AirSense: An Intelligent Home-based Sensing System for Indoor Air Quality Analytics

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ABSTRACT
In the U.S., people spend approximately 90 percent of their time indoors. Unfortunately, indoor air quality (IAQ) may be two to five times worse than the air outdoors, and is often overlooked. Existing IAQ monitoring technologies focus on IAQ measurements and visualization. However, the lack of information about the pollution sources as well as the seriousness of the pollution makes people feel powerless and frustrated, resulting in the ignorance of the polluted air at their homes. In this work, we fill this critical gap by presenting *AirSense*, an intelligent home-based IAQ sensing system that is able to automatically detect pollution events, identify pollution sources, estimate personal exposure to indoor air pollution, and provide actionable suggestions to help people improve IAQ. We have deployed AirSense at five homes to evaluate its performance and investigate how users interact with it. We demonstrate that AirSense can accurately detect pollution events, identify pollution sources, and forecast IAQ information within five minutes in both controlled and real-world settings. We further show the great potential of AirSense in increasing users' awareness of IAQ and helping them better manage IAQ at their homes.

ACM Classification Keywords
C.3 Special-Purpose and Application-Based Systems: Real-time and embedded systems

Author Keywords
indoor air quality; IAQ; smart home; Internet of Things; IoT; human factors; behavior change technology.

INTRODUCTION
Indoor air quality (IAQ) plays a significant role in our daily lives. In the United States, people spend approximately 90 percent of their time indoors, consuming about 3400 gallons of air on average every day [24]. Unfortunately, according to Environmental Protection Agency (EPA), indoor air pollution may be two to five times – and on occasion more than 100 times – worse than the air outdoors. Poor IAQ could pose significant risks to people's health and is the leading cause of respiratory infections, chronic lung diseases, and cancers [17].

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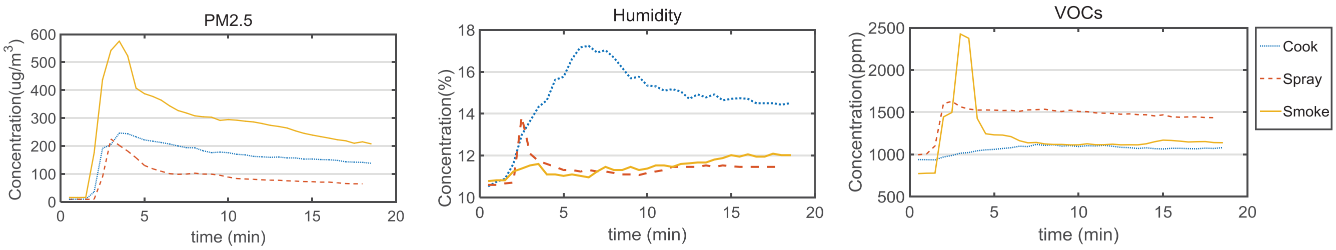
A majority of indoor air pollution is caused by people's daily household activities. For example, oil-based cooking could generate remarkable amounts of harmful airborne particulate matter (PM) with a diameter of 2.5 micrometers or less (PM 2.5) [15]. Tobacco smoking produces more than 4000 types of chemicals (with many of them identified as carcinogens) in the form of PM 2.5 and gases including volatile organic compounds (VOCs) [6, 12]. Many household products for cleaning and maintenance such as disinfectants and pesticides contain and release PM 2.5 and numerous VOCs more or less that lead to long-term health concerns such as child developmental and hormonal issues [9, 13].

Although we are potentially exposed to such a variety of air pollution at home, IAQ is often overlooked for two reasons. First, although some of the indoor air pollutants like formaldehyde have irritating odor, the majority of them is colorless, odorless, or too tiny to be seen. This makes indoor air pollutants almost impossible to be detected by human beings. Second, many adverse health conditions caused by indoor air pollution such as cancer have no severe symptoms until years after long period of exposure [23]. For immediate adverse health effects, some of them such as coughs and headaches are very similar to symptoms of colds or other viral diseases. Therefore, it is very difficult to determine whether the symptoms are results of exposure to indoor air pollutants.

Due to its critical role in health and wellbeing, IAQ has attracted considerable attentions in the ubiquitous computing community in recent years. Pioneer work focused on developing IAQ monitoring systems for measuring and visualizing indoor air pollution levels [8, 16, 18, 26]. Although these systems could increase users' awareness of IAQ, *the lack of information about the pollution sources, the seriousness of the pollution, and the actionable suggestions to help users reduce the pollution makes people feel powerless and frustrated, leading to the ignorance of the indoor air pollution levels provided by the IAQ monitoring systems*.

In this work, we bridge this critical gap by developing *AirSense*, an intelligent home-based IAQ monitoring and analytics system that is capable of automatically detecting indoor air pollution events, identifying pollution sources, forecasting pollution levels to estimate the seriousness of the pollution, and providing actionable suggestions to help people improve IAQ in a timely manner. Specifically, AirSense is developed upon commercial off-the-shelf air quality sensors that continuously monitor the ambient temperature and humidity as well as the concentrations of PM 2.5 and VOCs, which are two of the most common air pollutants in the indoor environment [23]. To detect the occurrence of air pollution event,



(a) (b) (c)

Figure 1: The (a) PM 2.5, (b) humidity, and (c) VOCs sensor measurements of indoor air pollution generated by cooking, smoking, and spraying pesticide.

AirSense uses a normalized standard deviation based scheme to detect the sharp increase of the pollution level at the beginning of air pollution event in real-time. To identify the source of the pollution event, AirSense extracts a set of features from sensor data that are able to discriminate different pollution sources. Based on the identified pollution source, AirSense uses a non-parametric regression scheme to predict the pollution levels in the near future to estimate the seriousness of the pollution. Finally, AirSense provides suggestions tailored to the identified pollution source to guide people to taking appropriate actions to minimize their exposure to indoor air pollution. It also provides a detailed weekly IAQ profiling report that helps people better understand how their household activities impact IAQ and pinpoint household activities that pollute their indoor air the most.

Summary of Experimental Results: We focus on three of the most common household activities that generate significant indoor air pollution – cooking, smoking, and spraying pesticide – to examine the feasibility of AirSense. We have evaluated the performance of AirSense by conducting experiments at two homes for ten weeks for controlled evaluation as well as at three homes for nine weeks for uncontrolled real-world deployment. The results of our experiments show that:

- In controlled settings, AirSense can accurately detect the pollution events and identify cooking, smoking, spraying pesticide and their combinations as pollution sources with an average accuracy of 95.8%. It can forecast pollution levels with an average error of less than or equal to 8.1% within five minutes after occurrences of pollution events.
- Through controlled experiments, we have also demonstrated that AirSense is robust to different deployment locations as well as diverse pollution source subcategories.
- When deployed in the real world, AirSense shows the great potential in increasing users' awareness of IAQ and helping them better manage IAQ at their homes.

Summary of Contributions: We introduce AirSense as the first IAQ monitoring and analytics system that is able to identify pollution sources, estimate the seriousness of pollution, and provide early warnings to users and assist them to reduce indoor air pollution. Equipped with both monitoring and analytics capabilities, AirSense would be very helpful for people who are sensitive to air quality. Although currently designed for home uses, AirSense can be extended and find its applications in public buildings such as office rooms, shopping malls and subway stations. Therefore, we believe AirSense has tremendous potential to be widely adopted in real world.

MOTIVATING OBSERVATIONS

Figure 1 illustrates the PM 2.5, humidity and VOCs sensor measurements of indoor air pollution generated by cooking, smoking and spraying pesticide. The design of AirSense is motivated by two key observations from Figure 1. First, these three household activities all cause changes in PM 2.5, humidity, and VOCs levels. This motivates us to use PM 2.5, humidity, and VOCs sensors to detect indoor air pollution caused by them. For example, it is known from the literature that cooking, smoking and spraying pesticide all generate PM 2.5 [15, 12, 9]. As shown in Figure 1(a), there is a sharp increase in PM 2.5 measurements at the beginning of these three household activities. This indicates that PM 2.5 sensor could be helpful in detecting them. Second, there are unique patterns embedded in the sensor measurements which can be leveraged to differentiate these three household activities. This motivates us to develop pattern recognition and classification algorithms to recognize these household activities as pollution sources from sensor measurements. For example, in Figure 1(b), the humidity level changes only 1% for smoking while it increases about 7% for cooking. As another example, in Figure 1(a), the decreasing rate after the peak value of cooking is slower than the ones of both smoking and spraying pesticide. We can extract features to capture these patterns to help identify pollution sources.

AIRSENSE OVERVIEW

Figure 2 provides an overview of the system architecture of AirSense. As illustrated, AirSense consists of three components: an IAQ sensing platform, a cloud server and a smartphone application. The *IAQ Sensing Platform* is the host of four air quality sensors including temperature, humidity, PM 2.5 and VOCs sensors. It continuously samples these sensors and uploads the sensor data onto the cloud server. The cloud server stores the sensor data into the cloud database. It also runs an *Analytics Engine* that analyzes the collected sensor data. In particular, the analytics engine is able to detect the occurrences of indoor air pollution events, identify the sources of the pollution events, and forecast the pollution levels in the near future to estimate the expected personal exposure to indoor air pollution. AirSense will generate suggestions that are specific to the identified pollution sources. It will then deliver the suggestions to users via a *Smartphone Application* to assist them to reduce the pollution. Finally, a weekly IAQ profiling report is generated which summarizes the amount of indoor air pollution produced within each week. In the following sections, we describe all the three components of AirSense in details.

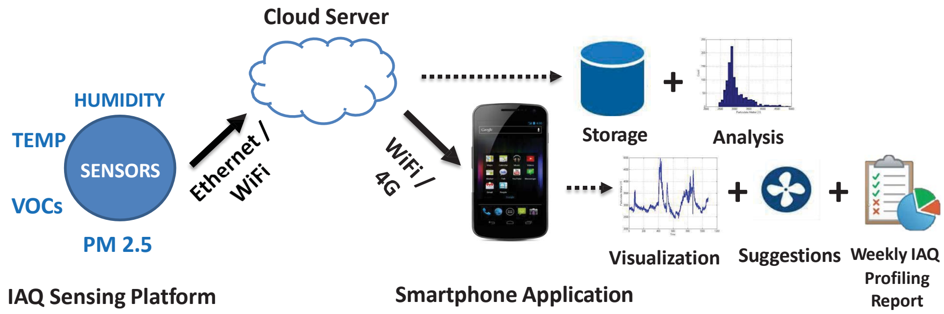


Figure 2: The overview of the system architecture of AirSense.

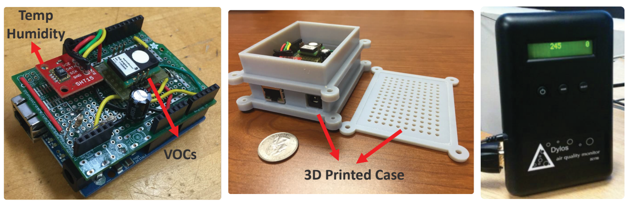


Figure 3: The IAQ sensing platform (left), the 3D printed case (middle), and the PM sensor (right).

IAQ SENSING PLATFORM

The IAQ sensing platform is developed on top of the Arduino Uno Ethernet board [2]. The platform has three onboard sensors including temperature, humidity and VOCs sensors (Figure 3 (left)) and is enclosed in a 3D printed case (Figure 3 (middle)). The sampled sensor data are transmitted to the cloud server via the onboard Ethernet port. Besides the onboard sensors, AirSense also incorporates a standalone consumer-grade Particulate Matter (PM) sensor DC1700 from Dylos to measure the concentration of indoor PM 2.5 [4] (Figure 3 (right)). We connect DC1700 to a mini laptop and use the Processing software [5] to retrieve PM 2.5 measurements from DC1700. The sampled sensor data are transmitted to the cloud server via WiFi. The sampling rate of all the sensors is set to one sample per five seconds. Table 1 summarizes the air quality sensors included in AirSense. It should be noted that all these sensors are factory calibrated with ensured measurement accuracy, repeatability and sensitivity. The measurement ranges of these sensors all meet the requirements of the national standards for IAQ monitoring.

Air Quality Sensor	Manufacturer
Particulate Matter (PM 2.5)	Dylos DC1700
Volatile Organic Compounds (VOCs)	AppliedSensor iAQ-engine
Humidity	Sensirion SHT15
Temperature	Sensirion SHT15

Table 1: Air quality sensors included in AirSense.

ANALYTICS ENGINE FOR IAQ ANALYSIS

Pollution Event Detection

Given the streaming air quality sensor data, the first stage of the analytics engine is to detect the occurrence of air pollution event. Indoor air pollution generated by pollution events usually stays in the air for a very long time. People might have already inhaled a large amount of polluted air before the end of events. To reduce the negative impact of indoor air pollution to people's health, it is critical to detect the occurrence of the pollution event as soon as possible.

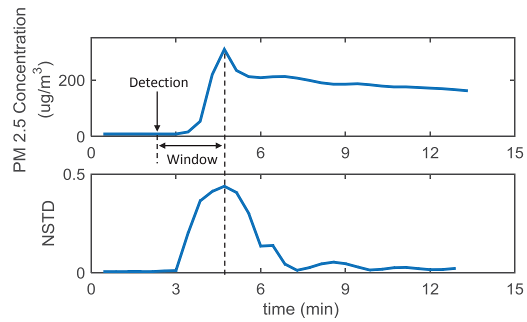


Figure 4: The illustration of the principle of the pollution event detection algorithm. The upper plot shows the PM 2.5 sensor data of the pesticide spray pollution event. The lower plot shows the corresponding NSTD values.

To achieve this goal, we adopt a normalized standard deviation (NSTD) based scheme to detect the beginning of the air pollution event in real time. As an illustration of our scheme, Figure 4 presents an example of the PM 2.5 sensor data of pesticide spray and its corresponding NSTD values. The key intuition behind our scheme is the observation that the beginning of an air pollution event is characterized by a sharp increase of sensor data. To capture this sharp increase, we first use a sliding window of size β and a step size of one data point to segment the sensor data stream. We then compute the NSTD of the data points inside the window. Specifically, let w be a window with β data points $s_1, s_2, \ldots, s_\beta$. The NSTD of window w is calculated as

$$NSTD(w) = \frac{1}{max(w)} \sqrt{\frac{1}{\beta} \sum_{j=1}^{\beta} (s_j - \mu)^2} \qquad (1)$$

where μ is the average of β data points and $max(w)$ is the maximum s_j in window w. As shown in Figure 4, the NSTD value is low before the window reaches the sharp increase. As the window slides forward and gradually covers the sharp increase, the NSTD value increases until it reaches the maximum. As the window keeps sliding forward, the NSTD value decreases and goes back to the low value in the end. Given this observation, we define the left end of the sliding window as the detection point of the event when the right end of the sliding window reaches the maximum NSTD value.

There are two key parameters in our pollution event detection scheme. The first parameter is the window size β. We have empirically tested a number of window sizes and have found that β equal to three minutes works robustly across all the

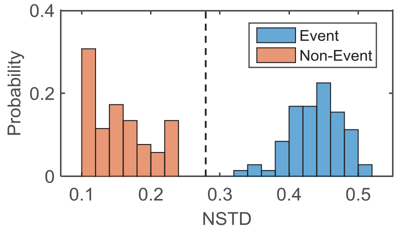


Figure 5: The normalized histogram of maximum NSTD values of pollution events vs. non-pollution events.

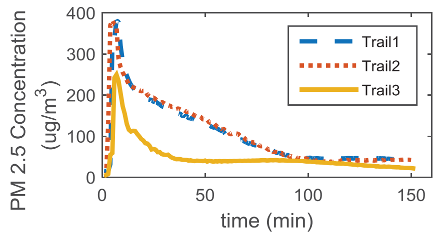


Figure 6: The illustration of the principle of the IAQ forecast algorithm.

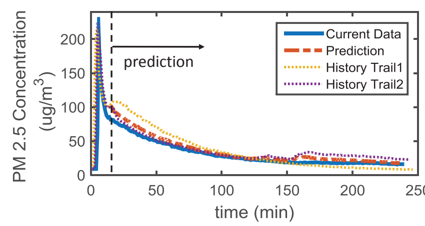


Figure 7: The illustration of the IAQ forecast algorithm in the context of predicting the PM 2.5 sensor values of a trial of pesticide spray.

PM 2.5 and VOCs Features		
Increase Rate	2	The increasing rate bewteen the peak and the first data point of the window
Increase Magnitude	2	The difference bewteen the peak and the first data point of the window
Decrease Rate	2	The decreasing rate bewteen the peak and the last data point of the window
Decrease Magnitude	2	The difference bewteen the peak and the last data point of the window
Standard Deviation	2	The standard deviation of all data points in the window
Humidity Features		
Change Magnitude	1	The difference between the maximum and minimum data points in the window
Standard Deviation	1	The standard deviation of all data points in the window
Cross-Sensor Features		
Change Magnitude Ratio	3	The change magnitude ratio among the three sensors
Standard Deviation Ratio	3	The standard deviation ratio among the three sensors

Table 2: List of features for pollution source identification. These include single-sensor features extracted from PM 2.5, VOCs and humidity sensor individually as well as cross-sensor features extracted from more than one sensors. The table lists the counts of features as well as the name and definition of each feature.

targeted pollution events. This is because air pollutants disperse very fast in the ambient atmosphere such that the peak of the concentrations of the air pollutants exhibits shortly after the occurrence of the air pollution event [22]. As such, this result indicates that AirSense could detect the air pollution event within three minutes after the event occurs. The second parameter is the threshold of the maximum NSTD value γ which we use to determine whether there is a pollution event or not. Moreover, this threshold is also used to filter out non-pollution events including confounding events (e.g. vacuuming, walking on the carpet) and cases where nothing happens. Figure 5 shows the normalized histogram of maximum NSTD values of the three targeted pollution events and the non-pollution events. As illustrated, all the trials of the three pollution events have the maximum NSTD values larger than 0.3 while all the trials of non-pollution events have the maximum NSTD values less than 0.24. Based on this result, we set the threshold γ to be 0.27.

Pollution Source Identification

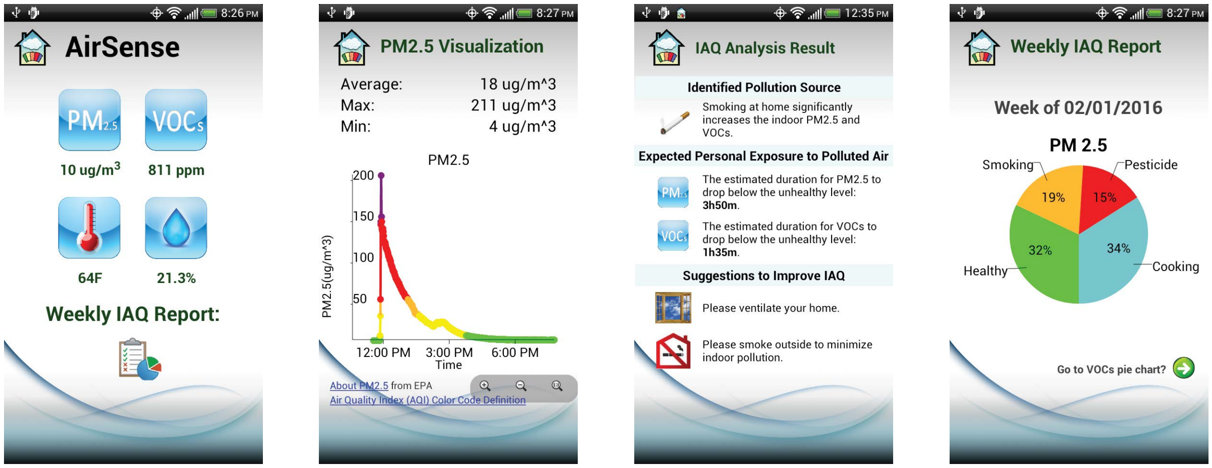
After detecting the occurrence of the air pollution event, the second stage of the analytics engine is to identify the source of the pollution event. We frame the pollution source identification problem as a classification problem. As the first step, we need to extract features that are able to discriminate different types of pollution events. As illustrated in Figure 1, the key intuition behind feature extraction is the observation that air pollution sensor data within the window starting from the beginning of the pollution event to two minutes after the peak value contains enough information that captures the unique characteristics of the pollution events. This is also due to the fact that air pollutants (i.e., PM 2.5, VOCs) disperse very fast in the ambient atmosphere [22]. In the meantime, although humidity sensor data within the same window may not exhibit peak values, they contain distinctive patterns that, combined with the characteristics captured by PM 2.5 and VOCs sensors, can be used to identify pollution sources.

Based on our observations, we have carefully designed a total of 18 features that capture the unique characteristics of the targeted pollution events. These include *single-sensor features* extracted from PM 2.5, VOCs, and humidity sensor individually as well as *cross-sensor features* extracted from more than one sensors. Table 2 lists the features and their definitions. We then extract those features from a window of five minutes starting from the beginning of the air pollution event. Finally, we stack the extracted features into a feature vector and import the feature vector into a linear kernel-based Support Vector Machine (SVM) for classification.

It is worthwhile to note that our identification algorithm could identify pollution sources within five minutes after the occurrence of the pollution event. Considering the fact that it may take six to seven hours for the PM 2.5 and VOCs levels to drop back to the healthy levels, AirSense can notify people about the identified pollution sources at a much earlier time so that they can take immediate actions to reduce pollution.

IAQ Forecast

The final stage of the analytics engine is to forecast the air quality sensor values of the detected air pollution events. Based on the IAQ forecast, AirSense can estimate the seriousness of the pollution so as to increase people's awareness of the potential harm of the pollution. To forecast IAQ, one straightforward scheme is to build a parametric regression model for each type of the air pollution events. However, such scheme is unsuitable for AirSense because air pollution events have high within-class variances. As such, it is very challenging to build one parametric model that can make predictions reasonably well for all possible trials of the same type of the pollution events.



(a) (b) (c) (d)

Figure 8: The AirSense smartphone application screenshots: (a) dashboard screen, (b) IAQ data visualization screen, (c) IAQ analytics result screen, and (d) weekly IAQ report screen.

To resolve the issue of high within-class variances, AirSense adopts a non-parametric regression model to forecast future air quality sensor values of air pollution events. The key intuition behind our non-parametric scheme is the observation that different trials of the same air pollution event have very similar shapes if their peak values are similar. As an example, Figure 6 illustrates the PM 2.5 sensor data of three trials of smoking. As shown, trial 1 and 2 have similar peak values of about $380ug/m^3$ and they exhibit very similar shapes. For trial 3, its peak value is about $250ug/m^3$, and it has a very different shape compared to trial 1 and 2.

Based on this observation, our non-parametric IAQ forecast algorithm first identifies q ($q = 3$ in our implementation) nearest historical trials of the same pollution event whose peak values are within a threshold of η ($\eta = 10\%$ in our implementation) difference from the peak value of the current trial. It then calculates the squared error between the current trial and its q nearest historical trials respectively, with a sliding window of n ($n = 10$ in our implementation) data points starting right after the peak value. Mathematically, let the current trial in the sliding window be $M_c = \{m_1, m_2, m_3, \ldots, m_n\}$, and the corresponding data points of the historical trial j be $M_{h_j} = \{m_{h_j,1}, m_{h_j,2}, m_{h_j,3}, \ldots, m_{h_j,n}\}$. The squared error between these two trials is calculated as:

$$SE_j = \sum_{i=1}^{n} (m_i - m_{h_j,i})^2 \tag{2}$$

We define a similarity metric s_j based on the squared error to measure the similarity between the current trial and the historical trial j among its q nearest historical trials:

$$s_j = \frac{1}{q-1}\left(1 - \frac{SE_j}{\sum_{i=1}^{q} SE_i}\right) \tag{3}$$

where s_j is normalized and $\sum_{i=1}^{q} s_j = 1$. The higher the s_j, the more similar between current trial and the historical trial j. Based on the q nearest historical trials and their corresponding similarity metrics, we can predict the future air quality sensor values of the current trial for a prediction length l:

$$M_{predict} = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_q \end{bmatrix}^T \begin{bmatrix} m_{h_1,n+1} & m_{h_1,n+2} & \cdots & m_{h_1,n+l} \\ m_{h_2,n+1} & m_{h_2,n+2} & \cdots & m_{h_2,n+l} \\ \vdots & \vdots & \ddots & \vdots \\ m_{h_q,n+1} & m_{h_q,n+2} & \cdots & m_{h_q,n+l} \end{bmatrix} \tag{4}$$

where $M_{predict} = \{m_{n+1}, m_{n+2}, m_{n+3}, \ldots, m_{n+l}\}$ is the predicted sensor values of the current trial and $\{m_{h_j,n+1}, m_{h_j,n+2}, m_{h_j,n+3}, \ldots, m_{h_j,n+l}\}$ is the sensor values of the historical trial j.

Figure 7 illustrates an example of the performance of our IAQ prediction algorithm in the context of predicting PM 2.5 sensor values of a trial of pesticide spray. The two dotted lines represent the two nearest historical trials of the current trial. The peak values of the two historical trials and the current trial are 224, 229 and $215ug/m^3$ respectively. The prediction starts at the 11th data point after the peak value. As illustrated, the predicted sensor values match the real sensor data very well from the prediction starting point to 250 mins.

SMARTPHONE APPLICATION

The design goal of the smartphone application is to increase users' awareness of IAQ, help users understand how their household activities impact IAQ, and assist users to take proper actions to reduce indoor air pollution in a timely manner. To achieve this goal, the smartphone application provides four different screens: (1) dashboard screen, (2) IAQ data visualization screen, (3) IAQ analytics result screen, and (4) weekly IAQ report screen. The screenshots of these four screens are illustrated in Figure 8.

Dashboard Screen: A dashboard screen is accessible by executing the application manually (Figure 8(a)). There are four icons each representing one air quality sensor included in AirSense. The number below each icon is the real-time measurement from each sensor. By pressing each icon, the IAQ data visualization page will be displayed. At the bottom of this screen, users can check their weekly IAQ reports by pressing the weekly IAQ report icon.

IAQ Data Visualization Screen: The IAQ data visualization screen (Figure 8(b)) provides a detailed visualization of the air quality sensor data in the past as well as IAQ forecast data generated by the IAQ forecast scheme described before. By zooming in and out on the visualization, users can examine the sensor data in great details. Furthermore, to draw users' attention when the air quality degrades, we map the sensor data to the official air quality index (AQI) from EPA based on a standard lookup table [3]. We use the same color codes of AQI to visualize the sensor data in different colors [1]. At the bottom of this screen, a web link on the background knowledge of the air pollutant from EPA is also provided.

IAQ Analytics Result Screen: Once an indoor air pollution event is detected and its source is identified, the analytics engine on the cloud server immediately sends a notification to the smartphone application, which provides a link to the IAQ analytics result screen (Figure 8(c)). The screen lists the air pollution sources identified by the source identification algorithm. Moreover, based on the result of the IAQ forecast algorithm, it also shows the estimated duration until IAQ will return back to healthy level to let users understand how serious the indoor air pollution is. This design is based on the previous observation that proper use of simulations is known to be effective in persuading people to change their attitudes or behaviors by enabling them to observe immediately the link between cause (e.g., no action) and effect (e.g., exposure to pollution for 30 minutes) [11]. Finally, to guide users to taking appropriate actions to cope with the detected indoor air pollution event, detailed pollution source-specific suggestions are provided on the screen. These suggestions are adopted from the authoritative guidance provided by EPA [23]. Table 3 lists the pollution sources considered in this work and the corresponding suggestions.

Pollution Source	Suggestion
Cook	Please turn on the range hood when cooking and ventilate your home.
Smoke	Please smoke outside to minimize indoor pollution and ventilate your home.
Spray Pesticide	Please ventilate your home after spraying pesticide.

Table 3: Pollution sources and the corresponding suggestions.

Weekly IAQ Report Screen: The analytics engine generates a weekly IAQ report which summarizes the amount of indoor air pollution caused by pollution events every week (Figure 8(d)). This screen is designed for self-monitoring, which is known to be beneficial for people in understanding how well they are performing the target behavior, increasing the likelihood that they will continue to produce the behavior [11]. The weekly IAQ report is illustrated using a pie chart, which shows the percentage of time during one week for IAQ being either healthy or polluted by the three pollution source categories. We followed the AQI standard from EPA to group the AQI categories of good and moderate as healthy and group the other four AQI categories as unhealthy [1]. Figure 8(d) shows a sample weekly IAQ report, illustrating that the PM 2.5 is at healthy level for 32% of the week while the PM 2.5 is at unhealthy level for 19%, 15%, and 34% of the week due to smoking, spraying pesticide, and cooking.

SYSTEM PERFORMANCE EVALUATION

As the first part of the evaluation, we conduct experiments to benchmark the performance of AirSense on pollution event detection, pollution source identification, and IAQ forecast. We also conduct another two experiments to examine the impact of deployment location and diversity of pollution sources on the performance of AirSense.

Experimental Setup

Participants: We recruited two families who volunteered to help collect data and conduct evaluation experiments at their home. Family 1 has three members: 1) P_{11} is a 32-year-old male; 2) P_{12} is a 31-year-old female; and 3) P_{13} is a 59-year-old female. Family 2 only consists of one member, P_{21}, a 25-year-old male.

Deployment Site: We deployed AirSense in the living room at each home. The approximate size of the living room of two homes is 56 m^2 and 25 m^2, respectively. Figure 13 illustrates the deployment of AirSense at one home. We choose living room as the deployment site of AirSense because it is the central place that is close to kitchen, bedrooms, restrooms as well as windows for ventilation.

Data Collection: We deployed AirSense at each home for a duration of ten weeks. To collect IAQ data, two families were instructed to regularly cook in the kitchen as well as smoke and spray pesticide in the living room. It should be emphasized that the occupants were allowed to conduct multiple pollution activities simultaneously (e.g., P_{11} is smoking while P_{12} is cooking). Therefore, there are in total seven types of pollution events (individuals plus combinations). Table 4 lists these seven types of pollution events and their abbreviations. For ground truth collection, the participants were asked to label the pollution events and record the timestamps of the events using Google Sheets. The time periods other than pollution events during the ten-week deployment are categorized as non-pollution/null events. Table 5 lists the number of pollution events and their corresponding time durations collected during the ten-week deployment.

Event	Cook	Smoke	Spray	Cook+Smoke	Smoke+Spray	Cook+Spray	All
Abbreviation	C	S	P	CS	SP	CP	CSP

Table 4: The list of seven types of pollution events and their abbreviations.

Event		C	S	P	CS	SP	CP	CSP	Total
Family 1	No. of Sample	23	22	24	18	18	19	15	139
	Duration (h)	140	112	101	84	89	93	69	688
Family 2	No. of Sample	25	25	25	20	20	20	15	150
	Duration (h)	180	146	164	112	122	108	78	910

Table 5: Summary of data collected from two families during the ten-week deployment (see Table 4 for pollution event abbreviations).

Evaluation Results

Performance of Pollution Event Detection

Table 6 presents the confusion matrices for detecting the pollution events at two families. We observe that the pollution event detection rates at both families are very high, which demonstrates our algorithm is very accurate at detecting pollution events regardless of the differences in floor plans of the

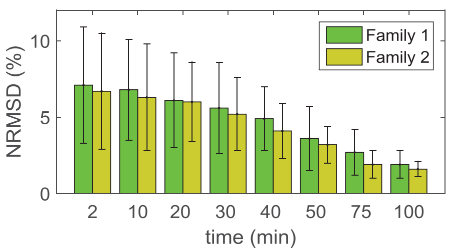


Figure 9: Performance of IAQ forecast algorithm on PM 2.5 prediction at two families.

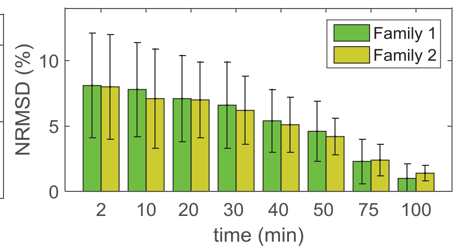


Figure 10: Performance of IAQ forecast algorithm on VOCs prediction at two families.

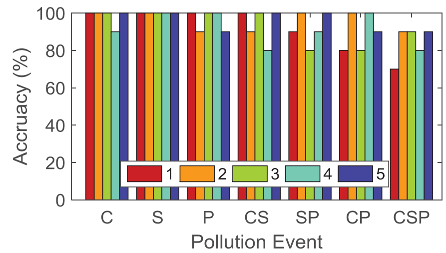


Figure 11: Pollution source identification accuracy at five deployment locations (see Figure 14 for deployment location information).

	Actual/Predicted	Event	Null
Family 1	Event	99.8%	0.2%
	Null	1.1%	98.9%
Family 2	Event	100.0%	0.0%
	Null	0.5%	99.5%

Table 6: Confusion matrices of pollution event detection at two families.

homes as well as living styles of occupants at two families. In addition, we also observe that the false positive rates at both families are very low. This result indicates that our algorithm is very robust to noises caused by environmental changes and other human behaviors.

	C	**S**	**P**	**CS**	**SP**	**CP**	**CSP**	**Recall (%)**
C	23	0	0	0	0	0	0	100.0
S	0	22	0	0	0	0	0	100.0
P	0	0	24	0	0	0	0	100.0
CS	0	1	0	17	0	0	0	94.1
SP	2	0	0	0	16	0	0	88.9
CP	0	1	0	1	0	17	0	89.5
CSP	0	1	0	1	0	1	12	80.0
Precision (%)	92.0	88.0	100.0	89.5	100.0	94.4	100.0	

Table 7: Confusion matrix of pollution source identification at Family 1 (see Table 4 for pollution event abbreviations).

	C	**S**	**P**	**CS**	**SP**	**CP**	**CSP**	**Recall (%)**
C	25	0	0	0	0	0	0	100.0
S	0	25	0	0	0	0	0	100.0
P	0	0	25	0	0	0	0	100.0
CS	0	0	0	20	0	0	0	100.0
SP	0	0	1	0	19	0	0	95.0
CP	1	0	0	0	0	19	0	95.0
CSP	0	0	0	0	1	1	13	86.7
Precision (%)	96.1	100.0	96.1	100.0	95.0	95.0	100.0	

Table 8: Confusion matrix of pollution source identification at Family 2 (see Table 4 for pollution event abbreviations).

Performance of Pollution Source Identification

Next, we evaluate the performance of our pollution source identification scheme using leave-one-trail-out cross validation strategy. Table 7 and Table 8 show the confusion matrices for the source identification of pollution events at two families. Each row denotes the actual pollution event conducted and each column represents the pollution source identified by AirSense. Overall, the average pollution source identification accuracy is 94.2% for Family 1 and 97.3% for Family 2. This result demonstrates that our scheme can accurately identify sources of the pollution events across different families because of the highly discriminative features we carefully designed. By taking a closer look at the identification accuracies of different events, we observe that the pollution events that involve more than one pollution sources have relatively lower identification accuracies than pollution events that involve only one pollution source. This is because when multiple pollution sources exhibit at the same time, the air pollutants generated by different sources are mixed together, making the source identification problem more challenging.

Performance of IAQ Forecast

To examine the performance of our IAQ forecast scheme, we use the normalized root mean square deviation (NRMSD) as the evaluation metric. Formally, NRMSD is defined as

$$NRMSD = \frac{\sqrt{\frac{1}{l}(\sum_{i=1}^{l}(\hat{m}_i - m_i)^2)}}{\hat{m}_{max} - \hat{m}_{min}} \tag{5}$$

where $\hat{m}_i$ and m_i are the observed value and predicted value respectively, l is the prediction length, and $\hat{m}_{max}$ and $\hat{m}_{min}$ are the maximum and minimum of the observed values over the prediction length l. NRMSD is often expressed as a percentage, where lower values indicate better performance.

We evaluate our IAQ forecast algorithm on every trial of the pollution events based on leave-one-trial-out cross validation strategy. For each trial, we set the ending point of our prediction at the point where the air quality data reaches the healthy level provided by the EPA standard [23]. The prediction starting point is defined as the time duration after PM 2.5 or VOCs reaches the peak value. The prediction length l is the distance between the ending point and the starting point.

Figure 9 illustrates the performance of our IAQ forecast algorithm on PM 2.5 prediction across seven pollution events at two families. The horizontal axis represents the prediction starting point. The vertical axis represents the NRMSD value calculated over the prediction length. As illustrated, the NRMSD values decrease as the prediction starting point moves forward. This result indicates that IAQ information can be forecasted more accurately when time elapses. Moreover, we observe that our IAQ forecast algorithm performs very well even if we start predicting the future PM 2.5 sensor values at two minutes after the peak value, achieving an average NRMSD of 6.8% for Family 1 and 6.5% for Family 2. This forecast is accurate enough to capture the trend and severity of the PM 2.5 pollution. Similar results are observed in Figure 10 for forecasting the VOCs sensor values, with an average NRMSD of 8.1% for Family 1 and 8.0% for Family 2. In all, our results demonstrate that our IAQ forecast algorithm can provide a reasonably accurate prediction on future IAQ within a very short time after the occurrences of the pollution events.

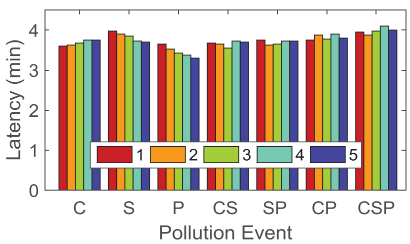


Figure 12: Pollution source identification latency at five deployment locations (see Figure 14 for deployment location information).

Figure 13: The deployment of AirSense in the living room at one home.

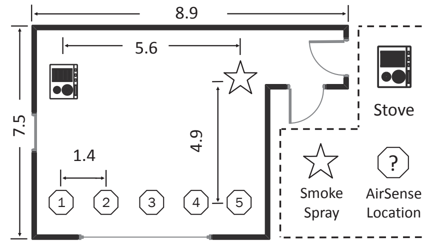


Figure 14: The illustration of the floor plan of the living room and the deployment locations of AirSense (measure unit: meter).

In-depth Analysis: Impact of Variation of Deployment Location

In this experiment, we examine the impact of system deployment location on the performance of AirSense. In particular, we examine the pollution source identification accuracy as well as the pollution source identification latency when deploying AirSense at different room locations. Specifically, we conducted the experiment in the living room at Family 1. Figure 14 illustrates the floor plan of the living room and the deployment locations of AirSense in the experiment. As shown, AirSense was deployed at five different locations with 1.4 meters apart. The occupants in Family 1 were instructed to cook at the stove as well as smoke and spray pesticide at the location marked as a star. Each of the seven types of pollution events listed in Table 4 was conducted ten times while AirSense was placed at each deployment location.

Figure 11 presents the average pollution source identification accuracies across ten trials at five deployment locations. We observe that although the accuracies at different deployment locations vary, the differences among the five deployment locations are not significant. Figure 12 presents the average pollution source identification latencies across ten trials at five deployment locations. The latency is defined as the duration starting from the occurrence of the pollution event to the time when the pollution source is identified. We observe that the longest latency among all five deployment locations is 4.1 mins. This result indicates that even if the living room is large (56 m^2), AirSense is able to identify the pollution source in a timely manner. Moreover, we observe that although the latencies at different deployment locations vary, the differences among the five deployment locations are not significant. In all, our results indicate that the impact of variation of deployment location on the accuracy and latency of pollution source identification is minor.

In-depth Analysis: Impact of Diversity of Pollution Sources

Finally, we examine the impact of the diversity of pollution sources on the performance of AirSense. In particular, we examine the pollution source identification accuracy on different cooking styles, numbers of cigarettes being smoked and brands of pesticide. Table 9 summarizes the subcategories within each pollution source. To examine the impact, the occupant at Family 2 was instructed to perform ten trials for each pollution event for all the subcategories. We use these trials as the test set and test them using the pollution source identification models we built from the data in Table 5. As shown in Table 9, AirSense is able to accurately identify pollution sources across diverse subcategories.

Source	Subcategory	Accuracy
Cook	Grill	100.0%
	Barbecue	90.0%
	Fry	100.0%
	Steam	100.0%
	Stew	80.0%
Smoke	2 Cigarettes SI	100.0%
	2 Cigarettes CO	100.0%
	3 Cigarettes SI	90.0%
	3 Cigarettes CO	100.0%
	2 (SI) + 1 (CO) Cigarettes	100.0%
Spray	Pesticide brand one	100.0%
	Pesticide brand two	100.0%
	Pesticide brand three	90.0%

Table 9: Subcategories within each pollution source and their performance. Abbreviation: SI – simultaneously; CO – consecutively.

REAL-WORLD DEPLOYMENT STUDY

As the second part of the evaluation, we conduct a real-world deployment study to 1) evaluate the system performance of AirSense in uncontrolled, daily life settings and 2) examine the potential of AirSense in increasing users' awareness of IAQ and promoting behavioral changes to improve their IAQ.

Method

Participants: We recruited additional three families who volunteered to participate in the study. Family 3 has two members: 1) P_{31} is a 56-year-old female and 2) P_{32} is a 58-year-old male. Family 4 also has two members: 1) P_{41} is a 29-year-old female and 2) P_{42} is a 30-year-old male. Family 5 has one member: P_{51} is a 23-year-old male. Before recruit, we have conducted a survey to make sure that the three families met the criteria: 1) at least one member of each family is a smoker; 2) they have habits of spraying pesticide; and 3) they cook at home frequently.

Study Design: The real-world deployment study consists of two phases. In phase one, AirSense without the smartphone application was deployed to continuously collect the IAQ data at three families in their living rooms (size: 31, 44 and 19 m^2 respectively) for six weeks. The occupants at three families

Event		C	S	P	CS	SP	CP	CSP	Total
Family 3	**No. of Sample**	80	23	12	3	4	1	0	123
	Duration (h)	480	128	70	19	23	6	0	726
Family 4	**No. of Sample**	120	17	25	4	4	1	0	171
	Duration (h)	710	80	140	21	29	6	0	986
Family 5	**No. of Sample**	28	53	16	3	0	3	0	103
	Duration (h)	150	270	93	19	0	15	0	547

Table 10: Summary of data collected from three families in the real-world deployment study (see Table 4 for pollution event abbreviations).

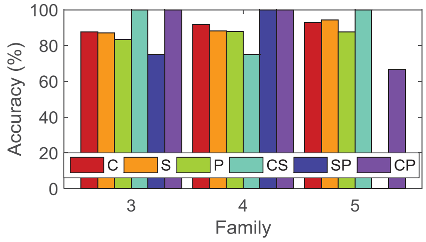


Figure 15: Pollution source identification accuracy in daily life settings (no SP event from Family 5 and no CSP event from all three families).

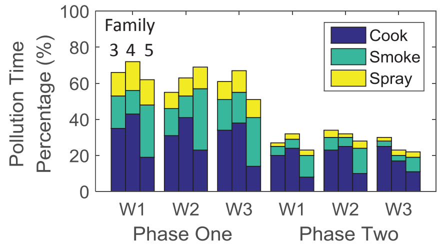


Figure 16: The weekly PM 2.5 profiling of indoor air pollution at three families.

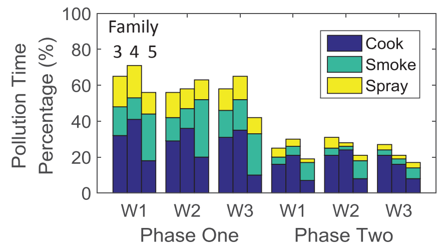


Figure 17: The weekly VOCs profiling of indoor air pollution at three families.

were asked to log the ground truth of the pollution events using Google Sheets. The collected IAQ data and the ground truth were used to build models for pollution event detection, pollution source identification and IAQ forecast. In phase two, we installed the smartphone app on the participants' smartphones and deployed AirSense at the same three families for another three weeks. The occupants could use the app to check IAQ information and get notifications about the detected pollution events, identified pollution sources, IAQ forecast and the suggestions. In this phase, the occupants were encouraged to think aloud [25] about their experiences with AirSense and take a memo. Table 10 lists the number of pollution events and the corresponding time durations collected from the three families in this real-world study.

Analysis: To examine the potential of AirSense, a semi-structured interview was conducted at the end of phase two. During the interview, we asked the participants about their overall experiences of AirSense, including their behavioral changes related to IAQ at their homes. All think-aloud and interview data were transcribed and analyzed using open coding [21] to examine emerging themes. We then created an affinity diagram [14] for axial coding to understand common themes and patterns across the codes that were generated. We used SaturateApp and MemoSort, online collaboration tools for open coding and affinity diagramming, respectively.

Findings

System Performance in Daily Life Settings

We evaluate the system performance of AirSense in daily life settings at the recruited three families. In terms of pollution event detection, the average true positive and true negative rates across the three families are 99.0% and 99.5%. In terms of pollution source identification, as illustrated in Figure 15, we have achieved an average source identification accuracy of 87.0%, 90.7% and 92.2% across all pollution events at three families respectively. It should be noted that there was no CSP event performed by all three families during the deployment. Moreover, there was no SP event performed by Family 5. In terms of IAQ forecast, the average NRMSD when starting prediction at two minutes after the peak value is 7.3% for Family 3, 7.9% for Family 4, and 7.5% for Family 5.

IAQ Changes between Two Phases

Figure 16 and Figure 17 present the weekly profiling of indoor air pollution caused by cooking, smoking and spraying pesticide at three families in terms of PM 2.5 and VOCs, respectively. In order to make a clear comparison between the two phases of our real-world deployment study, we put the 3-week profiling of phase one (the last 3 weeks of the total six weeks) and the 3-week profiling of phase two into the same figure, with phase one on the left and phase two on the right. The three-stack bars represent the time percentages of indoor air polluted by one of the three pollution sources, with the remaining percentage representing time of having healthy air. As shown in both figures, the pollution time percentage of phase one is much higher than that of phase two. This result demonstrates the significant potential of AirSense in leading to better IAQ.

At last, we describe our findings from the semi-structured user interview in the remaining of this section.

Increase in Awareness of IAQ

Participants first talked about how much they were unaware of IAQ or pollution sources before trying AirSense. They were able to notice the air quality was not good without the system, but did not have concrete idea on how bad the air quality was: *"Sometimes, I don't feel very well, and I guess it's related to the air quality at home, but I don't know how exactly (it was)."* (P_{41}); *"It feels good to see actual numbers [...] rather than just guessing (the quality)."* (P_{32}) This finding agrees with prior studies in that lack of detailed information can lead to lower level of awareness or even overlooking [18].

Visual and quantified representations of air quality were recognized as contributing factors toward increased awareness of the participants, which is consistent to the prior study of IAQ visualizer [18]: *"The graphs with waves of numbers are pretty intuitive. [...] (it was) good to see the actual numbers that can tell me how good air quality is at my home."* (P_{32})

Building Personalized Mapping

Participants noted that they were curious about which pollution source leads to specific subjective feeling or sense: *"I often asked myself what were the reasons for the changes"* (P_{32}). Detailed information of pollution source provided by AirSense helped them in mapping specific feeling or sense with corresponding air pollution source: *"When I was browsing those data, I really enjoyed thinking about which aspect of air quality might be related to my bad feeling. [...] it gave me lots of useful hints."* (P_{41})

AirSense as a Motivational Trigger

The participants shared opinions about the role of AirSense as a trigger for their actions toward better IAQ. P_{51} talked that the timely notification of AirSense reminded him to cope with bad air quality condition which can be easily overlooked:

"When I was cooking steak, the air quality plumped greatly and AirSense gave me a warning and asked me to turn on the range hood." Also, pollution notifications motivated users to follow the suggestions of AirSense: *"Whenever I saw the red dots that tell me something was not good, I always checked the suggestions on the mobile app."* (P_{42})

Increased Competence in IAQ Control
For IAQ control, participants also talked about their increased competence [20, 10], which is one key factor of intrinsic motivation from the viewpoint of Self-Determination Theory [10], due to accurate and timely feedback of IAQ changes provided by AirSense. The system actually helped them have air quality in control: *"it told me to open the window, which really helped to bring the numbers back to the normal range."* (P_{42}); *"when I cooked, AirSense can detect my cooking activities and I found that range hood really helped to lower down both gas and particle pollutants."* (P_{31}) Also, once they realize their actions can make meaningful changes of IAQ, they became more engaged in the active behavior for IAQ control: *"But since I found it's useful to bring me better air, I wouldn't mind doing it, and it's becoming something that is on the top of my head now."* (P_{42}).

DISCUSSION
The evaluation results demonstrate AirSense is a very promising ubiquitous computing technology for IAQ monitoring and analytics. However, we made a few restrictions in our experimental setup which reveal some limitations of our work. We discuss these limitations and future work in this section.

Limitation on Detectable Air Pollution Sources: In this work, we focus on three of the most common indoor air pollution events – cooking, smoking, and spraying pesticide – to demonstrate the feasibility of AirSense. In the future, we plan to expand the capability of AirSense on identifying more pollution sources. For example, burning wood in wood stoves or fireplaces could generate a significant amount of CO_2. By adding a CO_2 sensor, AirSense would be able to detect this pollution source according to the changes of CO_2 levels. As another example, during ventilation, contaminants from outdoors could also be brought into homes to cause indoor air pollution. We plan to expand AirSense to detect air pollutions from outdoors and warn users to close doors or windows.

Limitation on IAQ Analytics Algorithms: There are also a few limitations on our IAQ analytics algorithms. First, our pollution event detection algorithm relies on the sharp increase of sensor data at the beginning of the pollution event. Although the sharp increase is a robust signature for cooking, smoking, and spraying pesticide which generate heavy pollution, it may not apply to mild pollution sources that cause slow and gradual increase of sensor data. Second, our IAQ forecast algorithm is developed by only taking into consideration the historical data from similar indoor air pollution events. A more accurate model can be developed by including other information such as weather and outdoor air pollution report from the local meteorology department. We will keep improving our IAQ analytics algorithms in the future to make them capable of detecting mild pollution sources and more accurate on IAQ forecast.

RELATED WORK
There are a number of work on IAQ in the ubiquitous computing community. These work mainly focus on measuring and visualizing the measurements of indoor air pollution. In [19], Kobayashi et al. developed a wearable system that senses scent in the air. In [16], Jiang et al. developed a mobile sensing system that measures the concentrations of CO_2 in workplaces and classrooms to provide personalized CO_2 information. The system incorporates a participatory sensing strategy to share concentrations of CO_2 at different rooms. In [7], Chen et al. developed a cloud-based PM 2.5 monitoring system in office buildings. The system collects both indoor PM 2.5 from an off-the-shelf PM 2.5 monitor as well as outdoor PM 2.5 from public websites. A computational model is developed to automatically turn on HVAC systems inside office buildings a few hours earlier before working hours when air is heavily polluted. In [8], Cheng et al. also developed a cloud-based PM 2.5 monitoring system but with a different goal. The work mainly focuses on designing a low-cost PM 2.5 sensor and developing analytics algorithms running on the cloud to calibrate the low-cost PM 2.5 sensors and to infer PM 2.5 concentrations at locations where PM 2.5 sensors are not available. Finally, in [18], Kim et al. developed a home-based system using an off-the-shelf PM 2.5 monitor and an iPod Touch to visualize IAQ information. Results from the user study indicate that visualizing the IAQ information is effective in increasing people' awareness of IAQ.

Different from all these existing systems, AirSense goes beyond IAQ measurements and visualization. It represents the first effort of developing an intelligent IAQ analytics system that is able to identify pollution sources, estimate how long the pollution will stay, and provide actionable suggestions to help people reduce indoor air pollution.

CONCLUSION
In the paper, we present the design, implementation and evaluation of AirSense, an intelligent IAQ sensing system that continuously monitors and analyzes IAQ at homes. AirSense bridges the gap of existing IAQ monitoring systems by leveraging machine learning-based algorithms to identify pollution sources of the detected pollution events as well as forecast future IAQ changes to estimate the personal exposure to indoor air pollution. Experiments in both controlled and uncontrolled daily life settings have been conducted to evaluate the performance of AirSense. Our results show that AirSense can identify cooking, smoking, spraying pesticide pollution events and their combinations, which are among the most common household activities that generate significant indoor air pollution. It can also forecast future air quality sensor values with a high accuracy. Finally, our deployment study shows the potential of AirSense in increasing users' awareness of IAQ and helping them reduce air pollution at homes.

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