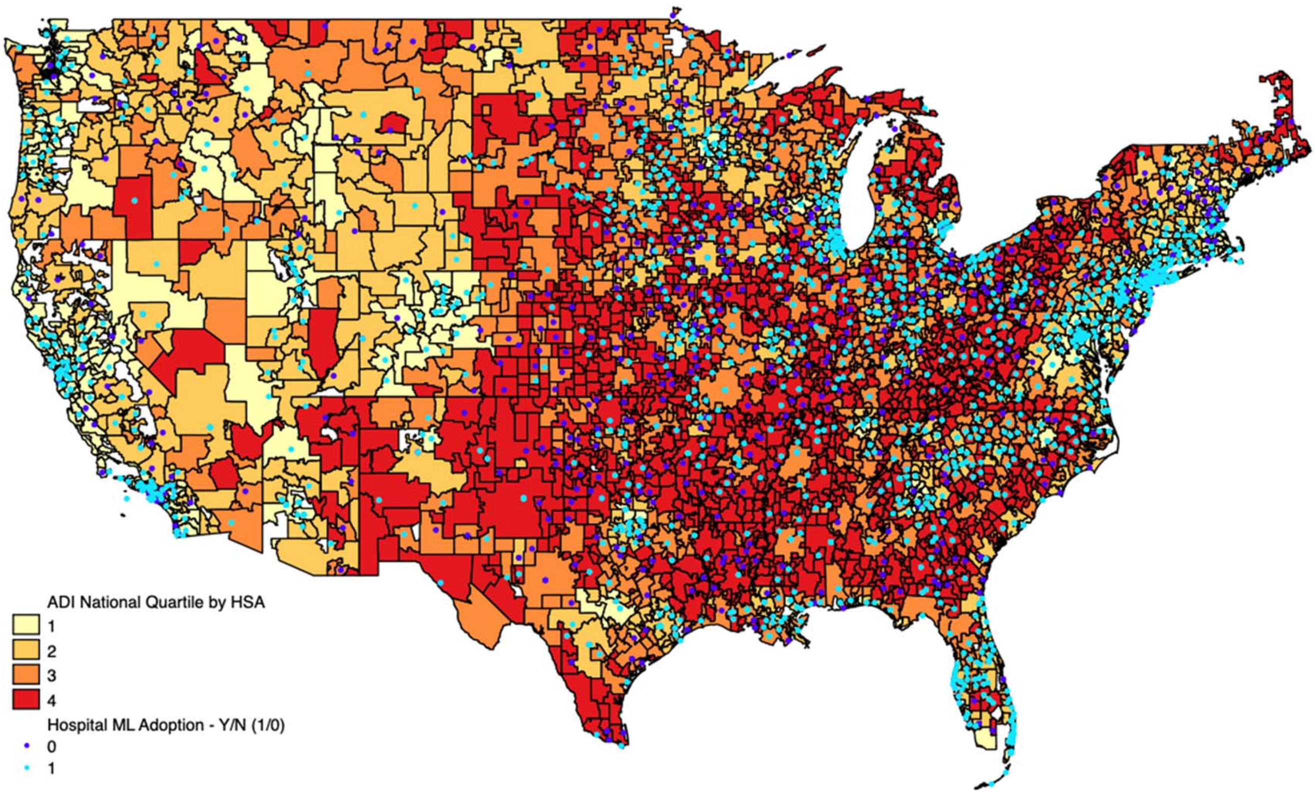

FIGURE 1. Hospital AI/ML adoption in 2022–2023 by hospital service area deprivation. Source: Author's analysis of linked datasets from the 2022 AHA Annual Survey, the 2023 AHA Information Technology Supplement, and ADI for each hospital's service area. We tested Moran's *I* index to assess the degree of spatial autocorrelation and clustering in the data. The result, Moran's $I = 0.181$, indicates that the measure of hospital AI/ML shows a certain degree of positive spatial autocorrelation, meaning that AI/ML values in adjacent regions tend to cluster. However, the value of Moran's *I* is not particularly high, suggesting that this clustering tendency may not be very strong. ADI indicates Area Deprivation Index; AHA, American Hospital Association; AI, artificial intelligence; IT, information technology; ML, machine learning.

significantly explained the disparities in ML application and EHR adoption by ~23%. ACO affiliation accounted for 12%–25% of these differences across all AI/ML measures, which suggested that if hospitals located in ADI Q4 were affiliated with ACOs, their likelihood of adopting AI/ML would increase significantly.

DISCUSSION

Our findings indicate that hospitals' adoption and application of ML predictive modules, EHR adoption, and AI/ML application in the workforce vary significantly by geographic and socioeconomic contexts. Such disparities in technological adoption could exacerbate existing healthcare inequalities. We speculate that the underuse of AI/ML in economically disadvantaged areas, particularly in workforce management and EHR implementation, may suggest that disadvantaged communities have not fully benefited from advancements in AI-enabled health care. Under-resourced communities often lack the technology infrastructure or funding necessary to support AI-powered health care.[13] To make matters worse, their community partners, including non-hospital settings like public health agencies and primary care settings, may struggle to adopt AI infrastructure. Patients in these areas may face challenges such as limited internet connectivity and broadband issues, which remain significant concerns in regions affected by poverty.[25,26]

In addition, we acknowledge the importance of conducting needs assessments in these areas. Comprehensive cost-effectiveness analyses can provide valuable evidence for AI-driven practices. Research has shown that while the adoption of health IT generally increases costs, it can be cost-saving for racial and ethnic minority dementia patients and those living in socially vulnerable areas.[16,27] A more systematic and comprehensive assessment of AI/ML infrastructure's impact on health outcomes is necessary. Compared with health IT, AI/ML has the potential to discover patterns in clinical data and identify predictors for clinical outcomes, help with the early detection of diseases, the development of individualized treatment plans, and the recognition of illness trends, etc.[28,29] If the benefits of utilizing AI/ML/health IT models exceed the costs of adoption for patients in disadvantaged areas, it may be wise to enhance such infrastructure in these communities.

The results of our study also indicated significant variation in hospital-based AI/ML adoption by rurality.

TABLE 2. State-Fixed Multivariate Regressions of Hospital Application of ML and Other Predictive Modeling and Adoption of AI/ML in Workforce Development

Characteristic	Margins 100%	95% CI		P
Indicator of whether the hospital uses ML or other predictive models (n = 2286)				
Non-for-profit hospital		Reference		
For-profit hospital	−0.22	−0.30	−0.13	< 0.001
Government-owned hospital	−0.25	−0.30	−0.20	< 0.001
Bed size small		Reference		
Bed size medium	0.01	−0.04	0.06	0.62
Bed size large	0.11	0.06	0.17	< 0.001
Teaching hospital	−0.16	−0.08	0.05	0.65
ACO affiliation	0.15	0.10	0.19	< 0.001
Urban		Reference		
Rural	−0.09	−0.15	−0.03	0.004
Primary care HPSA	−0.01	−0.07	0.05	0.72
% population Black	0.29	0.07	0.51	0.01
ADI quantile 1		Reference		
ADI quantile 2	−0.04	−0.10	0.01	0.12
ADI quantile 3	−0.09	−0.15	−0.02	0.01
ADI quantile 4 (the most vulnerable)	−0.10	−0.18	−0.03	0.01
No. ML and other predictive modules adopted ranged from 1 to 8 (n = 1671)				
Non-for-profit hospital		Reference		
For-profit hospital	−0.54	−1.01	−0.06	0.03
Government-owned hospital	−0.18	−0.48	0.11	0.22
Bed size small		Reference		
Bed size medium	−0.12	−0.38	0.13	0.35
Bed size large	−0.09	−0.37	0.18	0.51
Teaching hospital	0.50	0.18	0.81	0.002
ACO affiliation	0.25	0.03	0.48	0.03
Urban		Reference		
Rural	−0.27	−0.61	0.06	0.11
Primary care HPSA	0.01	−0.28	0.29	0.97
% population Black	−0.10	−1.18	0.98	0.86
ADI quantile 1		Reference		
ADI quantile 2	−0.02	−0.29	0.24	0.86
ADI quantile 3	−0.19	−0.50	0.12	0.23
ADI quantile 4 (the most vulnerable)	0.02	−0.35	0.39	0.92
No. domains in which EHR was used ranged from 1 to 6 (n = 2391)				
Non-for-profit hospital		Reference		
For-profit hospital	−1.03	−1.31	−0.74	< 0.001
Government-owned hospital	−0.62	−0.81	−0.44	< 0.001
Bed size small		Reference		
Bed size medium	0.11	−0.06	0.29	0.21
Bed size large	0.26	0.06	0.46	0.01
Teaching hospital	0.26	0.01	0.51	0.05
ACO affiliation	0.36	0.21	0.51	< 0.001
Urban		Reference		
Rural	−0.34	−0.54	−0.14	0.001
Primary care HPSA	−0.05	−0.25	0.15	0.64
% population Black	0.13	−0.63	0.89	0.73
ADI quantile 1		Reference		
ADI quantile 2	0.01	−0.19	0.22	0.90
ADI quantile 3	−0.40	−0.63	−0.17	0.001
ADI quantile 4 (the most vulnerable)	−0.26	−0.51	0.001	0.05
No. areas in which AI/ML was used in workforce applications ranged from 1 to 5 (n = 1704)				
Non-for-profit hospital		Reference		
For-profit hospital	−1.01	−1.37	−0.65	< 0.001
Government-owned hospital	−0.82	−1.04	−0.60	< 0.001
Bed size small		Reference		
Bed size medium	−0.06	−0.27	0.15	0.57
Bed size large	0.02	−0.22	0.27	0.84
Teaching hospital	0.97	0.67	1.27	< 0.001
ACO affiliation	0.65	0.47	0.84	< 0.001
Urban		Reference		
Rural	−0.11	−0.36	0.14	0.40
Primary care HPSA	−0.09	−0.34	0.16	0.49
% population Black	0.51	−0.42	1.44	0.28
ADI quantile 1		Reference		
ADI quantile 2	−0.21	−0.46	0.03	0.09
ADI quantile 3	−0.16	−0.44	0.12	0.25
ADI quantile 4 (the most vulnerable)	−0.40	−0.70	−0.09	0.01

Data source: 2022 AHA Annual Survey and the 2023 AHA IT Supplement.

The state fixed-effect logistic model was applied to "Hospital uses ML or other predictive models." State fixed-effect linear regressions were applied to other outcome measures. Marginal effects were reported for all models.

Specific AHA survey questions:

Indicator of whether the hospital uses ML or other predictive models: Does your hospital use any ML or other predictive models that display output or recommendations (e.g., risk scores or clinical support) in your EHR or an App embedded in or launched by your EHR? 1 = yes, 0 = no.

The number of ML and other predictive modules adopted: Which of the following uses has your hospital applied ML or other predictive models? Please check all that apply.

a. Predicting health trajectories or risks for inpatients.
b. Identify high-risk outpatients to inform follow-up care.
c. Monitor health.
d. Recommend treatments.
e. Simplify or automate billing procedures.
f. Facilitate scheduling.
g. Other (operational process optimization).
h. Other (clinical use cases).

The number of domains in which EHR was used: Please indicate whether you have used electronic clinical data from the EHR or other electronic system in your hospital to:

a. Create an approach for clinicians to query the data.
b. Assess adherence to clinical practice guidelines.
c. Identify care gaps for specific patient populations.
d. Support a continuous quality improvement process.
e. Monitor patient safety (e.g., adverse drug events).
f. Identify high-risk patients for follow-up care using algorithms or other tools.

The number of areas in which AI/ML was used in workforce applications: Does your hospital use AI or ML in the following?

a. Predicting staffing needs.
b. Predicting patient demand.
c. Staff scheduling.
d. Automating routine tasks.
e. Optimizing administrative and clinical workflows.
f. None of the above.

ACO indicates accountable care organization; ADI, Area Deprivation Index; AHA, American Hospital Association; AI, artificial intelligence; EHR, electronic health record; HPSA, health professional shortage area; IT, information technology; ML, machine learning.

TABLE 3. Decomposition Results Comparing Hospital AI/ML Adoption by ADI Q4 Versus ADI Q1–Q3

	No. ML and other predictive modules adopted		No. domains in which EHR was used		No. areas in which AI/ML was used in workforce applications	
Characteristic	**Coef**	***P***	**Coef**	***P***	**Coef**	***P***
ADI Q1–Q3	0.80	< 0.001	5.18	< 0.001	1.56	< 0.001
ADI Q4 (the most vulnerable areas)	0.62	< 0.001	4.59	< 0.001	0.89	< 0.001
Difference	0.18	< 0.001	0.59	< 0.001	0.67	< 0.001
	%	*P*	%	*P*	%	*P*
Explained by the model	78.94	< 0.001	95.73	< 0.001	65.94	< 0.001
Explained by the individual factor						
Government-owned hospital	22.74	< 0.001	14.28	< 0.001	28.35	< 0.001
Bed size large	23.68	< 0.001	15.42	0.002	—	—
Teaching hospital	—	—	—	—	21.39	< 0.001
ACO affiliated	16.59	< 0.001	12.41	< 0.001	24.78	< 0.001
Rural	22.72	< 0.001	22.64	0.003	—	—

Data source: 2022 AHA Annual Survey and the 2023 AHA IT Supplement.

Decompositions were applied to 3 outcomes where ADI differences were significant: An indicator of whether a hospital uses ML or other predictive models, the number of domains in which EHR was used, and the number of areas in which AI/ML was used in workforce applications. Factors that significantly contributed to the observed differences > 5% were presented.

Specific AHA survey questions:

The number of ML and other predictive modules adopted: Which of the following uses has your hospital applied ML or other predictive models? Please check all that apply.

a. Predicting health trajectories or risks for inpatients.
b. Identify high-risk outpatients to inform follow-up care.
c. Monitor health.
d. Recommend treatments.
e. Simplify or automate billing procedures.
f. Facilitate scheduling.
g. Other (operational process optimization).
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a. Create an approach for clinicians to query the data.
b. Assess adherence to clinical practice guidelines.
c. Identify care gaps for specific patient populations.
d. Support a continuous quality improvement process.
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b. Predicting patient demand.
c. Staff scheduling.
d. Automating routine tasks.
e. Optimizing administrative and clinical workflows.
f. None of the above.

ACO indicates accountable care organization; ADI, Area Deprivation Index; AHA, American Hospital Association; AI, artificial intelligence; EHR, electronic health record; IT, information technology; ML, machine learning.

Financial, technological, and human resource challenges—such as a lack of qualified professionals and broadband internet connectivity—are the main factors that drive differential access to AI/ML and other care coordination resources.[30,31] We also note that there is great potential for AI-powered solutions to enhance rural medical practice, particularly their uses in disease epidemiology and profiling environmental risk factors unique to rural areas.[30,32] Future studies are needed to improve our understanding of the supply and demand side incentives for hospital adoption of these technologies, including reimbursement schemes that may improve the capacity for AI/ML infrastructure, such as the ACO model.

The results of our study further suggested that reimbursement models aimed at improving care coordination and population health could support the integration of AI in health care. A recent study demonstrated that patients enrolled in ACOs encountered lower Medicare costs after 3 years of dementia diagnosis, especially for dementia patients living in the most vulnerable neighborhoods.[33] Future studies may further examine the combined impact of AI/ML/health IT on health and health disparities under such financial incentives. For example, the ACO Realizing Equity, Access, and Community Health model mandates that all participating ACOs develop comprehensive plans to serve individuals in underserved communities and tackle health disparities.[34] We believe innovative reimbursement models could be crucial in promoting AI innovations that focus on improving population health, especially in underserved areas.[35]

Our study has several limitations. First, it primarily focuses on the provider side of healthcare delivery without addressing the demand side for IT infrastructure. Second, the application of ML, predictive modeling, and AI in workforce management should be more clearly defined in future studies. As the report on AI measures is now required under the 21st Century Cures Act, a consistent and precise definition of AI is needed. Finally, we emphasize that AI models require careful oversight to ensure they are effective and equitable.[36] Future research should include systematic checks to mitigate bias and ensure fairness in AI/ML applications.

CONCLUSION

Our study confirms the varied adoption and application of AI/ML in hospitals and highlights the potential of using reimbursement models to promote population health to advance AI/ML equity. It calls for a coordinated effort to tailor AI applications to meet the diverse needs of all population segments, ensuring that technological advancements in health care reduce, rather than widen, health disparities. It is imperative to gain a deeper understanding of the barriers and perceptions surrounding AI in different communities to enable broader and more equitable implementation.

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