Real-World Evaluation of an Automated Algorithm to Detect Patients with Potentially Undiagnosed Hypertension in Hawai‘i

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Background

Automated algorithms are a type of health information technology that often leverage the electronic health records (EHR) of patients to support clinical diagnostic and management decisions;[1] these algorithms may be important tools to identify patients with undiagnosed conditions, such as hypertension, and bring about timely intervention to treat and manage those conditions.[2,3] The potential for such algorithms to improve quality of care has long been recognized by federal organizations, such as the Centers of Medicare and Medicaid;[4] however, limited empirical research tests the application of such technology in real-world clinical settings.[5,6] This real-world evaluation considers an algorithm designed to detect patients with undiagnosed hypertension, implemented in a large health system in Hawai‘i serving an ethnically diverse panel receiving routine care.

Objectives

- Quantify patients identified as undiagnosed with hypertension by the algorithm,
- Summarize the individual characteristics, clinical and health system factors associated with undiagnosed hypertension, as identified by the algorithm, and
- Examine if the COVID-19 pandemic affected detection of undiagnosed patients by the algorithm.

Methods

We analyzed the de-identified EHR data of patients treated across 6 clinics in the Queen’s Clinically Integrated Physician Network from 2018-2021. The EHR algorithm (Fig 1) flagged patients with potentially undiagnosed hypertension, defined as patients without physician-diagnosed hypertension with two or more consecutive blood pressure readings of ≥140/90 over the past 3 years or one reading of ≥160/100 in the past year. We compared patients flagged by the algorithm for potentially undiagnosed hypertension to those with diagnosed hypertension. Crude and adjusted relative risk (RR) and 95% confidence intervals (CI) were calculated across individual characteristics, clinical and health system factors, and timing of blood pressure readings before and after the COVID-19 Stay-At-Home Order in Hawai‘i on 3/25/2020, utilizing modified Poisson models with robust error variance.

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Results

Fig 2. Adjusted RR and 95%CI for Undiagnosed Hypertension Across 3 Multivariable Models

	Model 1. Individual Characteristics		Model 2. Clinical and Health System Factors		Model 3. Timing	
	aRR (95% CI)	**p-value**	**aRR (95% CI)**	**p-value**	**aRR (95% CI)**	**p-value**
Age (ref. 18-39 years)						
* 40-64 years	1.44 (1.07,1.95)	0.0165	1.55 (1.13, 2.13)	0.0061	1.42 (1.04, 1.95)	0.0286
* 65-84 years	1.40 (1.02,1.92)	0.0355	1.83 (1.14, 2.95)	0.0131	1.62 (1.01, 2.59)	0.0451
85+ years	0.96 (0.57,1.60)	0.8649	1.29 (0.67, 2.47)	0.4474	1.21 (0.63, 2.32)	0.5612
Gender (ref. Male)						
Female	0.90 (0.73,1.11)	0.3315	0.90 (0.73, 1.11)	0.3156	0.89 (0.72, 1.10)	0.2687
Race and Ethnicity (ref. White)						
Native Hawaiian	1.01 (0.70,1.45)	0.9583	1.32 (0.92, 1.91)	0.1344	1.28 (0.89, 1.85)	0.1827
Other Pacific Islander	0.88 (0.46,1.67)	0.6905	1.45 (0.76, 2.79)	0.2607	1.46 (0.76, 2.81)	0.2547
Filipino	0.78 (0.57,1.06)	0.1162	1.25 (0.90, 1.74)	0.1812	1.22 (0.88, 1.69)	0.2407
East Asian	0.82 (0.62,1.07)	0.1411	1.11 (0.84, 1.46)	0.4736	1.10 (0.84, 1.45)	0.475
Other	0.75 (0.53,1.05)	0.0938	1.05 (0.74, 1.48)	0.7809	1.07 (0.76, 1.51)	0.6928
Tobacco (ref. No)						
Yes	0.90 (0.63,1.29)	0.561	0.89 (0.62, 1.27)	0.5297	0.90 (0.63, 1.28)	0.5577
Alcohol (ref. No)						
Yes	0.97 (0.78,1.20)	0.7922	0.83 (0.67, 1.03)	0.0875	0.82 (0.66, 1.02)	0.0718
Clinic (ref. Clinic 1)						
Clinic 2			0.72 (0.39, 1.32)	0.2899	1.19 (0.64, 2.23)	0.5844
Clinic 3			1.49 (0.82, 2.71)	0.1855	1.54 (0.85, 2.80)	0.1523
* Clinic 4			2.01 (1.20, 3.36)	0.0081	2.02 (1.21, 3.39)	0.0073
* Clinic 5			1.86 (1.17, 2.96)	0.0089	2.30 (1.45, 3.66)	0.0004
* Clinic 6			5.91 (3.80, 9.21)	<0.0001	6.81 (4.38,10.6)	<0.0001
Insurer (ref. Medicare)						
BCBS	1.08 (0.72, 1.64)	0.7038	1.13 (0.76, 1.70)	0.5419		
* Medicaid	1.72 (1.05, 2.84)	0.0322	1.74 (1.06, 2.86)	0.0289		
Other	1.02 (0.65, 1.61)	0.9313	1.12 (0.71, 1.78)	0.6148		
BMI Category (ref. Normal)						
Overweight	1.26 (0.97, 1.62)	0.0789	1.26 (0.98, 1.62)	0.0741		
Obese	1.19 (0.90, 1.56)	0.2166	1.22 (0.92, 1.60)	0.1637		
Underweight	1.36 (0.78, 2.37)	0.2715	1.40 (0.81, 2.42)	0.2278		
Mental Health (ref. No)						
Yes	1.17 (0.94, 1.47)	0.1538	1.12 (0.90, 1.40)	0.3092		
(Pre)Diabetes & A1C (ref. Diagnosed Diabetes)						
* Diagnosed Prediabetes	2.27 (1.47, 3.51)	0.0002	2.22 (1.44, 3.43)	0.0003		
* A1C 5.7 or greater, No Diagnosis	3.28 (2.07, 5.18)	<0.0001	3.38 (2.14, 5.35)	<0.0001		
* A1C 4.3 to 5.6, No Diagnosis	3.44 (2.26, 5.25)	<0.0001	3.49 (2.29, 5.32)	<0.0001		
* No Diagnosis & No A1C	2.85 (1.87, 4.34)	<0.0001	3.33 (2.18, 5.09)	<0.0001		
COVID-19 Pandemic (ref. Before Stay-At-Home Order)						
* After Stay-At-Home Order			2.63 (1.96, 3.54)	<0.0001		

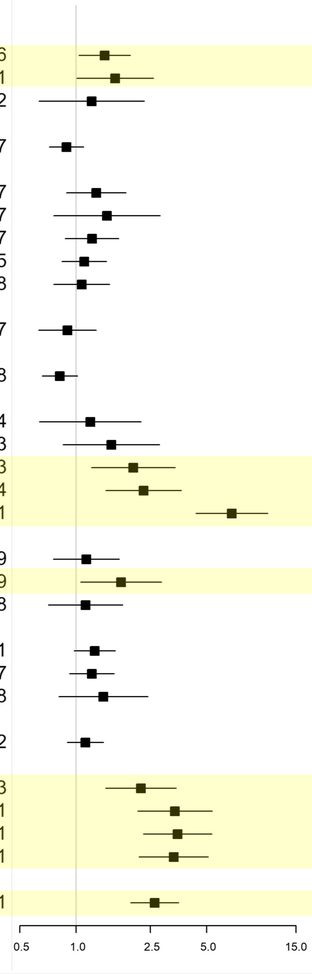


Fig 3. Potentially Undiagnosed Hypertension Before and After the First COVID Stay-At-Home Order in Hawai‘i by Clinic

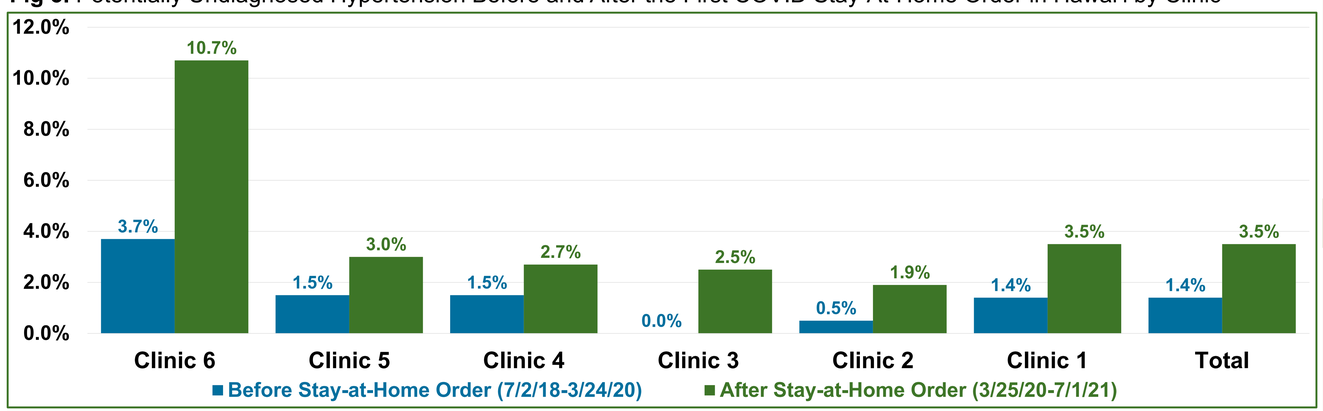
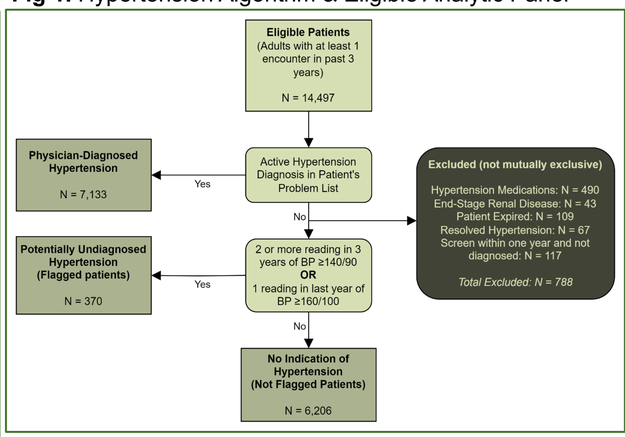


Fig 1. Hypertension Algorithm & Eligible Analytic Panel



Conclusion

Factors associated with a higher risk of potentially undiagnosed hypertension included: individual characteristics (ages 40-84 compared to 18-39 years), clinical (lack of diabetes diagnosis) and health system factors (clinic site and being a Medicaid versus a Medicare beneficiary), and timing (readings obtained after the COVID-19 Stay-At-Home Order in Hawai‘i). This real-world evaluation provided evidence that a clinical algorithm implemented within a large health system’s EHR could detect patients in need of follow-up to determine hypertension status. Moreover, we identified key individual characteristics, clinical and health system factors, and timing considerations that may contribute to undiagnosed hypertension among patients receiving routine care. A crucial future direction would be to explore which actions were taken following a flag, the time between the flagging and changes made in the care process, and whether individuals were able to achieve a normotensive status through these actions.

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