

# Influenza Surveillance Using Wearable Mobile Health Devices

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## Objective

To describe population-level response to influenza-like illness (ILI) as measured by wearable mobile health (mHealth) devices across multiple dimensions including steps, heart rate, and sleep duration and to assess the potential for using large networks of mHealth devices for influenza surveillance.

## Introduction

Influenza surveillance has been a major focus of Data Science efforts to use novel data sources in population and public health [1]. This interest reflects the public health utility of timely identification of flu outbreaks and characterization of their severity and dynamics. Such information can inform mitigation efforts including the targeting of interventions and public health messaging. The key requirement for influenza surveillance systems based on novel data streams is establishing their relationship with underlying influenza patterns [2]. We assess the potential utility of wearable mHealth devices by establishing the aggregate responses to ILI along three dimensions: steps, sleep, and heart rate. Surveillance based on mHealth devices may have several desirable characteristics including 1) high resolution individual-level responses that can be prospectively analyzed in near real-time, 2) indications of physiological responses to flu that should be resistant to feedback loops, changes in health seeking behavior, and changes in technology use, 3) a growing user-base often organized into networks by providers or payers with increasing data quality and completeness, 4) the ability to query individual users underlying aggregate signals, and 5) demographic and geographic information enabling detailed characterization. These features suggest the potential of mHealth data to deliver “faster, more locally relevant” surveillance systems [3].

## Methods

During the 2017/2018 influenza season, surveys were conducted within the Achievement platform, a health app that integrates with a variety of wearable trackers and consumer health applications [4]. The Achievement population has given consent agreeing to participation in studies like the one presented here and permitting access to their data. Surveys queried users as to whether they had experienced flu-like (ILI) symptoms in the preceding 14 days. Respondents who had experienced symptoms were then asked to identify symptom days. Those who had not experienced symptoms were queried again two weeks later. Positive responses were re-indexed to align by date of symptom onset. Individual respondent’s measures were standardized on a per-individual level in the 6 week period centered on the index date. Population-level mean signals were directly computed across several dimensions including steps, sleep, and heart rate. Uncertainty was quantified using resampling.

## Results

Beginning February 17th, 2018, surveys were distributed to Achievement users. Within the first week 31,934 users had responded to the survey. Over a 12- week period, 124,892 individuals completed the survey with 25,512 reporting flu-like symptoms in a two week period prior to the survey. Of these, 9,495 had wearable device data in the 90-day window surrounding their symptom dates and 3,362 respondents had “dense” data defined as no more than 4 consecutive missing days in the 6-week period surrounding the index date.

Population-level signals to ILI were clearly evident for five measures across the three dimensions. Step count [fig. 1] and time spent active [fig. 2] decreased 1 day prior to reported symptom onset date (index date), with a minimum at day 2 of  $-.24$  std. dev. for step count and  $-.25$  std. dev. for time spent active, and a return to baseline at day 8. Sleeplessness [fig.3] and time spent in bed [fig. 4] increased one day prior to index, peaking 4 days after index at a mean increase of  $.16$  std. dev. for sleeplessness and  $.13$  std. dev. for time spent in bed, and returning to baseline at 7 days. Heart rate was elevated from 1 day before index to day 6 with a peak increase of  $.18$  std. dev. on days 2 and 3 after index.



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## Conclusions

The potential of mHealth devices to register illness has been recognized [5]. This study is the first to present population-level influenza signals in a large network of mHealth users. Mobile health device data linked to ILI-specific survey responses taken during the 2017/18 flu season demonstrate clear aggregate patterns across several dimensions including sleep, steps, and heart rate. These signals suggest the potential for systems to rapidly process individual-level responses to classify ILI and to use such classifiers for ILI surveillance. The data described here, high resolution individual-level behavioral and physiological data linked to timely survey responses, suggests the potential to further enhance outbreak detection and improve characterization of ILI patterns. The setting of our study, a very large network of mobile health device users who have consented to the prospective use of their data and to being queried about their health status, could provide a framework for automated prospective influenza surveillance using “real world evidence” [6]. Employed over a population-representative sample, this approach could provide adjunct to standard clinically-based sentinel systems.

## References

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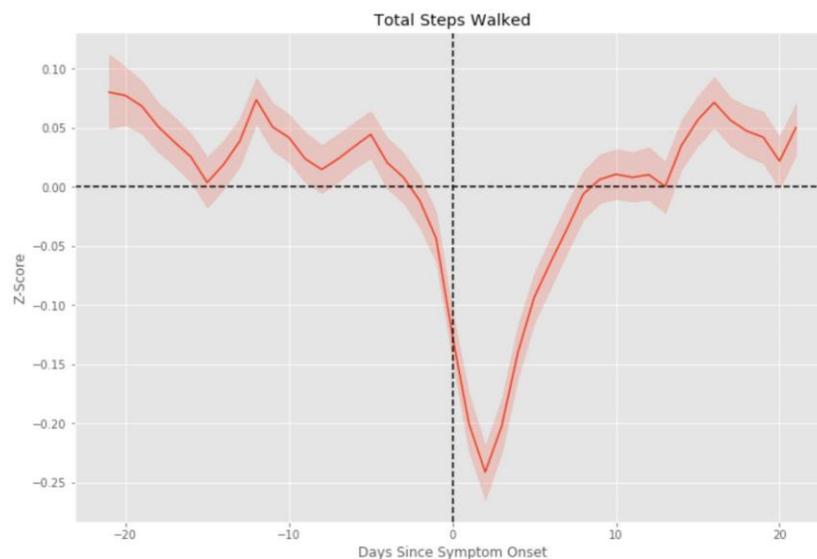


Figure 1: Mean standardized total steps around reported ILI symptom onset date



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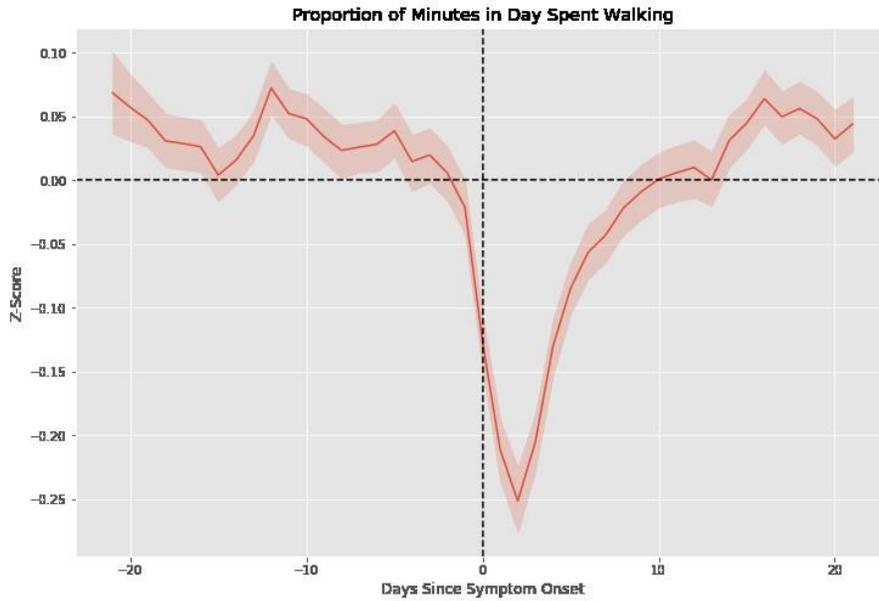


Figure 2: Mean standardized active minutes around reported ILI symptom onset date

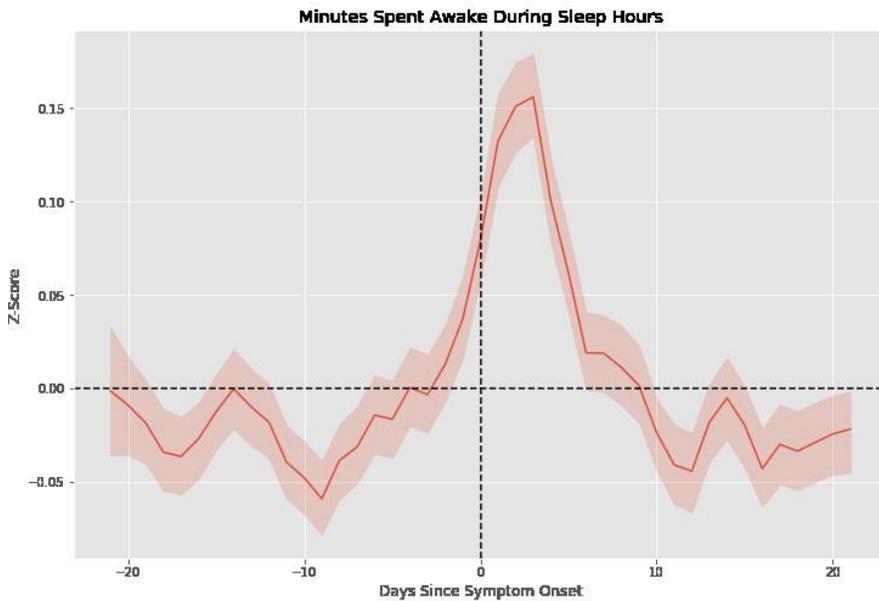


Figure 3: Mean standardized minutes awake around reported ILI symptom onset date



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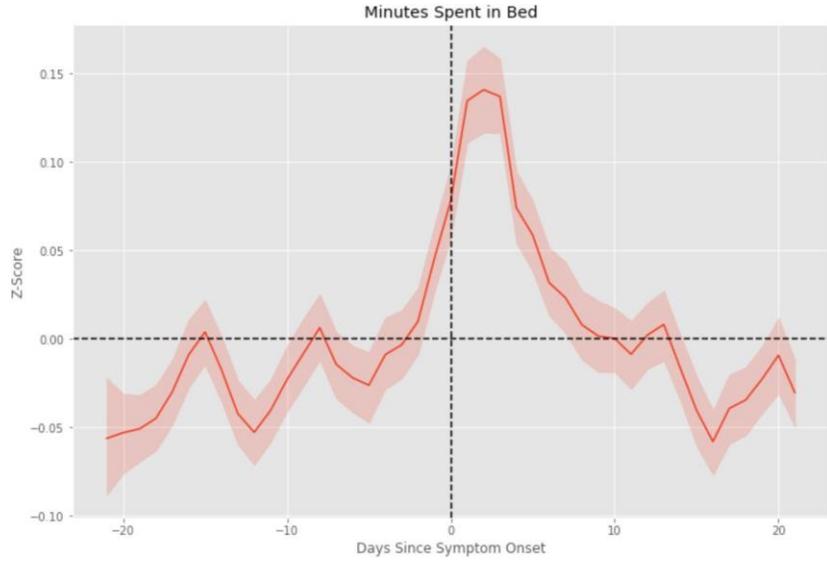


Figure 4: Mean standardized time in bed around reported ILI symptom onset date



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