# OPTIMIZING HINI VACCINATION EFFORTS THROUGH PREDICTIVE MODELING

A PRESENTATION BY LISA MWIKALI

### INTRODUCTION

The HINI virus remains a global health concern. Predictive modeling offers insights into vaccination strategies, enhancing preparedness and response. This project aims to predict the likelihood of individuals receiving the HINI vaccine to enhance public health strategies

### **BUSINESS PROBLEM**

Optimizing public health efforts related to HINI vaccination by accurately predicting vaccination uptake and identifying key influencing factors.

### PROJECT GOALS

**Primary Goal:** To predict individuals' likelihood of receiving the HINI vaccine to improve vaccination campaigns.

### **Specific Objectives:**

- Identify significant predictors of vaccination uptake.
- Explore interaction effects between predictors.
- Develop a predictive model for classification.

### STAKEHOLDERS

### **Key Stakeholders:**

- Public Health Authorities: To enhance vaccination campaigns and outreach initiatives.
- Policymakers: To make informed decisions about vaccination policies and resource allocation.
- Healthcare Providers: To identify high-risk communities for targeted interventions.

### DATA OVERVIEW

Training Set Features: Includes demographics, health behavior, and vaccination status.

- **Demographics**: Age group, education level, marital status, income, and employment status.
- **Health Behavior**: Doctor's recommendation, perceived risk of contracting HINI, health insurance status, and previous vaccination history.
- Vaccination Status: Whether the individual received the HINI and seasonal flu vaccines.

**Test Set Features**: Similar to the training set, with demographics and health behavior data used to predict vaccination status.

Labels: HINI and seasonal vaccine status.

### **METHODOLOGY**

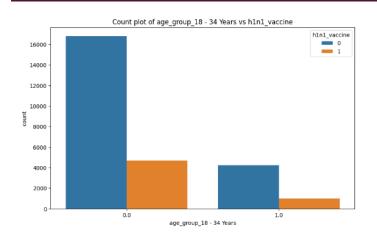
#### Steps:

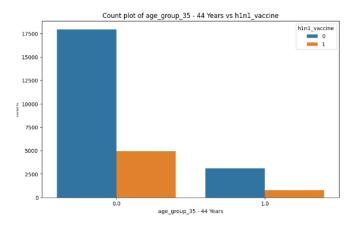
- Data Loading and Inspection: Cleaning and understanding the dataset.
- Data Cleaning and Preprocessing:
- Handling missing values and normalizing data.
- Mapping coded variables to meaningful labels for better interpretability.
- Model Training: Using various classification models to predict vaccination status.
- Evaluation: Comparing model performance using metrics like accuracy, precision, recall, and ROC-AUC.

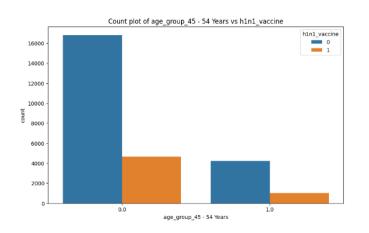
### SAMPLE DATA VISUALIZATIONS

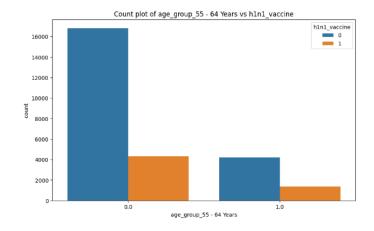
- Demographics Distribution: Visual representation of age groups, education levels, and income brackets.
- Health Behavior Insights: Charts showing the correlation between doctor's recommendations and vaccination uptake.

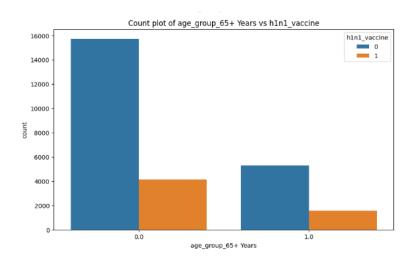
### VISUAL REPRESENTATION OF AGE GROUPS VS HINI CONCERN



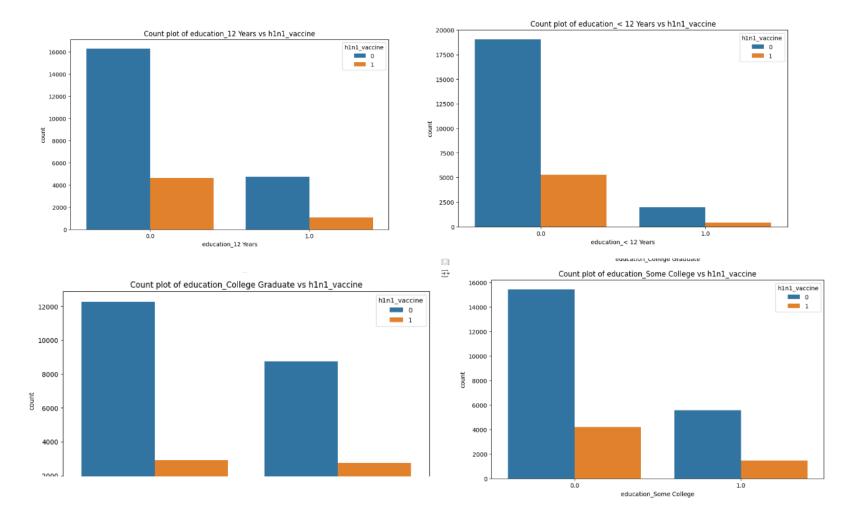




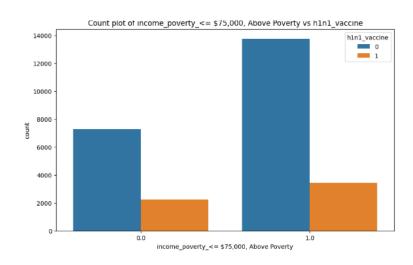


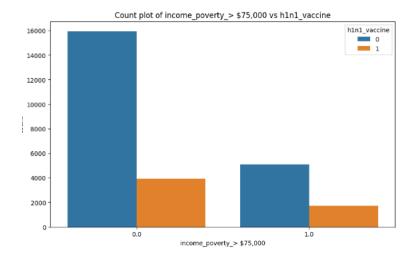


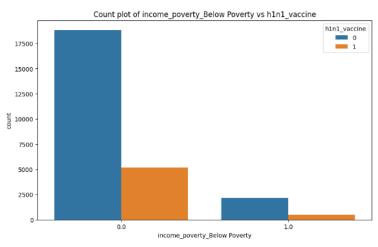
## VISUAL REPRESENTATION OF EDUCATION LEVELVS HINI CONCERN



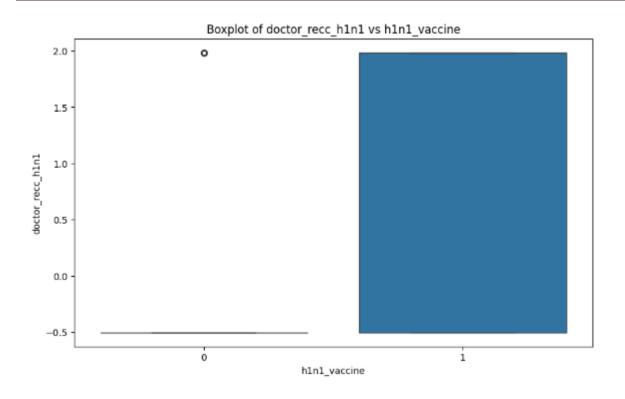
### VISUAL REPRESENTATION OF INCOME LEVELVS HINI CONCERN







## BOX PLOT SHOWING DOCTOR RECOMMENDATION NOTEVS HINI VACCINE



### SIGNIFICANT PREDICTORS

- Demographics: Age, education level, employment status.
- Health Factors: Doctor recommendations, perceived risk, and vaccine effectiveness.
- Socioeconomic Factors: Income, marital status.

### KEY INSIGHTS FROM DATA EXPLORATION

- Demographic Trends: Younger individuals and those with higher education levels are more likely to get vaccinated.
- **Health Influences**: Doctor's recommendation significantly increases the likelihood of vaccination.
- Socioeconomic Factors: Income and employment status influence vaccine uptake, with higher-income individuals more likely to get vaccinated.

### BASELINE MODEL USING RANDOM FOREST RESULTS

Validation Accuracy: 0.8367652564582553 Validation ROC AUC: 0.8259515585474287

Classification Report:

	precision	recall	f1-score	support
9	0.85	0.96	0.90	4212
1	0.72	0.38	0.49	1130
accuracy			0.84	5342
macro avg weighted avg	0.79 0.82	0.67 0.84	0.70 0.82	5342 5342

### PREDICTIVE MODELING

### **Evaluation Metrics:**

- Accuracy
- Precision
- Recall
- FI Score

#### PREDICTIVE MODEL PERFORMANCE OF OTHER MODELS

Precision: 0.6986 Recall: 0.4265 E1-score: 0.5297 ROC-4HC: 0.8314 Model: Decision Tree Cross-Validation Accuracy: 0.7530 +/- 0.0032 Validation Accuracy: 0.7551 Precision: 0.4253 Recall: 0.4487 F1-score: 0.4367 ROC-AUC: 0.6430 Model: Random Forest Cross-Validation Accuracy: 0.8341 +/- 0.0027 Validation Accuracy: 0.8373 Precision: 0.7208 Recall: 0.3770 F1-score: 0.4951 ROC-AUC: 0.8319

Model: Support Vector Machine

Cross-Validation Accuracy: 0.8362 +/- 0.0045

Validation Accuracy: 0.8398

Validation Accuracy: 0.8398

Precision: 0.6986 Recall: 0.4265 F1-score: 0.5297 ROC-AUC: 0.8052 -----

Model: Gradient Boosting

Cross-Validation Accuracy: 0.8380 +/- 0.0032

Validation Accuracy: 0.8411

Precision: 0.6993

Recall: 0.4363

F1-score: 0.5373 ROC-AUC: 0.8390

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Best performing model: Gradient Boosting with an accuracy of 84.11%.

### RECOMMENDATIONS

- Targeted Educational Campaigns: Focus on low-education groups to increase vaccine awareness.
- Improved Access: Enhance healthcare services and outreach programs for low-income individuals.
- Cultural Tailoring: Address cultural beliefs and preferences in vaccination campaigns.
- Policy Adjustments: Allocate resources to areas with low vaccination uptake.
- Healthcare Provider Training: Strengthen provider recommendations through education and training.
- Clear Communication: Address misconceptions with accurate information about HINI risks and vaccine effectiveness.

### CONCLUSION

Our data-driven approach provides valuable insights into vaccination behaviors, enabling stakeholders to design more effective public health strategies.