Table 1. This table shows the Google queries and their corresponding SVIs for states that have the highest and lowest number of confirmed COVID-19 cases

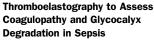| Google Queries	States most affected by COVID-19 (# of confirmed cases)	States least affected by COVID-19 (# of confirmed cases)	Mean SVI for top 5 states (SD)	Mean SVI for bottom 5 states (SD)	P-value
"Do I have coronavirus"	New York (732) Washington (643) California (426) Massachusetts 164) Colorado (131)	Oklahoma (7) Hawaii (6) Idaho (5) Missouri (5) Wyoming (3)* Alaska (1)* North Dakota (1)*	76 (7)	54 (11)	0.005
"How to get tested for coronavirus"	59 (5)	38 (14)	0.01		
"Signs and symptoms of coronavirus"	28 (4)	45 (16)	0.05		
"What is coronavirus"	81 (7)	85 (10)	0.48		
"How is coronavirus spread"	56 (7)	65 (13)	0.21		

* For some queries, these states did not yield an SVI due to insufficient data in Google Trends and were therefore not included in the analysis.

tracker provided by Johns Hopkins University. Scatterplots were then created to compare SVI and number of COVID-19 cases on a state level. Pearson correlations were determined to examine the association between SVI and the number of COVID-19 confirmed cases as of March 16, 2020.

Results: Peak SVI for all queries took place on March 12, just a day prior to the U.S. declaration of national emergency. "Do I have coronavirus" (p=0.005), "How to get tested for coronavirus" (p=0.01), and "Signs and symptoms of coronavirus" (p=0.05) were identified as having statistically significant differences in mean SVI between states with the highest and lowest number of COVID-19 cases (Table 1). Mean SVI for "Do I have coronavirus" and "How to get tested for coronavirus" was higher in the states with the most COVID-19 cases compared to the bottom 5 states with the least cases. However, mean SVI for "Signs and symptoms of coronavirus" was higher in the bottom 5 states compared to the top 5 states. There were no statistically significant differences in mean SVI for the remaining queries: "What is coronavirus" (p=0.48) and "How is coronavirus spread" (p=0.21).When looking at all 50 states and the District of Columbia, we found that SVI also positively correlated with the number of confirmed COVID-19 cases for "Do I have coronavirus" and "How to get tested for coronavirus" (R=.387, p=0.005; R=0.367, p=0.008). No statistically significant correlations were found for "How is coronavirus spread" (p=0.45), "What is coronavirus" (p=0.39), and "Signs and symptoms of coronavirus" (p=0.22).

Conclusion: Non-generic queries in Google Trends may yield better insights into health information-seeking behavior. Specifically, queries formatted as "How to get tested for _____" and "Do I have _____" could reflect perceived exposure to a communicable disease on a population level. To our knowledge, our study is the first to use Google Trends to distinguish queries that reflect perceived exposure to COVID-19 from those that are borne out by general interest in the United States. Early access to population health data is crucial and potentially life-saving during outbreaks. Digital tools such as Google Trends may help bridge the gap in knowledge and transparency.

EMF
284
Thromboelastography to Assess Coagulopathy and Glycocalyx Degradation in Sepsis

Tyler PD, Uchimado R, Hippensteel JA, Burke RC, Lindsell CJ, Linhardt RJ, Schmidt EJ, Shapiro NI/Beth Israel Deaconess Medical Center, Boston, MA; University of Colorado, Denver, CO; Vanderbilt University Medical Center, Nashville, TN; Rensselaer Polytechnic Institute, Troy, NY

Study Objectives: Sepsis is a common and deadly clinical syndrome that affects many patients presenting to the emergency department (ED). Sepsis-induced inflammation leads to abnormal coagulation. Additionally, one potential mechanism for abnormal coagulation and organ dysfunction in sepsis is injury to the endothelial glycocalyx; the glycocalyx contains heparans which are released during degradation and may cause mild coagulopathy. We hypothesize that coagulation abnormalities detected by bedside viscoelastic monitoring (VEM), such as thromboelastography, are associated with organ dysfunction and death (suggesting abnormal coagulation as a mediator). We

further hypothesize that heparinase R-time, a VEM measurement that may detect glycocalyx degradation, will be associated with organ dysfunction.

Methods: Patients >18 years old with a diagnosis of sepsis were recruited from an urban ED (~55,000 visits per year) as part of an ongoing observational study of a convenience sample of patients. After informed consent was obtained, blood samples are to measure VEM. VEM measurements include the R time, K time, alpha angle, maximum amplitude (MA), lysis percent at 30 minutes (LY30), and change in R time with the addition of heparinase (ΔR). We also collect demographic information, comorbidities, sepsis severity, the information necessary to determine the Sequential Organ Failure Assessment (SOFA) score, and mortality data. We calculated descriptive statistics for VEM measurements, and Pearson correlations between VEM measurements and SOFA score on enrollment and on days 1-3.

Results: We have enrolled 79 subjects thus far (study is ongoing). The baseline VEM parameters, expressed as median (IQR), are as follows: R, 5.3 minutes (4.2-6.4); K, 1.2 minutes (0.9-1.8); alpha angle, 72.0 degrees (65.7-75.8); MA, 68.3 millimeters (63.2-73.5); and LY30, 0.1 percent of maximum amplitude (0-1). The baseline ΔR is 0.4 minutes (IQR, 0.1-55). For patients enrolled to date, ΔR was correlated with day 1 SOFA score (r = -0.21, p < 0.03). Additionally, K was correlated with SOFA score on day 1 (0.22, p < 0.02) and day 2 (0.26, p < 0.03). Further results, delayed due to the impact of coronavirus on this project, will be available at the time of the Research Forum.

Conclusion: It is feasible to obtain VEM measurements in patients with sepsis. Our ongoing work will recruit additional patients, measure syndecan-1 levels (a marker of glycocalyx degradation), determine illness severity scores (using Sequential Organ Failure Assessment scores) on days 0-3 and mortality outcomes, and determine whether syndecan-1 levels, VEM measurements, and patient outcome measurements are associated.

285
Deployment of Artificial Intelligence for Radiographic Diagnosis of COVID-19 Pneumonia in the Emergency Department

Carlile M, Hurt B, Hsiao A, Hogarth M, Longhurst C, Dameff C/UC San Diego, San Diego, CA; UC San Diego, San Diego, CA; UC San Diego Health, San Diego, CA

Study Objectives: The surge and long tail of patients in acute respiratory distress during the coronavirus-19 (CoVID19) pandemic has inspired new innovations in diagnosing, treating and dispositioning patients during high census conditions with constrained resources. During the first wave of the pandemic, we deployed an artificial intelligence (AI) algorithm for assisted interpretation of chest x-ray for use by radiologists and emergency department (ED) physicians. We report first experiences of physician interaction with this novel AI algorithm designed to enhance physician abilities to identify ground glass and consolidation on chest radiographs.

Methods: Design: We created a fully-automated pipeline into the clinical environment to provide AI augmentation of chest x-rays, utilizing a previously developed deep learning-based AI algorithm. Trained with 22,000 annotations by radiologists, the algorithm overlays X-rays with color-coded maps that indicate pneumonia probability. This was provided alongside standard chest x-ray images for physicians to use in real-time at the point of care with existing imaging software. For

this prospective observational study, we developed a 3-point survey to characterize experiences with the tool regarding ease of use and impact on clinical decision-making.

Setting: Surveys were conducted during a one-month period surrounding the projected CoVID-19 surge locally (April 8-May 9) at two academic hospitals in Southern California. A federal declaration of emergency occurred March 13, 2020 and the tool was urgently deployed on March 25.

Types of Participants: Emergency medicine resident and attending physicians surveyed in real time by telephone.

Results: Of the 5,125 total visits and 1,960 chest radiographs obtained in the ED during the study period, 1,855 were analyzed by the algorithm. Among these, emergency physicians were surveyed for their experiences on 202. Real-time computation and delivery of the tool took four minutes on average.

Overall, 86% either strongly agreed or somewhat agreed that the intervention was easy to use in the existing workflow. 20% of all respondents reported that the algorithm impacted their clinical decision making. In general, resident physicians found the AI implementation easier to use than attendings (Mann Whitney U, p=0.005). Descriptive statistics regarding further impact are summarized below (table 1).

Conclusion: This AI technology was rapidly deployed in a large academic health system in the first wave of a global pandemic. Surveyed ED physicians found this implementation easy to use within existing workflows. Twenty percent of physicians reported that the tool changed clinical decision making, and approximately one third of those found that it impacted diagnostic testing decisions and treatment plans. Several physicians reported ordering COVID-19 PCR testing as a direct result of the AI, resulting in positive tests and subsequent quarantining of patients who otherwise might not have been appropriately diagnosed. To our knowledge, this is the first published study evaluating the impact of medical imaging AI on clinical decision making in the ED setting and may prove to be a powerful tool during the pandemic response.

Survey Information					
Total X-rays in ED during Study Period	Total X-rays with Colormap Applied during Study Period	Total Number of Surveys	Total Providers in ED	Attendings Surveyed	Residents Surveyed	Avg Time to Generate Heat Map (mins)
1960	1885	202		53 Attendings, 49 Residents	26 (38% of all scheduled)	21 (53% of all scheduled)	4

Question 1: The AI-augmented overlay was easy to use in my existing workflow					
	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly Disagree
Overall Cohort (n = 202)	150 (74%)	28 (14%)	15 (7%)	1 (0%)	8 (4%)
Resident Cohort (n = 70)	61 (87%)	6 (9%)	3 (4%)	0 (0%)	0 (0%)
Attending Cohort (n = 132)	89 (67%)	22 (17%)	12 (9%)	1 (1%)	8 (6%)

Question 2: Did the AI-augmented overlay contribute to your medical decision making?	
	Yes	No
Overall Cohort (n = 202)	41 (20%)	161 (80%)
Resident Cohort (n = 70)	18 (26%)	52 (74%)
Attending Cohort (n = 132)	23 (17%)	109 (83%)

Question 3: If the AI-augmented contributed to medical decision making, in what way did it contribute?					
	Diagnostic Testing (more or less lab/radiology studies)	Final Diagnosis	Treatment Plan	Disposition time (longer or shorter time in ED)	Disposition Location (admit vs discharge)	Other
Overall Cohort (n = 41)	11 (27%)	6 (15%)	12 (30%)	11 (27%)	4 (10%)	9 (22%)
Resident Cohort (n = 18)	6 (33%)	2 (11%)	5 (28%)	1 (6%)	1 (6%)	5 (28%)
Attending Cohort (n = 23)	5 (22%)	4 (17%)	7 (30%)	10 (43%)	3 (13%)	4 (17%)

286 Firearm Injuries: Long-Term Health Outcomes and Health Care Expenditures for Children

Pulcini CD, Goyal MK, Hall M, Gruhler H, Chaudhary S, Alpern E, Fein JA, Fleegler E/ Children's Hospital of Philadelphia, Philadelphia, PA; Children's National Medical Center, Washington, DC; Children's Hospital Association, Topeka, KS; Lurie Children's Hospital, Chicago, IL; Children's Hospital of Boston, Boston, MA

Study Objectives: To evaluate health care encounters and expenditures for children one year before and following firearm injury.

Methods: Cohort study of children 0-18 years identified using ICD-9/ICD-10 diagnosis codes for firearm injury in the ED or inpatient setting from 2010-2016 in the Medicaid MarketScan (IBM Watson, Armonk, New York) claims database. Subjects met inclusion criteria if they were continuously enrolled in Medicaid with data availability one year before and one year after a firearm injury during the study period. We identified index injuries by ensuring that each child did not have a firearm injury diagnosis in the year prior. Outcomes included: 1) difference in health care encounters for one year before and after injury (outpatient visits, physical, occupational and mental health therapy, emergency department visits, and inpatient admissions); 2) difference in health care expenditures pre- and post-firearm injury. Descriptive statistics

characterize patient demographics. Health services and expenditures utilized before and after firearm injury evaluated with Wilcoxon Sign Rank Tests.

Results: Of 3,296 children, 83.4% were male (n=2,750), and approximately half were 15-18 years of age (n=1,646) and non-Hispanic African-American/black (n=1,699). Healthy children with low prior health care utilization were the largest subgroup (n=2,823). For the entire cohort there were 109,320 health care encounters during the entire study period (Table 1); 47,660 before the firearm injury and 61,660 afterward (p<0.001). There was a higher rate of inpatient encounters (post-pre=0.9 visits/patient, p=<0.001) and outpatient encounters (post-pre=0.7 visits/patient, p=<0.001) after the firearm injury. Concomitantly, there was an overall increase of $18.5 million in health expenditures for the entire cohort one-year post-firearm injury, 80% of which were for inpatient health care encounters ($14.7 million). Healthy children with low prior health care utilization who were injured by a firearm experienced the largest and most significant increases in inpatient health care encounters and expenditures after their injury.

Conclusion: Children who experience firearm injury show increases in health care encounters and expenditures one-year after the injury. Public health programs that reduce the incidence and impact of childhood firearm injury can also lead to considerable savings in health care expenditures. Future research is needed to more fully elucidate the long-term impact of firearm injuries on children, families, health care utilization, and expenditures.

Table 1. Healthcare resource utilization for children ages 0-18 from on Medicaid one year pre- and one-year post- firearm injury

All subjects (N (subjects)=3,296; n (encounters)=109,320)						
	pre	post	Difference (post-pre)			
	Encounters, n (%)	Encounters, n (%)	Encounters	Mean difference per subject (N)	Median	p-value
Healthcare Encounters	47660	61660	14000	0.7	1	<.001
Outpatient (OP)*	47478 (99.6)	60781 (98.5)	13303	0.7	T1	<.001
OP PCP	5554 (11.6)	6762 (10.9)	1208	0.5	1	<.001
OP Specialists	6001 (12.5)	8374 (13.5)	2373	1	1	<.001
OP ED	2909 (6.1)	6152 (9.9)	3243	1	1	<.001
OP MHSA	20007 (41.9)	18448 (29.9)	-1559	-1.1	0	0.057
Inpatient	182 (0.3)	879 (1.4)	697	0.9	1	<.001
Low Prior Healthcare Utilization (N= 2,823; n=66,461)						
Healthcare Encounters	23582	42879	19297	1.2	1	<.001
Outpatient (OP)*	20779 (88.1)	42227 (98.4)	18645	1.2	1	<.001
OP PCP	4543 (19.2)	5688 (13.2)	1145	0.5	1	<.001
OP Specialists	3716 (15.7)	6170 (14.3)	2454	1.2	1	<.001
OP ED	2229 (9.4)	5044 (11.7)	2815	1.1	1	<.001
OP MHSA	3699 (15.6)	8532 (19.8)	4833	4.9	1	<.001
Inpatient	0 (0.0)	652 (1.5)	652	1.2	1	<.001
High Non-Mental Health Utilization (N=145; n=15,093)						
Healthcare Encounters	7745	7348	-397	-0.3	0	0.999
Outpatient (OP)*	7563 (97.6)	7209 (98.1)	-354	-0.3	0	0.619
OP PCP	550 (7.1)	505 (6.8)	-45	-0.3	0	0.264
OP Specialists	1465 (18.9)	1333 (18.1)	-132	-0.8	0	0.948
OP ED	393 (5)	561 (7.6)	168	0.9	1	<.001
OP MHSA	2914 (37.6)	2389 (32.5)	-525	-4	-1	0.031
Inpatient	182 (2.3)	139 (1.8)	-43	-0.3	-1	<.001
High Prior Mental Health Utilization (N=282; n=27,766)						
Healthcare Encounters	16333	11433	-4900	-2.5	1	0.012
Outpatient (OP)*	16333 (100)	11345 (99.2)	-4988	-2.7	1	0.134
OP PCP	461 (2.8)	569 (4.9)	108	0.5	1	0.001
OP Specialists	820 (5)	871 (7.6)	51	0.2	1	0.015
OP ED	287 (1.7)	547 (4.7)	260	1	1	<.001
OP MHSA	13394 (82)	7527 (65.8)	-5867	-20.8	-17	<.001
Inpatient	0 (0.0)	88 (0.7)	88	1.2	1	<.001

*Also includes outpatient testing, drug & injection, home health, outpatient not otherwise specified, outpatient therapy & treat, durable medical equipment, and dental