

A Novel Approach to Attribute Responsible Physicians Using Inpatient Claims

Michael Korvink, MA; German Molina, PhD; John Martin, PhD, MPH; Henry Sullivant, MD; and Laura H. Gunn, PhD

The health care industry has invested substantially in methods to fairly measure quality of care within and across acute inpatient care settings.¹⁻⁴ The Yale Center for Outcomes Research and Evaluation (CORE)^{5,6} and Agency for Health Research and Quality (AHRQ)⁷ risk-adjusted measure methodologies illustrate the lengths to which measure developers attempt to account for varying clinical and demographic characteristics within a facility's inpatient population. Although the sophistication of measure development has matured considerably, methods to properly attribute those risk-adjusted outcomes to a physician remain largely underdeveloped.⁸⁻¹⁰

Best practices for attribution of physicians to patients, and their resulting outcomes, remain a perennial challenge from a quality perspective, as no industry-accepted method of such assignment presently exists.⁸ A National Quality Foundation (NQF)-commissioned environmental scan of more than 170 proposed or implemented attribution models concluded that “the quality measurement field has not yet determined best practices for attribution models” and that the methods currently employed lacked necessary rigor.⁹⁻¹¹

The topic of physician attribution is broad and, as expected, the “appropriate” attribution method will “depend on the purpose, context, and stakeholder perspective.”⁹ Novel approaches are needed to retrospectively identify responsible physicians, specifically for episodes centered around hospitalizations. An improved retrospective and hospital-centered attribution method is especially necessary given the recent growth of hospital pay-for-performance (P4P) and public reporting programs managed by CMS. These programs include the Hospital Value-Based Purchasing Program (HVBP), Hospital Readmissions Reduction Program (HRRP), Hospital-Acquired Condition Reduction Program, Hospital Inpatient Quality Reporting Program, and Overall Star Rating Program.^{12,13} Within these programs, there are a variety of acute inpatient claims-based measures, such as the risk-adjusted patient safety indicators (PSIs)³ and Yale CORE 30-day risk-standardized readmissions and mortality measures,^{1,2} that have significant influence in hospital Medicare reimbursement.¹²

ABSTRACT

OBJECTIVES: More robust attribution methods are necessary to understand physician-level variation in quality of care across risk-adjusted inpatient measures. We address a gap in the literature involving attribution of physicians to inpatient stays using administrative claims data, in which rule-based methods often inadequately attribute physicians.

STUDY DESIGN: Methodology comparison study using a cross-section of inpatient stays.

METHODS: A novel approach is proposed in which physicians' relative degrees of responsibility for inpatient stays are expressed through physician-specific attribution ratios informed by existing patient characteristics and comorbidities. Attribution results are compared with the rule-based benchmark method for 7 CMS-defined clinical cohorts, including a COVID-19 cohort.

RESULTS: Using 6,835,460 unique patient encounters during 2020 (n = 136,339 in out-of-sample cohort), the proposed approach favored specialists generally considered responsible for primary clinical conditions when compared with the benchmark. The most salient shift within the acute myocardial infarction (+17.0%), heart failure (+20.2%), and coronary artery bypass graft (+4.0%) cohorts was toward the cardiovascular diseases specialty, and the chronic obstructive pulmonary disease (+24.0%) and pneumonia (+16.2%) cohorts resulted in a shift toward the pulmonary diseases specialty. The COVID-19 cohort resulted in considerable shifts toward infectious diseases and pulmonary diseases specialties (+17.4% and +14.1%, respectively). The stroke cohort experienced a considerable shift toward the neurology specialty (+42.2%).

CONCLUSIONS: We provide a robust method to attribute physicians to patients, which is a necessary tool to understand physician-level variation in quality of care within the inpatient acute care setting. The proposed method provides consistency across facilities and eliminates unattributed patients resulting from unsatisfied business rules.

Am J Manag Care. 2022;28(7):e263-e270. doi:10.37765/ajmc.2022.89185

TAKEAWAY POINTS

A novel approach is proposed in which physicians' responsibility for inpatient stays is expressed through physician-specific attribution ratios informed by patient characteristics.

- ▶ The proposed method provides an automated approach to attribute physicians to patients within any system capturing inpatient discharge data.
- ▶ The proposed method identifies patients most likely to be within the physicians' locus of control.
- ▶ The proposed method offers health care organizations a consistent tool to more fairly compare outcomes across physicians.

Prior research has shown that physician involvement has a meaningful impact on a patient's quality of care and, as such, the identification of physicians most responsible during an inpatient stay is an essential component in quality improvement endeavors.¹⁴⁻¹⁶ As a result, there is growing interest among hospital quality administrators in understanding physician-level quality variation for those measures that contribute to overall performance in hospital value-based programs. In its 2016 report discussing attribution approaches and principles, the NQF recommends that such models should "attribute results to entities who can influence care and outcomes."¹⁹ Although the inpatient facility is deemed the accountable entity within CMS hospital P4P programs, knowledge of physician-level quality variation, through improved attribution, is necessary to effect change and to conduct root-cause analyses.

A commonly employed attribution method in the industry is based on the "plurality rule,"^{17,18} in which the physician with the highest quantity of visits, or highest total cost for a given patient across a clinical episode, is marked as the responsible physician. The plurality method is not dependent on an inpatient stay and further, as observed by Pham et al,¹⁹ is largely unaffected by the inclusion of inpatient data. This approach is particularly common for assigning attribution to a primary care provider (PCP) during an episodic period spanning multiple visits. Given the hospital-centric nature of inpatient-based measures within hospital P4P programs, the scope of the data is limited to physicians recorded on singular patient hospitalizations. Further, outcomes typically measured within hospital P4P programs are inpatient outcomes (ie, PSIs) or 30-day outcomes for mortality, readmissions, and complications. The plurality rule for these measures likely produces erroneous attributions, as it is suboptimal for surgical complications, pressure ulcers, or 30-day mortality events to be attributed to the physician with the highest volume of visits within a larger temporal encounter, because the attributed physician is likely to be the patient's PCP. These findings indicate that the generally accepted method for episodic attribution does not translate well when evaluating outcomes resulting from an inpatient index stay.

Current methods for identifying the responsible physician for outcomes centered around an inpatient index stay are lacking; they rely on business rules that largely neglect the complexity of the patient-physician relationship, as well as of patient characteristics and comorbidities. The novel measure proposed in this study

builds upon a broader and more robust set of administrative claims data to produce a more informed estimate of the physician with greatest responsibility within inpatient settings.

METHODS

Data

This study uses data from the Premier Healthcare Database, an all-payer database composed of administrative and utilization

data concerning more than 121 million inpatient stays across 700 US hospitals, including more than 10 million stays per year since 2012, totaling approximately 25% of all US discharges.²⁰ The database houses more than 231 million unique patient records, with standard classifications for physician specialties and roles. Comorbidities for each patient encounter were identified through *International Classification of Diseases, Tenth Revision (ICD-10)* codes having a present-on-admission code of Y (yes) or W (clinically undetermined) and were further mapped to broader AHRQ Clinical Classification Software codes (n = 295).^{21,22}

Specialists unlikely to assume primary responsibility of a patient during an inpatient stay (eg, radiology, anesthesiology, pathology) were excluded.¹⁹ Nurse practitioners and physician assistants were further excluded because they provide care under the auspices of licensed medical doctors. Additionally, physicians with anomalous total visit quantities were excluded, as it is the practice of some facilities to create artificial placeholder physicians, accumulating large visit counts, who do not represent practicing physicians. A natural log transformation was applied to physician 2-year inpatient case quantities due to the strong positive skewness of the case count distribution. Physicians with z scores above 3 (0.8%) were excluded.

Features of interest included patient age, sex, primary reason for admission coded as a Medicare Severity–Diagnosis Related Group (herein referred to as DRG), and comorbidities. Patient comorbidities were extracted as binary variables. Additionally, the standardized role and specialty of each physician recorded on inpatient records were extracted.

The patient population was limited to inpatient visits with discharge dates from January 1 to July 31, 2020, to ensure that *ICD-10* coding reflected the most current industry practices and procedures, including data for COVID-19. A stratified randomized sample by DRG for each specialty stratum was created totaling 1,695,690 unique patient encounters and 133 strata, out of a superset of 6,835,460 encounters. The data were further randomly divided into derivation (80%; n = 1,356,552 unique patient visits across 700 facilities) and validation (20%; n = 339,138 unique patient visits from the same facilities) cohorts. Both the rule-based and our proposed approaches were applied to a third, out-of-sample cohort composed of 136,339 inpatient encounters between August 1 and September 30, 2020, across 698 distinct acute inpatient facilities ([eAppendix Figure 1](#) [eAppendix available at ajmc.com]).

Physician Attribution Ratio

Patients are often seen by multiple physicians during hospital visits. Physicians are assigned to care for both existing comorbidities and the patient's primary reason for the current visit, with the physician treating the primary reason for the visit (ie, the DRG) typically assigned as the attributable physician. Some physicians may have large probabilities of being assigned to patients' visits, regardless of the DRG, based on patient comorbidities. For example, patients with major renal problems may have a high probability of being seen by nephrologists during acute myocardial infarction (AMI)-related hospital stays. However, the DRGs of inpatient stays, instead of comorbidities, should be the primary factors influencing physician attributions.

Additionally, the most likely physicians given the patients' clinical conditions will tend to be physicians with generalized specialties, such as hospitalists and internists, as they are ipso facto more likely to occur on the patient record, regardless of clinical condition. Such approaches would fail to identify the specialists who actually have the major responsibility for treating the driving clinical conditions of the patients. Hence, absolute measures of physician probabilities to be assigned to a patient may not be as informative as relative increases of those physician probabilities upon identifying the patient's DRG for the current visit. In the previous example, the cardiovascular surgeon's probability will increase drastically whereas the nephrologist's probability may remain at high levels but with lower changes before and after the AMI episode.

The proposed measure, a physician attribution ratio (PAR), utilizes 2 probabilities that are estimated across all physicians who see the patient during the visit: (1) probability (P) of the physician being assigned, given the patient's demographic characteristics and comorbid conditions (prior to the patient's visit, denoted as F_j); and (2) updated probability (P^*) of the physician being assigned, given the patient's DRG, demographic characteristics, and comorbid conditions.

These probabilities are estimated through multivariate mixed-effects logistic regression models, and they are combined in patient (i)-physician (j)-specific ratios (see the equation below). Further model and PAR details are provided in the [eAppendix](#).

$$PAR_{i,j} = \frac{P_{i,j}^* (\text{Specialty } j \mid DRG_i, F_j) / P_{i,H}^* (\text{Hospitalist} \mid DRG_i, F_j)}{P_{i,j} (\text{Specialty } j \mid F_j) / P_{i,H} (\text{Hospitalist} \mid F_j)}$$

Logistic models are stratified such that a separate model stratum exists for each of the 133 possible standard specialties (binary responses). For each model stratum, a stratified random sample by DRG was extracted to ensure representation of the full range of coded clinical conditions and procedures. Analyses were conducted using the *lme4* package²³ in R statistical software version 3.6.2 (R Foundation for Statistical Computing).

Our proposed method adjusts for differences between absolute and relative physician relevance by formulating patient- and physician-specific attribution ratios that account for relative proportional increases in physician probabilities. Proportional increases in physicians' probabilities (before and after identification of the DRG

of the inpatient visit) are compared through the PARs with respect to a reference physician across visiting physicians. PARs larger than 1 indicate that the physician's specialty has a higher relative increase in relevance compared with a reference physician, driven by the patient's clinical condition (ie, DRG), while accounting for the patient's characteristics and comorbidities. The physician with the largest relative proportional increase (ie, largest PAR) is assigned as the responsible physician.

Performance Comparison

Physician attribution results that were derived from our proposed method were evaluated against a commonly employed rule-based attribution approach, in which responsibility is assigned to the attending physician for medical cases and the (principal) surgeon for surgical cases.¹¹ Although our proposed approach produces additional granularity (attribution ranking across physicians), for the purpose of the comparative analysis, the physician with the highest PAR is attributed to the patient so that a singular assignment can be compared between the 2 approaches (see eAppendix for details).

We evaluated differences between the rule-based method and our proposed PAR approach for each of the CMS clinical cohorts used within the 30-day mortality and readmissions measures included in the HVBP, HRRP, and CMS Overall Star Rating programs, as well as a COVID-19 cohort. These include AMI, coronary artery bypass graft (CABG), chronic obstructive pulmonary disease (COPD), COVID-19, heart failure (HF), pneumonia (PN), stroke (STK), and total hip arthroplasty/total knee arthroplasty (THA/TKA).

RESULTS

Table 1 illustrates PAR calculations for 4 patient encounters from the AMI, COVID-19, STK, and THA/TKA cohorts. Specialists most likely to be responsible for the care of the patient given the patient DRG, although not necessarily the ones selected under the rule-based approach, are associated with higher PAR values. Whereas rule-based methods overweigh hospitalists or internists, under our proposed PAR-based method, the cardiovascular diseases (CD) physician is attributed to the AMI patient, the neurologist is attributed to the STK patient, the orthopedic surgeon is attributed to the THA/TKA patient, and the pulmonary diseases (PD) physician is attributed to the COVID-19 patient. Performance across the 133 strata (ie, specialties) resulted in a mean area under the curve of 0.759 (95% CI, 0.738-0.780), demonstrating substantial differences between the 2 approaches.

Performance Comparison: PAR vs Rule-Based Approach

An out-of-sample cohort of 136,339 patient visits was defined across the following clinical cohorts: AMI (n = 14,918); CABG (n = 4896); COPD (n = 9882); COVID-19 (n = 47,211); HF (n = 14,817); PN (n = 7701); STK (n = 21,836); and THA/TKA (n = 15,078). We estimated physician attributions given the scope of data recorded in patient records. For example, 2349 of the 14,918 (15.7%) AMI patient visits evaluated in

METHODS

TABLE 1. PAR Calculations for a Set of 4 Patients From Different Cohorts Corresponding to Different DRGs^a

Patient ID	Clinical cohort	Age in years	Sex	DRG description	Physician specialty	PAR	$P_{ij}^*[Specialty j DRG_i, F_i]^b$	$P_{ij}^b[Specialty j F_i]^b$	Attributed physician by type
A	AMI	75	M	PERC CV PROC W DRG-ELUT STENT W/MCC OR 4+	CV diseases	5.413	0.233	0.051	PAR
					Internal medicine	1.132	0.139	0.146	
					Hospitalist	1.000	0.098	0.116	RB
B	COVID-19	57	F	RESPIRATORY INFECT & INFLAMMATIONS W/MCC	Pulmonary diseases	2.223	0.060	0.020	PAR
					Hospitalist	1.000	0.120	0.089	RB
					Internal medicine	0.951	0.211	0.164	
C	STK	64	M	INTRCRN HEMRG OR CEREB INFRC W/O CC/MCC	Neurology	4.364	0.182	0.025	PAR
					Hospitalist	1.000	0.143	0.085	RB
					Internal medicine	0.842	0.171	0.121	
D	THA/TKA	77	M	MAJ HIP/KN REPL/REATCH LO EXTRM WO MCC	Orthopedic surgery	14.886	0.419	0.042	PAR, RB
					Internal medicine	1.004	0.087	0.130	
					Hospitalist	1.000	0.060	0.089	

AMI, acute myocardial infarction; CV, cardiovascular; DRG, Medicare Severity–Diagnosis Related Group; ID, identifier; MCC, major complications or comorbidity; PAR, physician attribution ratio; RB, rule-based; STK, stroke; THA/TKA, total hip arthroplasty/total knee arthroplasty.

^aThe responsible physicians are identified according to the PAR and RB approaches.

^bThe probabilities provided in these columns are defined in the eAppendix.

TABLE 2. Unattributed (orphaned) Encounters Using the Rule-Based Approach in the Out-of-Sample Cohort

Cohort	Encounter total (n)	Unattributed (n _{unattributed})	Unattributed (%)
AMI	14,918	30	0.2%
CABG	4896	6	0.1%
COPD	9882	37	0.4%
COVID-19	47,211	245	0.5%
HF	14,817	60	0.4%
PN	7701	53	0.7%
STK	21,836	397	1.8%
THA/TKA	15,078	28	0.2%

AMI, acute myocardial infarction; CABG, coronary artery bypass graft; COPD, chronic obstructive pulmonary disease; HF, heart failure; PN, pneumonia; STK, stroke; THA/TKA, total hip arthroplasty/total knee arthroplasty.

TABLE 3. Agreement (matching) Rates Between the Rule-Based and Physician Attribution Ratio Approaches

Cohort	Mean match	95% CI	Facility count
AMI	0.646	0.623-0.670	567
CABG	0.841	0.813-0.868	244
COPD	0.659	0.637-0.681	650
COVID-19	0.577	0.555-0.600	637
HF	0.540	0.516-0.563	653
PN	0.480	0.452-0.509	553
STK	0.488	0.460-0.517	624
THA/TKA	0.961	0.948-0.974	538

AMI, acute myocardial infarction; CABG, coronary artery bypass graft; COPD, chronic obstructive pulmonary disease; HF, heart failure; PN, pneumonia; STK, stroke; THA/TKA, total hip arthroplasty/total knee arthroplasty.

our sample had no recorded physician with a specialty related to cardiology. In the absence of a specialist, it was not uncommon to see internists or hospitalists attributed to AMI patients. All physicians on the patient record were evaluated to identify the most probable responsible physician so that no patient encounter was left unattributed.

A common challenge with the rule-based approach is the occurrence of orphaned records, in which no attributed physician is identified through the attribution rules. The stroke cohort was most affected by orphaned records with a 1.8% orphaning rate (n = 397), followed by the PN cohort with a 0.7% orphaning rate (n = 53). Details are provided in [Table 2](#).

The degree of discord between the 2 methods is affected by the clinical cohort that is being evaluated. To measure the range

of discord, a match rate, defined as total attribution records in agreement between the 2 methods over the total encounters, was calculated for each facility and cohort. [Table 3](#) exhibits the match rate means and 95% CIs by clinical cohort across all hospitals included in the third, out-of-sample cohort. Match rates ranged from 46.2% (PN) to 96.1% (THA/TKA).

[Table 4](#) lists the top 5 specialties by cohort, using the rule-based method first and then the resulting shifts with the proposed PAR-based approach. Shifts toward specialists are seen across all cohorts. The most salient shifts within the AMI (+17.0%), CABG (+4.0%), and HF (+20.2%) cohorts were toward the CD specialty, and the COPD (+24.0%) and PN (+16.2%) cohorts resulted in shifts toward the PD specialty. The COVID-19 cohort resulted in a considerable shift toward the infectious diseases (IF) and PD specialties (+17.4% and

TABLE 4. RB vs PAR Attributed Specialty Shifts^a

Cohort	Physician specialty	RB (n)	PAR (n)	Diff (n)	RB (%)	PAR (%)	Diff (%)
AMI (n=14,918)	Cardiovascular diseases	6061	8600	2539	40.6%	57.6%	17.0%
	Internal medicine	2164	1041	-1123	14.5%	7.0%	-7.5%
	Hospitalist	2108	561	-1547	14.1%	3.8%	-10.4%
	Interventional cardiology	1731	2375	644	11.6%	15.9%	4.3%
	Cardiovascular surgery	693	800	107	4.6%	5.4%	0.7%
	Thoracic surgery	585	646	61	3.9%	4.3%	0.4%
	Other	1028	403	-625	6.9%	2.7%	-4.2%
	Family practice	353	140	-213	2.4%	0.9%	-1.4%
	Critical care medicine	60	107	47	0.4%	0.7%	0.3%
CABG (n=4896)	Pulmonary diseases	58	126	68	0.4%	0.8%	0.5%
	Cardiovascular surgery	2239	2436	197	45.7%	49.8%	4.0%
	Thoracic surgery	1928	2003	75	39.4%	40.9%	1.5%
	Cardiovascular diseases	282	147	-135	5.8%	3.0%	-2.8%
	Other	185	98	-87	3.8%	2.0%	-1.8%
	Other specialty	105	18	-87	2.1%	0.4%	-1.8%
	General surgery	97	60	-37	2.0%	1.2%	-0.8%
	Interventional cardiology	41	32	-9	0.8%	0.7%	-0.2%
	Internal medicine	8	31	23	0.2%	0.6%	0.5%
COPD (n=9882)	Pulmonary diseases	3	18	15	0.1%	0.4%	0.3%
	Endocrinology and metabolism	1	32	31	0.0%	0.7%	0.6%
	Hospitalist	4005	2846	-1159	40.5%	28.8%	-11.7%
	Internal medicine	3895	2463	-1432	39.4%	24.9%	-14.5%
	Family practice	807	762	-45	8.2%	7.7%	-0.5%
	Pulmonary diseases	223	2597	2374	2.3%	26.3%	24.0%
	Other	605	379	-226	6.1%	3.8%	-2.3%
	Other specialty	113	55	-58	1.1%	0.6%	-0.6%
	Emergency medicine	76	244	168	0.8%	2.5%	1.7%
COVID-19 (n=47,211)	Critical care medicine	57	225	168	0.6%	2.3%	1.7%
	Pulmonary critical care medicine	42	169	127	0.4%	1.7%	1.3%
	Unknown	18	94	76	0.2%	1.0%	0.8%
	Hospitalist	18,949	9372	-9577	40.1%	19.9%	-20.3%
	Internal medicine	16,215	8805	-7410	34.3%	18.7%	-15.7%
	Family practice	3765	3222	-543	8.0%	6.8%	-1.2%
	Pulmonary diseases	1215	7849	6634	2.6%	16.6%	14.1%
	Other	5107	5182	75	10.8%	11.0%	0.2%
	Critical care medicine	894	1169	275	1.9%	2.5%	0.6%
COVID-19 (n=47,211)	Emergency medicine	334	1139	805	0.7%	2.4%	1.7%
	Pulmonary critical care medicine	177	802	625	0.4%	1.7%	1.3%
	Infectious diseases	150	8356	8206	0.3%	17.7%	17.4%
	Nephrology	143	720	577	0.3%	1.5%	1.2%

(continued)

METHODS

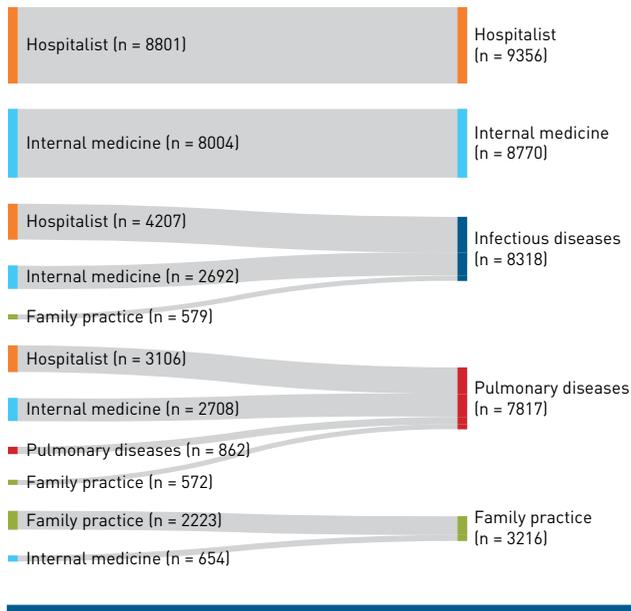
TABLE 4. (Continued) RB vs PAR Attributed Specialty Shifts*

Cohort	Physician specialty	RB (n)	PAR (n)	Diff (n)	RB (%)	PAR (%)	Diff (%)
HF (n = 14,817)	Hospitalist	5813	2818	-2995	39.2%	19.0%	-20.2%
	Internal medicine	5536	3095	-2441	37.4%	20.9%	-16.5%
	Family practice	1060	768	-292	7.2%	5.2%	-2.0%
	Cardiovascular diseases	743	5489	4746	5.0%	37.0%	32.0%
	Other	1219	670	-549	8.2%	4.5%	-3.7%
	Pulmonary diseases	110	266	156	0.7%	1.8%	1.1%
	Cardiac electrophysiology	81	90	9	0.5%	0.6%	0.1%
	Nephrology	67	1009	942	0.5%	6.8%	6.4%
	Interventional cardiology	66	394	328	0.4%	2.7%	2.2%
Unknown	50	127	77	0.3%	0.9%	0.5%	
PN (n = 7701)	Hospitalist	3088	1290	-1798	40.1%	16.8%	-23.3%
	Internal medicine	2556	1121	-1435	33.2%	14.6%	-18.6%
	Family practice	551	425	-126	7.2%	5.5%	-1.6%
	Pulmonary diseases	355	1604	1249	4.6%	20.8%	16.2%
	Critical care medicine	287	401	114	3.7%	5.2%	1.5%
	Other	555	557	2	7.2%	7.2%	0.0%
	General surgery	112	88	-24	1.5%	1.1%	-0.3%
	Emergency medicine	62	236	174	0.8%	3.1%	2.3%
	Pulmonary critical care medicine	45	135	90	0.6%	1.8%	1.2%
Infectious diseases	22	1612	1590	0.3%	20.9%	20.6%	
STK (n = 21,836)	Hospitalist	7452	3040	-4412	34.1%	13.9%	-20.2%
	Internal medicine	6757	2352	-4405	30.9%	10.8%	-20.2%
	Neurology	1511	10,732	9221	6.9%	49.1%	42.2%
	Neurological surgery	1359	1577	218	6.2%	7.2%	1.0%
	Family practice	1188	438	-750	5.4%	2.0%	-3.4%
	Other	2332	1546	-786	10.7%	7.1%	-3.6%
	Cardiovascular diseases	409	659	250	1.9%	3.0%	1.1%
	Critical care medicine	247	455	208	1.1%	2.1%	1.0%
	Emergency medicine	153	353	200	0.7%	1.6%	0.9%
Psychiatry	22	377	355	0.1%	1.7%	1.6%	
THA/TKA (n = 15,078)	Orthopedic surgery	14,430	14,507	77	95.7%	96.2%	0.5%
	Unspecified	223	18	-205	1.5%	0.1%	-1.4%
	Sports medicine – orthopedics	105	100	-5	0.7%	0.7%	0.0%
	General surgery	79	62	-17	0.5%	0.4%	-0.1%
	Other specialty	66	6	-60	0.4%	0.0%	-0.4%
	General practice	38	37	-1	0.3%	0.2%	0.0%
	Unknown	25	242	217	0.2%	1.6%	1.4%
	Hospitalist	15	26	11	0.1%	0.2%	0.1%
	Orthopedic surgery of the spine	10	11	1	0.1%	0.1%	0.0%
Internal medicine	8	23	15	0.1%	0.2%	0.1%	

AMI, acute myocardial infarction; CABG, coronary artery bypass graft; COPD, chronic obstructive pulmonary disease; diff, difference; HF, heart failure; PAR, physician attribution ratio; PN, pneumonia; RB, rule-based; STK, stroke; THA/TKA, total hip arthroplasty/total knee arthroplasty.

*Counts of unique patient visits (n) by clinical cohort and specialty of the attributed physician for both the RB approach and PAR approach. Percentage differences are provided in the 3 rightmost columns.

FIGURE. Sankey Diagram of Specialty Shifts From the Rule-Based Approach (left) to the Physician Attribution Ratio-Based Approach (right) for the COVID-19 Cohort*



*Patient counts from the physician attribution ratio-based approach (right) may be lower than those listed in Table 4, as shifts with quantities less than 500 are not visualized.

+14.1%, respectively), with IF attributions almost negligible under the rule-based approach. The most and least affected cohorts were STK (+42.2% shift to neurology) and THA/TKA (+0.5% shift to orthopedic surgery), respectively.

The Figure illustrates physician attribution shifts of 500 encounters or more from the rule-based approach to the PAR-based approach for the COVID-19, out-of-sample cohort. The largest shift within this cohort was toward the IF physician, drawing largely from the hospitalist (n=4207), internal medicine (n=2692), and family practice (n=579) specialties. A meaningful shift toward the PD physician can also be observed, pulling away from the hospitalist (n=3106), internal medicine (n=2708), and family practice (n=572) specialties.

DISCUSSION

Because plurality-based methods attribute physicians by calculating the one with the greatest quantity of visits or the highest total cost across visits, they are not suitable for identifying responsibility within the scope of a single inpatient stay. This study demonstrated the value of a novel method to identify physician attribution for patient outcomes during inpatient stays. The PAR approach provided a standardized method to attribute patient outcomes across a complete census of hospital inpatients by leveraging readily available data and an unbiased methodology, further allowing users of this methodology to fairly compare physician performance within and across hospitals and health systems.

Medical (vs surgical) cohorts are most affected by this PAR method, indicating that physicians assigned to the attending role are more likely to provide generalized care and are not the specialists of interest who would assume overall clinical responsibility of the patient. The PAR method proposed in this study improves upon rule-based attribution assignment by identifying those specialists who most closely manage the care of a hospitalized patient. Less discord can be observed with surgical cohorts, such as THA/TKA encounters, as physicians in the principal surgeon role are generally specialists who are, indeed, responsible for the primary condition of the patient.

The impact of enhanced attribution results will fluctuate depending on the operational practices to assign roles within individual facilities. For example, some hospitals may choose to assign all specialists to a consulting role (regardless of their degree of contact with the patient), whereas hospitalists are assigned the attending role. Other systems may choose to identify specialists as acting in the attending role.

Moreover, the PAR method improves the integrity of comparative evaluation of physicians by eliminating unattributed patients, as is seen with the rule-based approach, and provides a consistent approach to attribution regardless of the hospital-specific practices for coding physician roles.

Study Limitations and Future Research

The PAR methodology was demonstrated in our motivating example using a small set of commonly available patient-level characteristics so that PARs can be estimated in most real-world settings. The conditioning variables in the model could be further expanded in future research to enhance the estimation of the PAR's conditional probability inputs. Additional patient-level fixed effects could be incorporated, and facility, health care system, and/or physician-specific random effects could also be added to enhance the estimation of the conditional probabilities in future research. The addition of or stratification by conditioning variables that are not common to all patients would, however, limit the usability of PARs in new settings in which those variables may not yet be available for a sufficient number of patients (eg, facility-based random effects for new/low-volume facilities).

The PAR method is based on administrative data, which rely on consistent documentation by clinicians in medical records and coding practices across multiple institutions. This is a limitation facing all clinically abstracted data and, although coding practices can vary by institution, the impact of such variability should be minor given the large study size and could be further mitigated in practice through ininstitution clustering. Natural expansions of our approach could include a prospective form of attribution to be used at the point of care and variations of the model specific to targeted outcome measures.

Although the PAR approach identifies physicians assuming overall responsibility for an inpatient encounter, the desired attribution decision might vary according to the specific outcome being

METHODS

measured (eg, mortality, readmissions, patient experience, length of stay, complications, and cost).⁹ For example, an orthopedic surgeon might assume overall responsibility for a patient undergoing THA; however, an occurrence of deep vein thrombosis may be a result of care provided by the hospitalist or nursing team. A discharging internal medicine physician may be responsible for poor discharge instructions for a patient with AMI, rather than a cardiologist assuming overall responsibility. Therefore, in the evaluation of the length-of-stay measure, a hospitalist might be more appropriately attributed.

Despite the limitations, the PAR method has significant advantages over current attribution methods. It provides an automated approach that can be used with any system capturing inpatient discharge data, it identifies patients most likely to be within the physicians' locus of control for all patients' visits, and it offers health care organizations a tool to more fairly compare outcomes across physicians, allowing for both retrospective and live attribution.

CONCLUSIONS

The PAR-based method introduced in this study identifies and ranks physician specialties, based on their increased relevance due to the DRG driving the patient's visit, that are likely to provide specialized care unique to the patient's clinical condition(s), while accounting for patient-specific characteristics and comorbidities. Our results demonstrate that, compared with a rule-based method for inpatient attribution, the PAR-based method favors the specialist most likely to be responsible for the overall care of the patient during the inpatient stay. ■

Acknowledgments

Dena Richardson, MBA; Darla Belt, MSN; Patti Hollifield, MS; and Jennifer Pack, MHA, iteratively reviewed the results of the analyses and provided clinical guidance.

Author Affiliations: ITS Data Science, Premier Inc (MK, JM), Charlotte, NC; Independent Researcher (GM), Charlotte, NC; formerly of Baptist Memorial Healthcare (HS), Memphis, TN; Department of Public Health Sciences and School of Data Science, University of North Carolina at Charlotte (LHG), Charlotte, NC; School of Public Health, Faculty of Medicine, Imperial College London (LHG), London, UK.

Source of Funding: The authors received no specific funding for this work.

Author Disclosures: Mr Korvink reports that the model discussed in this paper will be employed within a commercial product. Dr Martin is employed by and has stock in Premier Inc. The remaining authors report no relationship or financial interest with any entity that would pose a conflict of interest with the subject matter of this article.

Authorship Information: Concept and design (MK, GM, HS, LHG); acquisition of data (MK); analysis and interpretation of data (MK, GM, LHG); drafting of the manuscript (MK, GM, LHG); critical revision of the manuscript for important intellectual content (MK, GM, JM, HS, LHG); statistical analysis (MK); provision of patients or study materials (MK); administrative, technical, or logistic support (JM); and supervision (JM, HS).

Address Correspondence to: Michael Korvink, MA, ITS Data Science, Premier Inc, 13034 Ballantyne Corporate Pl, Charlotte, NC 28277. Email: michael_korvink@premierinc.com.

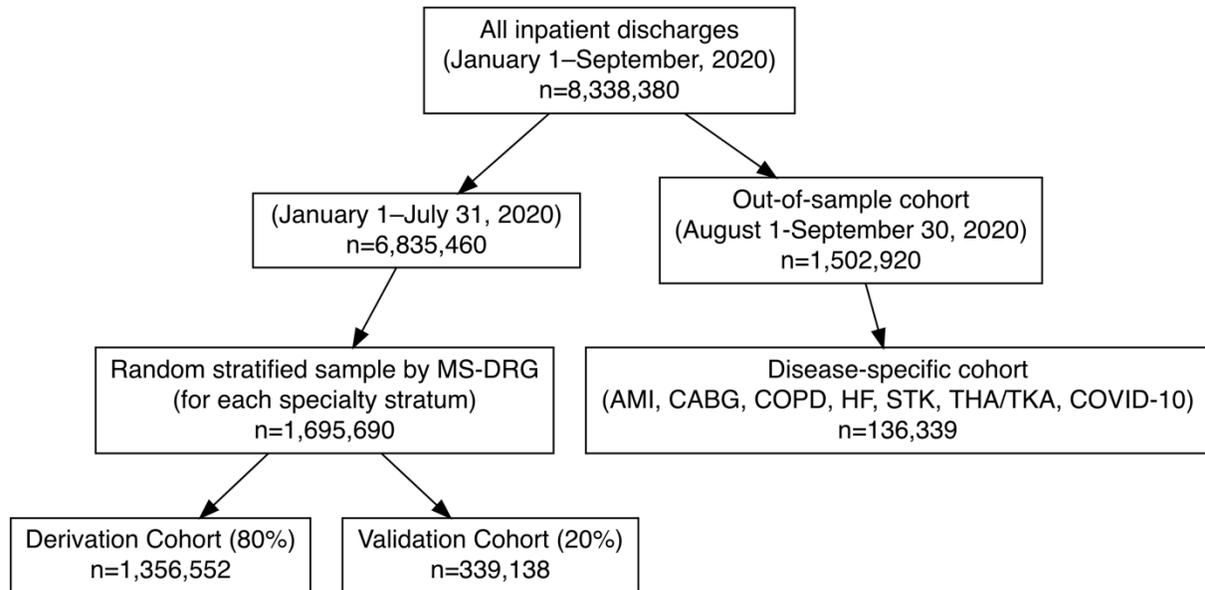
REFERENCES

1. Krumholz HM, Normand SLT, Spertus JA, Shahian DM, Bradley EH. Measuring performance for treating heart attacks and heart failure: the case for outcomes measurement. *Health Aff (Millwood)*. 2007;26(1):75-85. doi:10.1377/hlthaff.26.1.75
2. Lindenauer PK, Normand SLT, Drye EE, et al. Development, validation, and results of a measure of 30-day readmission following hospitalization for pneumonia. *J Hosp Med*. 2011;6(3):142-150. doi:10.1002/jhm.890
3. Krumholz HM, Coppi AC, Warner F, et al. Comparative effectiveness of new approaches to improve mortality risk models from Medicare claims data. *JAMA Netw Open*. 2019;2(7):e197314. doi:10.1001/jamanetworkopen.2019.7314
4. Zhan C, Miller MR. Administrative data based patient safety research: a critical review. *Qual Saf Health Care*. 2003;12(suppl 2):ii58-ii63. doi:10.1136/qhc.12.suppl_2.ii58
5. Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation (YNHHC/CORE). CMS QualityNet. 2020 condition-specific readmission measures updates and specifications report. March 2020. Accessed May 15, 2020. <https://www.qualitynet.org/inpatient/measures/readmission/methodology>
6. Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation (YNHHC/CORE). 2020 condition-specific mortality measures updates and specifications report. CMS QualityNet. March 2020. Accessed May 15, 2020. <https://www.qualitynet.org/inpatient/measures/mortality/methodology>
7. Quality indicator empirical methods. Agency for Healthcare Research and Quality. September 2019. Accessed May 15, 2020. https://www.qualityindicators.ahrq.gov/Downloads/Resources/Publications/2019/Empirical_Methods_2019.pdf
8. Mehrotra A, Burstin H, Raphael C. Raising the bar in attribution. *Ann Intern Med*. 2017;167(6):434-435. doi:10.7326/M17-0655
9. Attribution – principles and approaches. National Quality Forum. December 2016. Accessed May 15, 2020. https://www.qualityforum.org/Publications/2016/12/Attribution_-_Principles_and_Approaches.aspx
10. Ryan A, Linden A, Maurer K, Werner R, Nallamothu B. Attribution Methods and Implications for Measuring Performance in Health Care. National Quality Forum; 2019.
11. Pope GC. Attributing patients to physicians for pay for performance. In: Cromwell J, Trisolini MG, Pope GC, Mitchell JB, Greenwald LM, eds. *Pay for Performance in Health Care: Methods and Approaches*. RTI Press; 2011:181-201.
12. CMS, HHS. Medicare program; hospital inpatient prospective payment systems for acute care hospitals and the long-term care hospital prospective payment system and policy changes and fiscal year 2020 rates; quality reporting requirements for specific providers; Medicare and Medicaid promoting interoperability programs requirements for eligible hospitals and critical access hospitals. final rule. *Fed Regist*. 2019;84(159):42044-42701.
13. Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation (YNHHC/CORE). Overall hospital star rating on Hospital Compare methodology report (v3.0). CMS QualityNet. December 2017. Accessed May 15, 2020. https://qualitynet.cms.gov/files/5d0d3a1b764be766b0103ec1?filename=Star_Rtngs_CompMtdlgy_010518.pdf
14. McCoy RG, Bunkers KS, Ramar P, et al. Patient attribution: why the method matters. *Am J Manag Care*. 2018;24(12):596-603.
15. DiMatteo MR. The physician-patient relationship: effects on the quality of health care. *Clin Obstet Gynecol*. 1994;37(1):149-161. doi:10.1097/00003081-199403000-00019
16. Atlas SJ, Grant RW, Ferris TG, Chang Y, Barry MJ. Patient-physician connectedness and quality of primary care. *Ann Intern Med*. 2009;150(5):325-335. doi:10.7326/0003-4819-150-5-200903030-00008
17. Mehrotra A, Adams JL, Thomas JW, McGlynn EA. The effect of different attribution rules on individual physician cost profiles. *Ann Intern Med*. 2010;152(10):649-654. doi:10.7326/0003-4819-152-10-201005180-00005
18. Dowd B, Li CH, Swenson T, Coulam R, Levy J. Medicare's Physician Quality Reporting System (PQRS): quality measurement and beneficiary attribution. *Medicare Medicaid Res Rev*. 2014;4(2):10.5600/mmr.004.02.a04. doi:10.5600/mmr.004.02.a04
19. Pham HH, Schrag D, O'Malley AS, Wu B, Bach PB. Care patterns in Medicare and their implications for pay for performance. *N Engl J Med*. 2007;356(11):1130-1139. doi:10.1056/NEJMsa063979
20. Premier Applied Sciences. Premier Healthcare Database White Paper: data that informs and performs. Premier Inc. March 2, 2020. Accessed May 29, 2020. <https://learn.premierinc.com/white-papers/premier-healthcare-database-whitepaper>
21. Elixhauser A, Steiner CA, Whittington C, et al. Clinical classifications for health policy research: hospital inpatient statistics, 1995. Healthcare Cost and Utilization Project. 1998. Accessed September 30, 2021. <https://www.hcup-us.ahrq.gov/reports/natstats/his95/clinclas.htm>
22. Clinical Classifications Software Refined (CCSR). Healthcare Cost and Utilization Project. Accessed September 21, 2021. https://www.hcup-us.ahrq.gov/toolsoftware/ccsr/ccs_refined.jsp
23. Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. *J Stat Softw*. 2015;67(1):1-48. doi:10.18637/jss.v067.i01

Visit ajmc.com/link/89185 to download PDF and eAppendix

eAppendix

eAppendix Figure. Data Flow Diagram Illustrating the Sample Size of the Derivation, Validation, and Out-of-Sample Cohorts Relative to the Total Population



AMI, acute myocardial infarction; CABG, coronary artery bypass graft; COPD, chronic obstructive pulmonary disease; HF, heart failure; MS-DRG, Medicare Severity-Diagnosis Related Group; PN, pneumonia; STK, stroke; THA/TKA, total hip arthroplasty/total knee arthroplasty.

Physician Attribution Ratio Formulation:

The proposed approach in this manuscript relies on a physician attribution ratio (PAR) to produce a measure of association between physician specialty j and the clinical condition DRG for patient i which accounts for the patient's characteristics prior to that condition. The PAR is calculated from two conditional probabilities estimated via multivariate mixed effects logistic regression models: (1) probability, $P_{i,j}$, of specialty j for patient i prior to the patient's hospital visit, conditional on a set of patient-specific fixed effects F_i , an expandable list composed of age, sex, and patient comorbidities; and (2) an updated probability, $P_{i,j}^*$, of the specialty j for patient i , conditional on the DRG associated with the patient's hospital visit and also conditional on a set of patient-specific fixed effects F_i . The set of specialties is patient-specific, since only physicians who treated the patient can be attributed the care of the patient, hence $j=1, \dots, J(i)$.

$$\log \frac{P_{i,j}(\text{Specialty } j | F_i)}{1 - P_{i,j}(\text{Specialty } j | F_i)} = \alpha_j + \beta_j F_i \quad \text{for all } i, j \quad (1)$$

$$\log \frac{P_{i,j}^*(\text{Specialty } j | DRG_i, F_i)}{1 - P_{i,j}^*(\text{Specialty } j | DRG_i, F_i)} = \alpha_j^* + \beta_j^* F_i + \gamma_j DRG_i \quad \text{for all } i, j \quad (2)$$

Logistic regression coefficients are represented in the above models by α , α^* , β , β^* , and γ . The components are combined in equation (3) below to express the physician attribution ratio for patient i of specialist j (i.e. $PAR_{i,j}$). This PAR represents the percent increase/decrease in physician probability due to the DRG, relative to an equivalent percent increase for a reference physician (e.g. hospitalist in (3) below, identified with sub-index H), to produce a physician attribution ratio for each patient i and specialty j :

$$PAR_{i,j} = \frac{P_{i,j}^*(\text{Specialty } j | DRG_i, F_i) / P_{i,H}^*(\text{Hospitalist} | DRG_i, F_i)}{P_{i,j}(\text{Specialty } j | F_i) / P_{i,H}(\text{Hospitalist} | F_i)} \quad (3)$$

Since patients are visited by multiple physicians, neither $P_{i,j}$ nor $P_{i,j}^*$ sum to one across the $J(i)$ specialists attending patient i . Finally, patient i 's optimal specialty, $j^*(i)$, is identified using (4) below as the physician with the highest relative increase in probability of treating the patient after the patient's DRG diagnoses:

$$j^*(i) = \underset{j}{\operatorname{argmax}} PAR_{i,j}. \quad (4)$$

Note that this optimal specialty is uniquely defined for each patient i regardless of the choice of reference physician, which is a component of the ratio used solely for interpretability. A $PAR_{i,j}$ of one indicates equal relevance of specialty j and the reference specialty, while values larger/smaller than one indicate higher/lower, respectively, relevance for specialty j when compared to the reference specialty.

An alternative representation through the $\log(\text{PAR})$, which leads to equivalent optimal specialties ($\underset{j}{\operatorname{argmax}} PAR_{i,j} = \underset{j}{\operatorname{argmax}} \log(PAR_{i,j})$), provides an intuitive interpretation to the PAR. Let $I_{i,j}^*$ be the proportional increase of the probability of specialty j upon experiencing DRG_i . Then, the $\log(\text{PAR})$ approximates the differential in proportional increases of probabilities of each specialty j with the reference physician (see Equation (5)).

$$\log(PAR_{i,j}) = \log\left(1 + \frac{P_{i,j}^* - P_{i,j}}{P_{i,j}}\right) - \log\left(1 + \frac{P_{i,H}^* - P_{i,H}}{P_{i,H}}\right) = \log(1 + I_{i,j}^*) - \log(1 + I_{i,H}^*) \approx I_{i,j}^* - I_{i,H}^* \quad (5)$$