# HHeal: A Personalized Health App for Flu Tracking and Prevention

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## Abstract

We report a new mobile application, HHeal, that integrates individuals' flu risk information and flu-preventive behaviors. The app provides a personal flu risk bar that rises when the user is near someone with flu-like symptoms and drops when the user finishes one of the suggested flu-preventive behaviors. Preliminary results show that participants favored the personal flu risk bar design. Participants had positive experiences when their personal risk bars dropped. They were motivated to initiate flu-preventive behaviors when their personal risk bars rose. Our next step includes studying reward strategies, users' motivations to share personal health information, and building a more accurate model of flu risk.

## **Author Keywords**

Flu tracking; mHealth; Behavior change.

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## ACM Classification Keywords

H.5.2 User Interfaces: User-centered Design; J.3 Life and medical sciences: Health.

## Introduction

Nearly all people have had the experience of getting flu (influenza). Some people get the flu even after getting a flu vaccination. There is scientific evidence about several complementary health approaches for reducing flu. Table 1 notes six behaviors that have been studied and showed effects on flu contraction rates. In general, these approaches reduce the possibilities of contracting flu by boosting people's immune systems<sup>1</sup>. For example, in a large-scale longitudinal study [1] that tracked 641 healthy inactive and moderately active adults, researchers found that moderately active individuals reported 30% fewer infections than inactive individuals during the flu season. According to a 2011 meta-analysis of 10 studies [2], people taking probiotics were 42% less likely to get a cold than those on a placebo.

In addition to boosting your immune system to prevent the flu, avoiding contacts with infectious people could also help prevent flu. In a study during the spread of H1N1 flu in 2009 [3], researchers surveyed passengers on international flights. Passengers were found to be at

<sup>&</sup>lt;sup>1</sup> For details and cited studies, see the HHeal website http://www.nali4design.com/ - !hheal/c1lpe

Behavior	Effect
Moderate exercise 40 mins	30%
Take vitamin D supple- ments 5000 IU	50%
Take echinacea extract 2400 mg	20%
Drink 8 8-ounce glasses of water	42%
Take probiotics	42%
Sleep 8 hrs.	10%

**Table 1**. Six behaviors that haveshown effects on adults' flu contractionrates.

a 3.6% increased risk for flu if they sat within two rows of someone with symptoms, and the risk jumped to 7.7% for those who sat within two seats.

Many applications provide flu information organized by the transmissible disease around them, and if possible, alert users in high-risk areas. The main source of this information is from the Centers for Disease Control and Prevention (CDC)<sup>2</sup>. Google also provides flu trend information<sup>3</sup>. However, Google's algorithm that mainly uses search words to predict flu trends has been noted as being noisy and not accurate [4].

Nonetheless, neither of these two sources provides exact location information that is granular enough that can be used to inform individuals about their personal flu risks in actionable ways. Some flu information apps, such as *Flu near you*<sup>4</sup> and *SickWeather*<sup>5</sup> collect flu location information and notify susceptible users. These apps visualize flu cases as markers on a map. In this paper, we report on the design and preliminary evaluation of HHeal (pronounced 'heal'), which integrates an individual's flu risk information and fluprevent behaviors. Our overarching design goal was to convey local flu risk and promote flu-preventive behaviors. In a nutshell, HHeal provides a personal flu risk bar, which varies based on how close the user is to someone with symptoms and drops when the user fin-

- <sup>3</sup> https://www.google.org/flutrends/us/#US
- <sup>4</sup> https://flunearyou.org

<sup>5</sup> http://www.sickweather.com

ishes one of the six flu-preventive behaviors listed in Table 1. We conducted a six-week study with six participants to evaluate the initial design. Preliminary results showed that participants found the personal flu risk bar helpful in fostering flu-preventive behaviors.

# **HHeal Design**

Figure 1 shows the main HHeal screen. Object b in Figure 1 shows the flu-preventive behaviors that people committed that day. The six flu-preventive behaviors are framed as immune trainings. Detailed information about each training is presented on a training card. People can select, deselect, or report completed trainings daily. They will get notifications of unfinished trainings at certain times of a day. Object c links to a reporting page where users can report flu symptoms. Object D is a button that allows users who declined GPS location service to report their location manually. A numeric model calculates and updates the personal flu risk in real-time. The personal flu risk is determined by two factors—(1) immune-boosting (as flupreventive) behaviors and (2) infectious people nearby:

(1) The more an individual practices the suggested trainings, the lower their personal flu risk. Because every training represents a lifestyle that needs to be maintained for a while to see the effect, we designed a "drop and stay" visualization to help people understand the long-term effect. When an individual completes a training for the first time, for example, taking Vitamin D, his personal risk will immediately drop by 50% (the overall effect, see Table 1). If he stops taking Vitamin D in the following days, his risk will gradually rise (approximately 10.375% per day—the single day effect). If he does not take vitamin D for a week, excluding other factors, his personal risk will grow back as before. If he

<sup>&</sup>lt;sup>2</sup> See CDC weekly flu report dashboard, http://gis.cdc.gov/grasp/fluview/fluportaldashboard.ht ml



**Figure 1.** The main interface of HHeal. (a) The blue bar (left) represents the CDC local flu risk and the green bar (right) represents the personal flu risk. The grey numbers are the y-axis of the flu risk bar plots. Objects b, c, & d are explained in the text.

takes vitamin D again within seven days, his personal risk will be lowered by approximately 10.375% but the cumulative effect cannot exceed 50%. To maintain the overall effect of reducing 50% risk, he has to keep taking Vitamin D every day.

(2) People can self-report flu-like symptoms. The HHeal backend technology will automatically search for people who interacted with anyone who reported flu symptoms from 24 hours before the self-report to seven days after the report. The interaction is modeled as two users' geo-location closer than 20 meters at some time point. For users who are detected to have interacted with infectious users, their personal flu risk bar will rise by 1.036% per interaction (see [3]). These users are susceptible people. According to the CDC<sup>6</sup>, the typical incubation period for influenza is one to four days. After four days, one can either stay healthy indicating being clear of the virus or start to show symptoms indicating being affected by the virus. The HHeal system will reset a user's personal flu risk to his or her original value after the incubation period is over unless the user reports flu symptoms.

Because flu risk can change dramatically over an entire year, ranging from less than 0.2% per week in the summer to over 15% per week in a flu outbreak, we face two challenges in visualizing the flu data: (a) visualizing a small-probability hazard that is noticeable; (b) visualizing the change of risk that is easy to understand.

To address these challenges, we created a dynamic visualization mechanism to magnify small flu risks.

Specifically, we dynamically set the scale of the bars by the higher flu risk, such that the higher flu risk (either local risk or personal risk) always appears to be a full bar. This design magnifies the small risk numbers and makes the change of risk more noticeable. For example, in Figure 1, the local risk (approximately 0.7%) is higher than the personal risk (approximately 0.5%), so the y-axis is set from 0 to 0.7 (%). Users can easily estimate that the value of the green bar is about 0.5. If the y-axis is constantly set from 0 to 100 (%), it would be hard to view a bar that is 0.7% out of 100%, and it would be even harder to notice the difference between 0.7% and 0.5%, even if it's nearly a 30% drop.

## **User Study**

We recruited six graduate students to participate in a three-phased, six-week (2 weeks/phase) study to evaluate a test version of HHeal. Phase 1 was a control condition, in which participants were asked to record the six flu-preventive behaviors every day using a paper-based daily behavior tracking form. During Phase 2, participants used a partial system of HHeal with all the features enabled except the personal risk bar. During Phase 3, participants used the full HHeal system. During Phase 2 and 3, we asked participants to use the app at least once per day. We collected usage data, which included users' personal usage rates per day, selected and completed training cards, location information, and flu reports. We also interviewed the participants after Phase 3. In the interview, some participants revealed that they selected a card to indicate completion of the card. Due to the interchangeable usage of the two features, we chose not to distinguish selected cards and completed cards in this analysis. There was a slight increasing trend in terms of flu preventive behaviors between Phase 2 and Phase 3. In

<sup>&</sup>lt;sup>6</sup> http://www.cdc.gov/flu/professionals/acip/clinical.htm

	Phase 1 (cards/ week)	Phase 2 (cards/ week)	Phase 3 (cards/ week)
P1	7.5	2.5	11.5
P2	10	2	10
P3	11.5	1.5	2.5
P4	21	6.5	7.5
P5	9.5	11.5	8
P6	6.5	5	3

**Table 2**. The number of trainingscompleted per week\* for each participant in each phase.

\* Records in phase 1 are not included in the analysis. Although participants were instructed to only record their behaviors of the current day, they ended up reporting their records for several days before. However, in Phase 2 and 3, participants could not revise their records in the app. In fact, all the participants revealed that sometimes they forgot to select or report training in the app, when they remembered the day had passed and they could not added the record. Table 2, we show the average number of selected and completed training cards per week per individual for all phases. Phase 3 was from Dec. 7 to Dec. 21, 2014, during which all the participants were busy with finals or interviews. Nonetheless, four of six participants still followed the suggested trainings during Phase 3 better than Phase 2. During the exit interview, participants described how they interpreted and used the personal flu risk information—seeing a decrease in their personal risk made them feel accomplished while seeing an increase in the personal risk made them anxious. Several participants did trainings to keep their personal risk low.

It turned out that what mattered was not the exact percentage of personal flu risk, but the relative risk (i.e., the difference between the two risk bars) that affected participants' behavior. Only one participant (P4) noticed that the local CDC flu risk had increased from 1.7% to 2.7% during the last four weeks (Phase 2) and 3). P4 also accurately estimated that 2.7% was a high risk in the flu season. Even though P4 could make sense of the number, most of the time he only paid attention to the difference between the two bars, because they were "salient and easy to understand." Other participants admitted that they did not care about the exact percentage because they did not know how to interpret the risk information. However, they did care about the difference between the two bars. They related the decrease of the personal risk bar with feeling effective combating flu, and being healthier, happier, and relieved. They attributed these feelings to being able to control their health—a sense of self-agency that could in turn stimulate people's intrinsic motivation, an effect found in classroom and organizations when people were empowered with choices [5, 6].

To see if participants could easily understand how the personal risk bar works, we asked them to describe how they thought the personal risk bar changed. All the participants could figure out the mechanism—the two risk factors—that they inferred from simply using HHeal.

Based on people's flu symptom reporting and the post interview data, no participants contracted flu during the study; therefore, we could not obtain users' experience with reporting flu symptoms. One participant shared his concern about reporting flu symptoms. He did not want to share his location or his flu status, because this was "personal information."

To check participants' responses to others' flu report, a researcher falsely reported having a flu during Phase 3. Because all the participants and the researcher worked close to each other, the system detected the interactions and increased each participant's personal flu risk by 1.036%. When we asked if they noticed any increase in their personal risk bar, all the participants thought that the increase was due to lack of immune trainings, and that they would do more trainings to lower the risk. This response reassured us that the integrated visualization concept could protect users' privacy, while at the same time encouraging flupreventive behaviors.

## **Design Implications**

Persuading people to initiate immune-boosting practices (e.g., exercise) has a broad implication in public health. In epidemiology for example, the average transmission rate of the seasonal flu is about  $R_0=1.3$ [7]. This means that each infectious person will on av-

erage infect 1.3 people, and those people will in turn infect more people, and the outbreak will cascade. However, designing effective risk communication to encourage immune-boosting practice is a hard problem, especially when conveying small-probability risk (such as 2.3%). People may easily dismiss the risk because it feels like it is such a small number. However, there are ways to frame this information (e.g., using the raw count such as number of people) that can conform to people's expectation of significance [8]. We'll need to explore further how to design visualization to communicate risk such that it can enhance people's risk perception as well as motivate them to initiate healthy behaviors.

Previous work has explored visualizing aggregated data to communicate the effect at large scale or over time. For example, *HealthMap*<sup>7</sup> aggregates data across geographical locations and reports the total number of people who reported influenza-like illness in each city each week. In a literature review of risk communication using graphics [8], two studies showed that people who were shown cumulative risk over time got a better understanding of the risks (e.g., better estimation of the risk of exposure to radon in the long run and understanding the effects of carrier status on getting breast cancer over time). However, one drawback of this approach is that it is hard for a person to connect the effects to their individual situation and personal experience. Indeed, it is unclear whether this approach can stimulate people to change behaviors in their everyday life.

Our design of the personal flu risk bar provides flu information at an individual level, which has shown to be effective in fostering flu-preventive behaviors. The design implements a drop-and-stay visualization, which lowers the personal risk bar by the long-term cumulative effect of a training upon finishing. Participants reported a high sense of self-agency after seeing this visualization. In fact, this effect has just been studied in another domain. A recent study about sense of agency for motor movements showed that participants "felt a higher sense of agency for the incongruent outcome when false feedback was given" [9]. Studying the relationship between the magnitude of rewards and behavior change warrants further investigation. In our future work, we plan to alter the magnitude of the rewards to explore the best reward approach to promote behavior change. At the same time, we will make sure the cumulative effect conforms to the effects reported in the scientific studies (summarized in Table 1). To validate the effect of falsely enlarged rewards on people's attitude and behavior change, we plan to run a large-scale online study, testing multiple reward strategies and comparing their effects.

Another direction in our future work is to explore ways to encourage people to report flu symptoms. During our interviews, participants showed concerns about their privacy when reporting flu symptoms and locations. In fact, our personal flu risk bar integrates susceptible probability and flu-preventive training effects, so people cannot identify nearby infectious people. Despite the privacy concerns, people still are not always willing to share health information for the public good. In our future work, we plan to allow users to form groups and share flu symptoms and training achievements in their affiliated groups, because social attachment can help

<sup>&</sup>lt;sup>7</sup> http://healthmap.org

people feel more comfortable sharing health information among intimate group members such as families and classmates.

Finally, we will continuously refine the numeric model. HHeal collects users' age, gender, location and flu report. As more data coming in, we expect to build a model that more accurately reflects the effects of flupreventive behaviors on different people. Furthermore, the system can provide more personalized suggestions to these different people.

## Conclusion

In this paper, we presented HHeal, an iPhone app that communicates flu risks and encourages flu-preventive behaviors. The HHeal system used a new data model that integrates local CDC flu information and reporting of flu symptoms and flu-preventive behaviors. We visualized the data model as a personal flu risk bar, which dynamically changes in real-time. Preliminary results showed that participants found the personal flu risk bar helpful. During exit interviews, participants described that seeing dynamic personal flu risk gave them the feeling of being in control of their health, and that motived them to do more health trainings. In our future work, we will explore ways to maximize people's sense of self-agency to increase motivation to initiate healthy behaviors. We will also explore how to encourage people to report flu, as well as build a refined numeric model to provide personalized suggestions to different people.

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