



Hospital Adoption of AI/ML and Medicare Utilization Outcomes

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OBJECTIVE

- Hospitals are increasingly adopting artificial intelligence and machine learning (AI/ML) tools to support clinical decision making and care management, yet evidence is limited on how these tools relate to utilization-based quality outcomes.
- We examined associations between hospital adoption of patient-related AI/ML tools and utilization-based outcomes among Medicare beneficiaries aged 65 years and older.

APPROACH

- We conducted cross-sectional study using inpatient claims for Medicare fee-for-service and Medicare Advantage beneficiaries aged 65 years or older linked with the 2023 American Hospital Association Information Technology Supplement.
- Hospital adoption of patient-related AI/ML tools was measured across four functions: inpatient risk prediction, identification of high-risk outpatients, patient health monitoring, and treatment recommendations.
- Multivariable regression models adjusted for beneficiary and hospital characteristics and examined associations between hospital AI/ML adoption and utilization-based outcomes, including frequent hospitalizations, 30-day readmissions, and preventable hospitalizations for acute and chronic ambulatory care-sensitive conditions.

KEY TAKEAWAYS

- Treatment in hospitals adopting AI/ML tools was associated with lower odds of frequent hospitalizations, 30-day readmissions, and preventable hospitalizations compared with treatment in hospitals without such tools.
- Associations were strongest for tools supporting risk stratification and identification of high-risk patients, which are closely linked to care coordination and proactive management.
- Health monitoring models were associated with higher rates of chronic preventable hospitalizations, consistent with increased detection of previously unmet care needs.

RESULTS

Figure 1: . Variations of hospital adoption of patient-related AI/ML models by FFS and MA beneficiaries

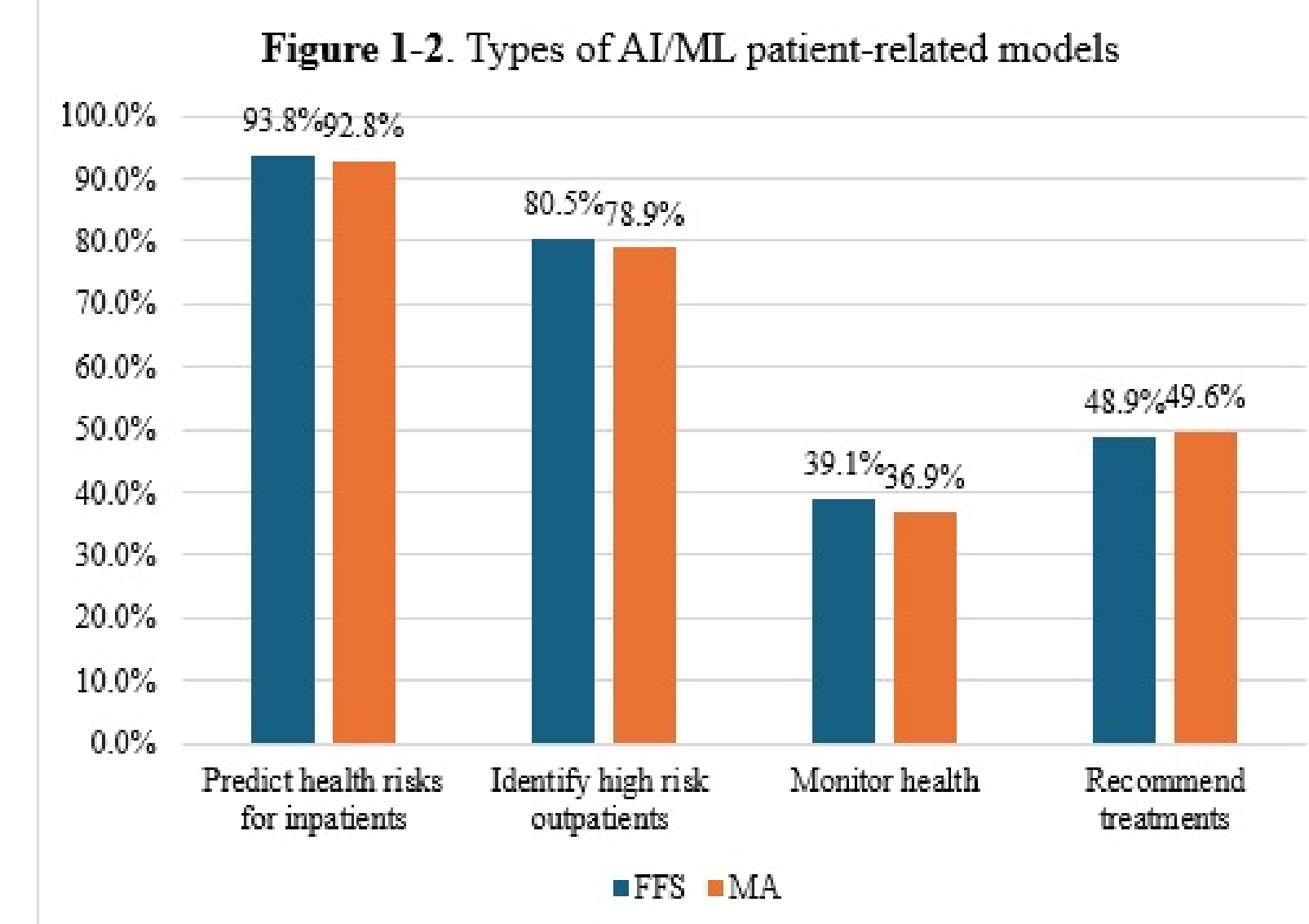
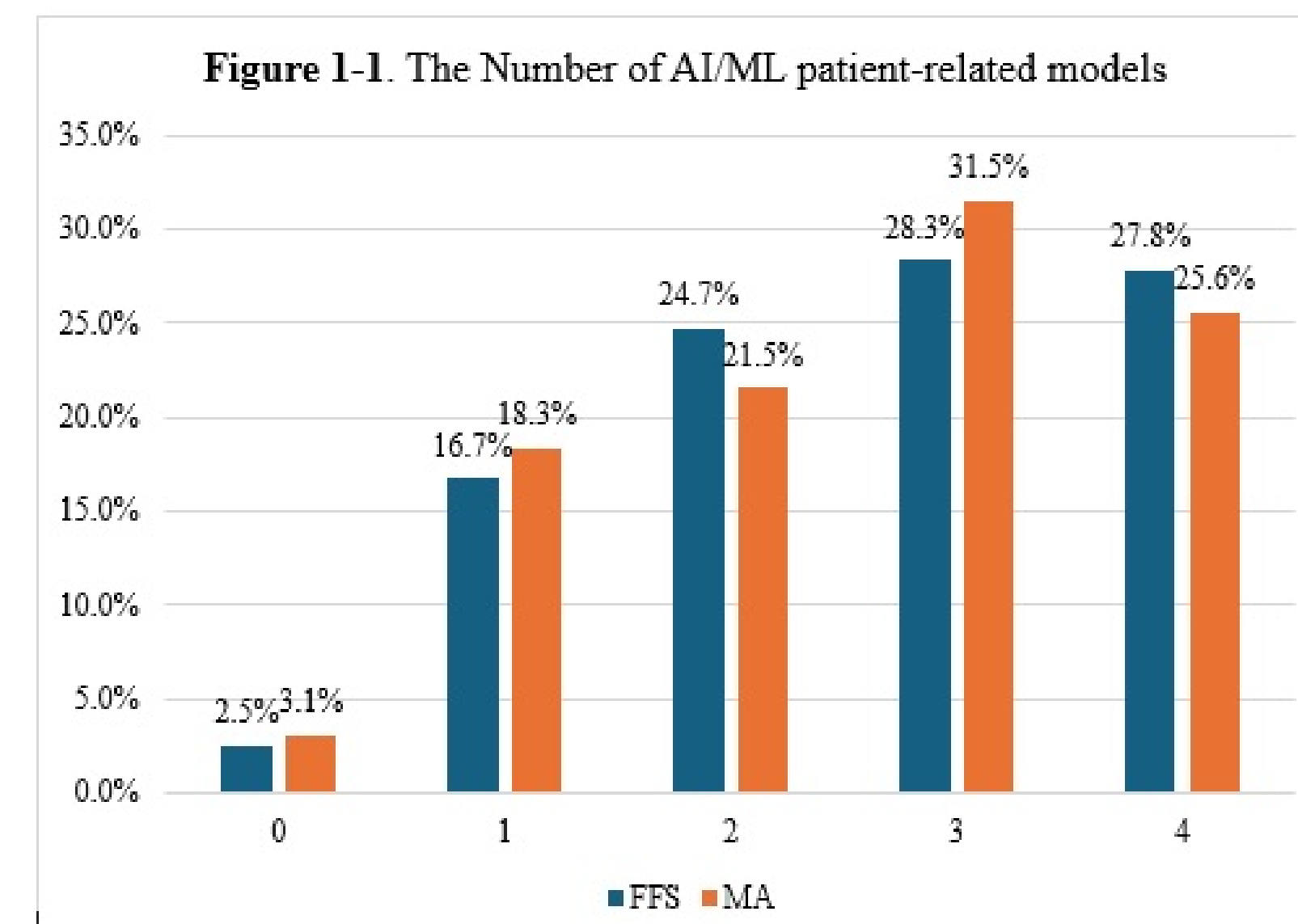


Table 1: Associations between hospital implementation of patient-related AI/ML models and frequent hospitalizations (i.e., 3 or more hospital visits annually)

	OR	p	OR	p
AI/ML patient models (ref: 0)				
1	0.93	0.199	0.88	0.027
2	0.98	0.786	0.86	0.007
3	0.88	0.027	0.85	0.006
4	0.83	0.002	0.8	<0.001
Individual AI/ML models (ref: No adoption)				
Predict health risks for inpatients	0.94	0.106	0.9	0.003
Identify high risk outpatients	1.02	0.44	0.96	0.146
Monitor health	0.99	0.699	0.98	0.21
Recommend treatments	0.88	<0.001	0.97	0.177

Notes: Values represent odds ratios from multilevel logistic regression models estimating the likelihood of experiencing 3 or more hospitalizations, with hospital-level random intercepts to account for clustering of beneficiaries within hospitals. For each patient-related AI/ML indicator, the reference category is hospitals without adoption of the specified patient-related AI/ML model. The models adjusted for individual (age, sex, race/ethnicity, dual eligibility, comorbidities) and hospital characteristics (urban/rural status, bed size, teaching status, ownership). Evaluation of AI/ML models for model accuracy and bias was also controlled. Patient-related AI/ML models were not mutually exclusive, and hospitals could select all models that applied. The full regression results are available in Supplemental Material. N=1,504,503 and N of groups=1,452 for FFS group; N=1,276,241 and N of groups=1,423 for MA group. Abbreviations: OR, odds ratios; 95% CI, confidence intervals.

Table 2: AI/ML and 30-day readmissions and PQIs

	PQI 91				PQI 92				30-Day readmissions			
Counts of patient-related AI/ML models												
First part: Logistic regression - Any event												
	FFS		MA		FFS		MA		FFS		MA	
	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
1	0.93	0.417	1	0.954	1.07	0.3	1	0.584	0.9	0.2	0.9	0.003
2	0.63	<0.001	0.5	<0.001	0.74	<0.001	0.7	<0.001	0.8	<0.001	0.8	<0.001
3	0.65	<0.001	0.6	<0.001	0.82	0	0.8	0.001	0.8	<0.001	0.8	<0.001
4	0.66	<0.001	0.6	<0.001	0.82	0	0.8	0.002	0.8	<0.001	0.8	<0.001
Second part: GLM - Number of events if any												
	FFS		MA		FFS		MA		FFS		MA	
	MR	p	MR	p	MR	p	MR	p	MR	p	MR	p
1	0.99	0.379	1	0.622	0.99	0.3	1	0.799	1	0.3	1	0.523
2	0.98	0.023	1	0.133	0.97	0	1	0.179	0.9	<0.001	0.9	<0.001
3	0.98	0.015	1	0.307	0.98	0.1	1	0.807	1	0	1	0.033
4	0.98	0.015	1	0.046	0.97	0	1	0.077	0.9	<0.001	0.9	0.001
Types of patient-related AI/ML models												
First part: Logistic regression - Any event												
	FFS		MA		FFS		MA		FFS		MA	
	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Predict health risks for inpatients	0.92	0.179	1	0.705	0.9	0.2	0.9	0.167	0.9	0	0.9	<0.001
Identify high risk outpatients	0.68	<0.001	0.5	<0.001	0.7	<0.001	0.7	<0.001	0.8	<0.001	0.9	<0.001
Monitor health	1.07	0.05	1.1	0.126	1.1	0	1.1	0.013	1	0.5	1	0.587
Recommend treatments	0.96	0.246	1	0.966	1	0.6	1.1	0.003	1	0	1	0.798
Second part: GLM - Number of events if any												
	FFS		MA		FFS		MA		FFS		MA	
	MR	p	MR	p	MR	p	MR	p	MR	p	MR	p
Predict health risks for inpatients	0.99	0.092	1	0.125	1	0.1	1	0.6	1	0.1	1	0.037
Identify high risk outpatients	0.99	<0.001	1	0.021	1	<0.001	0.98	0	1	<0.001	1	<0.001
Monitor health	1	0.482	1	0.44	1	0.9	0.99	0.1	1	0.8	1	0.272
Recommend treatments	1	0.615	1	0.913	1	0.7	1.01	0.2	1	0.3	1	0.077

Notes:
• For PQI 91, sample sizes for the fee-for-service (FFS) group were N = 1,504,503 with 1,452 hospitals (part 1) and N = 96,409 with 1,412 hospitals (part 2); corresponding values for the Medicare Advantage (MA) group were N = 1,276,241 with 1,423 hospitals (part 1) and N = 76,419 with 1,299 hospitals (part 2).
• For PQI 92, sample sizes for the FFS group were N = 1,504,503 with 1,452 hospitals (part 1) and N = 172,542 with 1,410 hospitals (part 2); corresponding values for the MA group were N = 1,276,241 with 1,423 hospitals (part 1) and N = 171,784 with 1,336 hospitals (part 2).
• For 30-day readmission: values represent estimates from two-part models: logistic regression for the likelihood of experiencing any readmission (part 1) and generalized linear model with log link and gamma distribution for the number of readmissions among those with ≥1 readmission (part 2). The full regression results are available in Supplemental Material. N=1,504,503 and N of groups=1,452 (part 1); N=216,285; No. of groups=1,424 (part 2) for FFS group. N=1,276,241 and N of groups=1,423 (part 1); N=169,982 and N of groups=1,327 (part 2) for MA group. Abbreviations: OR, odds ratios; MR, mean ratios=exp(Coeff.); 95% CI, confidence intervals.

CONCLUSIONS

- Hospital adoption of AI/ML tools is associated with lower rates of several utilization-based quality measures among Medicare beneficiaries, particularly when hospitals deploy multiple patient-related models supporting risk assessment, care coordination, and clinical decision making.
- Heterogeneous associations across AI/ML functions underscore the importance of distinguishing reductions in preventable acute utilization from increases in detected unmet need, especially for chronic conditions.
- These findings suggest that AI/ML may improve care for older adults by reshaping the timing, targeting, and coordination of care rather than increasing service intensity.
- Further research is needed to examine how AI/ML tools are implemented and integrated into clinical workflows, how they affect workforce demands, and whether observed benefits are sustained over time.
- The results are directly relevant to Medicare policy efforts focused on care coordination, value-based payment, and reducing avoidable utilization, where AI-enabled risk stratification tools may complement existing incentives and support more efficient, coordinated care for aging populations.

CONTACT INFORMATION

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