

Predicting Influenza Vaccinations using Administrative Claims and Consumer Health Data

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Background

- Influenza is a major public health and medical concern, affecting between 5-10% of adults and 20-30% of children worldwide on an annual basis¹
- Annual influenza vaccination is recommended for children and adults to reduce the individual burden of disease as well as strains on the health care system²
- Vaccination rates among adults, however, are low (estimated at about 40%) despite recommendations from the Centers for Disease Control and Prevention³
- Predictive models of influenza vaccination can play an important role in identifying behaviors and individual or population factors that are amenable to targeted interventions for increasing vaccination rates^{4,5}
- Current models, which rely on survey responses or medical claims, are limited by the need for active user input and the sporadic availability of data relative to the influenza event or vaccination
- Consumer Mobile Health data collected after user consent through wearable activity monitors (WAM), may potentially address these limitations by allowing unobtrusively monitoring for a number of individual behaviors at granular time scales of day, hour and even minute level summaries^{6,7}

Objective

- To compare and contrast the predictive ability of consumer health data from wearable activity monitors with conventional medical claims data for the prediction of influenza vaccinations in a large commercially insured population. We hypothesize that the inclusion of WAM data will provide additional information to predictive models beyond the use of conventional medical claims data alone.

Methods

STUDY DESIGN: Retrospective cohort

DATA SOURCE:

- Medical claims and enrollment records from commercial health coverage from Humana Inc, a national health and well-being company
- Humana wellness app for all members that can connect WAM and acts as a portal for logging wellness behaviors like obtaining an influenza vaccination

SELECTION CRITERIA:

- The predictive analysis period covers a one year period from June 1, 2015 to June 1, 2016.
- Training data for medical claims and for WAM were obtained from the June 1, 2014 – June 1, 2015 period.
- Eligible participants were adults (age 18– 64), with evidence of commercial coverage during the analysis period. Influenza vaccination status was based on medical claims data and participant reporting through the wellness app.

ANALYSIS:

- Two predictive models were compared:
 - The first model used medical and pharmacy claims data.
 - The second model used a subset of the first cohort that also had WAM data from the wellness platform.
- To be included in the second model using WAM data, individuals must have had tracking data available in the training period and at least one logged activity during the predictive period (June 1, 2015 – June 1, 2016).
- A total of 679 features were computed for analysis. For each model, we split the dataset into training and test sets. On the training set, we used L-1 regularized Lasso regression with influenza vaccination as the outcome to identify a subset of most predictive features. We then trained a random forest classifier on the training set and report predictive power with a Receiver Operating Curve and its Area-Under-Curve (AUC) on the test set as the performance metric for the models.

Results

Figure 1. Overview of Study Design and Analysis

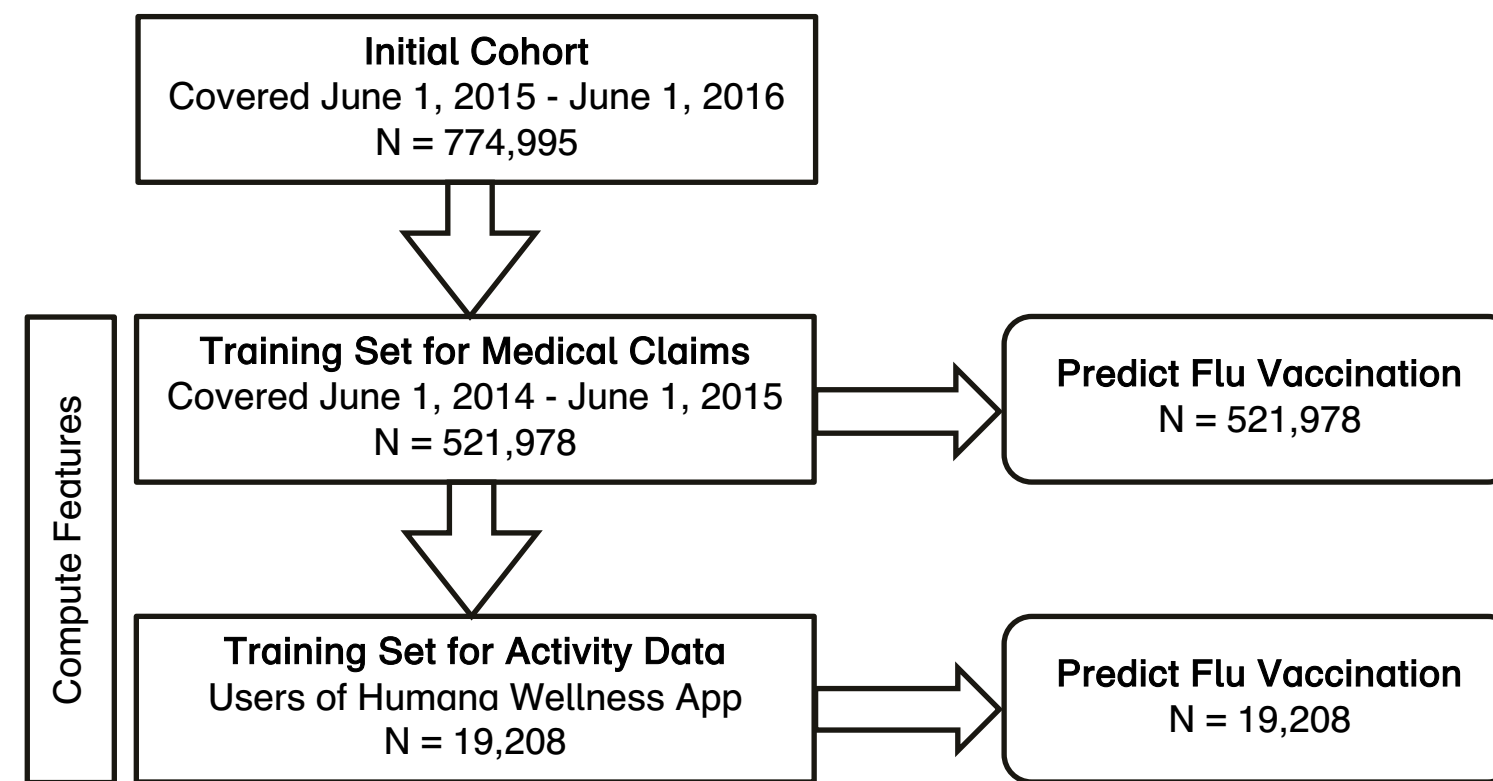


Table 1. Population Characteristics

WAM users are connected via the Humana wellness app

	WAM Use (N = 19,208)			No WAM Use (N = 502,770)		
	Total Cohort	Vaccinated	Non-Vaccinated	Total Cohort	Vaccinated	Non-Vaccinated
Demographics						
Percent female	63.4%	66.5%	60.8%	49.9%	56.8%	48.1%
Mean age	43.1	44.8	41.7	44.0	47.5	43.0
Mean annual income	\$46,192	\$46,312	\$46,096	\$47,407	\$46,897	\$47,545
Chronic Medical Conditions						
Hypertension	15.7%	19.8%	12.4%	18.5%	28.7%	15.8%
Lipid disorder	18.0%	22.7%	14.3%	18.9%	30.4%	15.8%
Diabetes	4.8%	6.2%	3.7%	6.2%	10.7%	5.0%
Coronary disease	5.0%	6.2%	4.1%	6.2%	9.6%	5.3%
COPD	2.5%	2.9%	2.3%	2.8%	4.3%	2.4%
Asthma	4.8%	6.1%	3.7%	3.9%	6.1%	3.3%

Table 2. Comparison of Predictive Models

	Previous Flu Vaccine (PF)	Medical Claims (MC)	Activity (A)	PF + MC	PF + A
Area Under Curve	0.774	0.635	0.584	0.787	0.793

We compared four predictive models: Previous year flu vaccine only (PF), medical claims data without previous year flu status (MC), Activity from WAM only (A), PF+MC and PF+A.

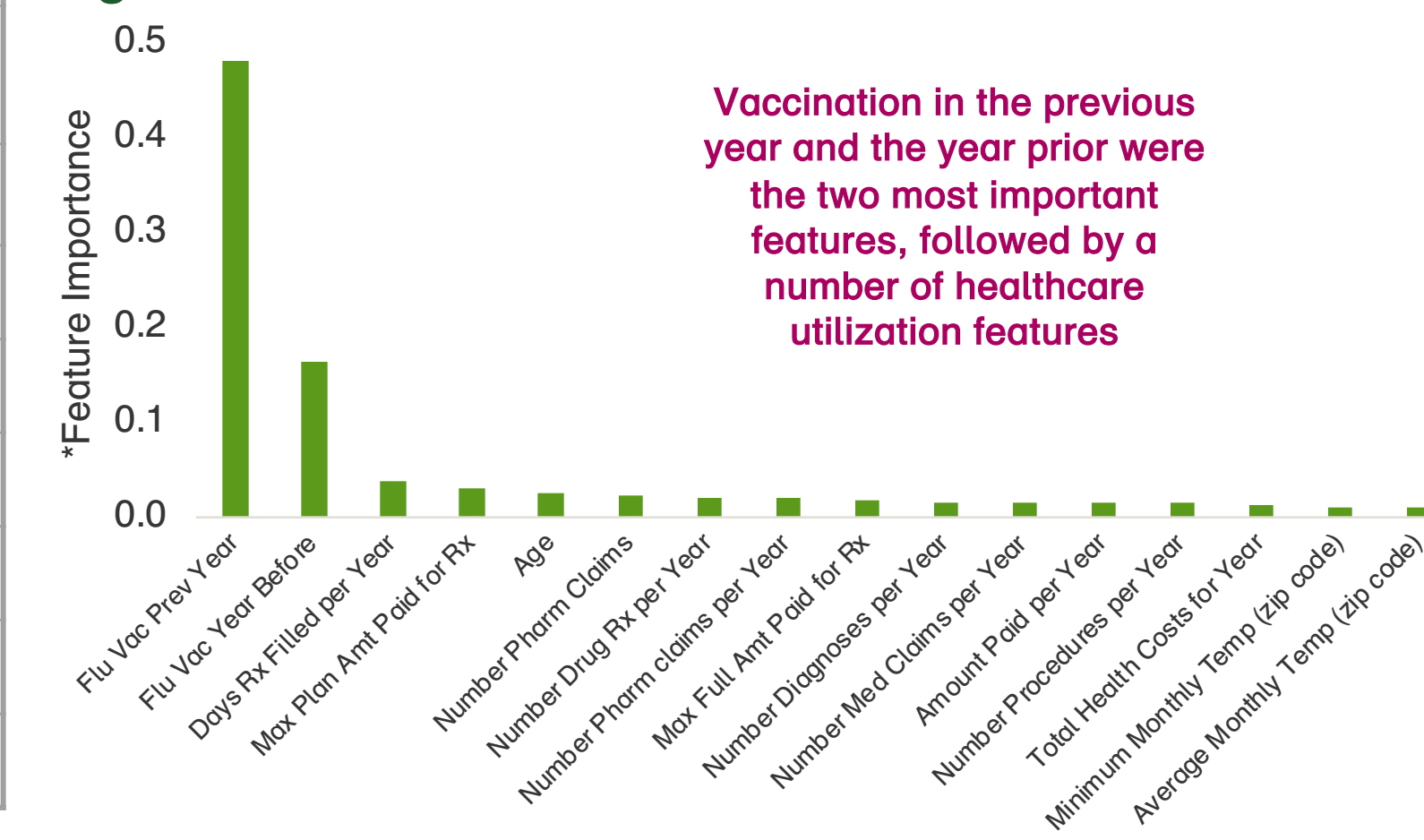
These results suggest that WAM data can perform comparably to medical claims data only when combined with previous year flu vaccination status

Table 3. Sample Features Analyzed in Model

Diagnosis of		Demographics	
COPD/Asthma	Diabetes	Age	Gender
Heart Disease	Lipid Disorders	Census based income	Number Children
Sleep Disorder	Obesity	Family Size	Number Relations
Health Services Utilized (averaged per week)		Pharmacy-Related	
Doctor Visits	Influenza Vaccination	Avg Medical Costs	Number Claim Delays
ER Visits	Hospital Visits	Max Paid for Meds	
Prescriptions Filled	Pharmacy Visits		
Mobile Device Activity Features			
		Steps	Sleep
		Food Diary	Self Reported Weight

679 total features in the analysis

Figure 2. Rank Order of Lasso Selected Features



*Feature importance was determined using the Gini impurity index.

Conclusions

- This study found that WAM data in combination with prior influenza vaccination status performed comparably to conventional medical and pharmacy claims data as is typically used in real world evidence
- Advantages to WAM data include: 1) Following user consent, WAM is unobtrusively collected and does not require active user engagement; and 2) information can be summarized over different time granularities of day, hour and even minute levels.
- WAM can interact with mobile applications and cloud based analytic engines for real time predictions and analysis. This enables the delivery of mobile app based interventions that are personalized and thereby relevant to the individual
- Current limitations in WAM data such as inconsistent use, device inaccuracies and a user profile that skews toward younger more affluent people will likely become less relevant as technologies improve and use becomes more commonplace within the consumer market
- Predictive models using consumer mobile health data gathered by wearable activity monitors in conjunction with prior year vaccination status can be used to predict influenza vaccination behaviors in a large population. This finding has implications on the development of interactive mobile technologies to positively influence healthy behaviors at a population level

Limitations

- Results are subject to limitations inherent to claims data (e.g., coding errors, missing data, fixed variables).
- These models included data from a single healthcare company and may not be generalizable to all populations.

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