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Smartphone App for Residential Testing of Formaldehyde (SmART-Form)

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ABSTRACT

Chemical contamination is ubiquitous in the indoor environment, but measurement options are often limited outside of research studies. This is especially true for formaldehyde, a known carcinogen and irritant. The goal of this project was to develop a novel screening tool: a smartphone-based app that can be paired with low-cost colorimetric badges for detection of indoor formaldehyde. The target users include citizen scientists, concerned citizens, public health nurses visiting homes, and researchers with relevant measurement needs. The user interface was designed using a collaborative development model. Badges were exposed to air for 72 h, and the user takes images that are analyzed in the phone. The app itself measures illumination (lightness) to determine color change, which was associated with formaldehyde concentration ($R^2 = 0.8811$, $P < 0.0001$). The detectable range was 20–120 ppb and the standard deviation of readings was 10.9 ppb. Warnings were integrated into the app to address current limitations, including sensitivity to extreme lighting conditions and elevated (> 80%) relative humidity. Co-exposure to acetaldehyde or a VOC mixture did not interfere with measurement ($P = 0.93$, $P = 0.07$, respectively). Overall, this screening tool can provide inexpensive, accessible information to users about their formaldehyde exposure, which can inform further testing and potential remediation activities.

1. Introduction

Formaldehyde is ubiquitous in the indoor environment, where this contaminant is released from various consumer products such as pressed wood, adhesives, paints, cleaners, and more [1]. Exposure to this compound can result in eye, nose, and throat irritation, and a range of other non-clinical ailments. Formaldehyde is also a known human carcinogen. Research began demonstrating the toxicity of this compound more than 100 years ago [2]. Recent concerns have arisen due to elevated presence in Federal Emergency Management Agency (FEMA) trailers such as those provided after Hurricane Katrina in 2005–2006 and in flooring retailed by Lumber Liquidators in 2015 [3–6].

1.1. Formaldehyde measurement options

Currently, measurement options for citizen scientists and concerned members of the general public are limited. A commonly-used method for formaldehyde measurement involves collecting samples in 2,4-dinitrophenylhydrazine (DNPH) cartridges to derivatize formaldehyde with later laboratory-based detection using high performance liquid chromatography [7,8]. This technique requires specific sampling equipment, uses expensive and complex analytical instruments, is prone to contamination, and is nearly impossible for a citizen scientist to perform. Other sampling technologies have recently been developed [1,9–13], but to our knowledge, are not commercially available or widely used by citizen scientists, and may also suffer from

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contamination either during transport or due to other compounds. Right now, we are missing a low-cost, accessible screening tool for formaldehyde in homes that may not require the same level of precision as the DNPH method. Our previous survey of 147 individuals indicated broad public interest in formaldehyde testing using smartphone technology. Poor reported health status was associated with increased desire for testing (odds ratio for very good to excellent health 0.31, 95% confidence interval 0.12–0.81). Location in our targeted area of community engagement was also associated with interest in testing [14].

1.2. Smartphone-based measurement

Smartphone technologies provide a new opportunity for formaldehyde detection. One downside to the currently available colorimetric badges is the low accuracy due to visible color comparisons by the human eye. This allows for concentration "binning" but not accurate, quantitative results. Fortunately, the use of digital image processing technologies provide the opportunity to more accurately read the color change on the badges that results from formaldehyde exposure as a continuous variable. This is especially important for a compound such as formaldehyde that is ubiquitous in the indoor environment, such that concentration level is more informative than simple detection (yes vs. no).

Others have also recognized the opportunity to pair colorimetric sensors with Smartphone detection for accurate measurements [15–18]. In this paired system, the camera function of the smartphone is utilized to record and analyze the color changes on the badge that occur as a result of contaminant exposure. An image formation model describes how the color images are produced by the camera that received light reflected from the badge surface. Colors are dependent upon both the material reflectance and the intensity of the environmental light. It is generally impossible to measure the exact environmental lighting conditions, so the colorimetric change is quantified using a color change ratio (based on measurement of lightness or illumination) of badge to a calibration patch [19,20]. Here, we refer to this as the color-change ratio of lightness, where lightness is a relative value (unitless) and is computed from standard RGB images with fixed value ranges. In this case, the variant of the environment lighting is the same on the reaction and calibration areas, leaving the material property as the only variant accounting for the colorimetric change. This material property, also known as the surface albedo, can be easily computed by analyzing digital photos through extracting the color values of the reacting and referencing area. The surface albedo correlates with the measured formaldehyde concentration.

1.3. Goal of this work

The goal of the work described here was to develop a novel screening tool for formaldehyde detection by pairing a color-changing badge with a smartphone app (Fig. 1). The target user is a citizen scientist or person concerned about formaldehyde exposure in their home environment. The system may also be useful for visiting nurses in asthma homecare programs [21], environmental health professionals, or in certain epidemiological research studies depending on measurement requirements. User input was invited at every stage of development of the low-cost smartphone-based formaldehyde measurement system to ensure that this technology is accessible and useful to the public. Community engagement was sought from both a national network of citizen scientists with high technological literacy and a community environmental group in a small city in southern Georgia with average to low technological literacy. Existing colorimetric badges used in occupational settings were modified by our industry partner for enhanced sensitivity in the residential environment and for an app-friendly configuration. The system was calibrated on both Android and iOS devices using exposure to known concentrations of formaldehyde. Community feedback had been collected previously to assess public

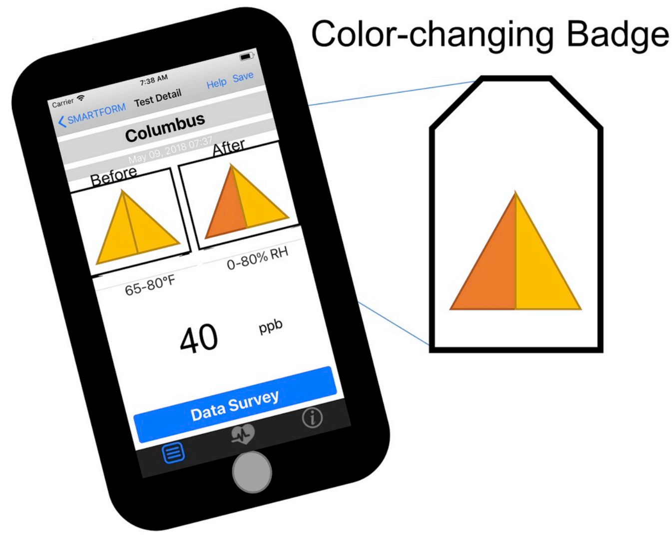

Fig. 1. System overview.

interest in residential formaldehyde and home testing, willingness to pay for test kits, smartphone access, and capacity to implement a multi-day sampling protocol [14]. Upon completion of a beta version of the app, community members were solicited to provide feedback about the design, clarity, and functionality of this novel system; that feedback was then incorporated into the app. The system was then field tested in 17 locations.

2. Methods

Our goal was to develop a smartphone app to measure changes in color (illumination or lightness) of low-cost colorimetric badges due to exposure to formaldehyde. Steps in this process included badge modification, prototype app development, quantification of color change (also see information on the lighting model in supporting information), system calibration, beta testing with feedback integration, field testing, and statistical analysis.

2.1. Badge modification

We used modified SafeAir® [22] formaldehyde detection badges (Morphix Technologies, Virginia Beach, VA) to detect formaldehyde concentrations typically found in the indoor environment. The badges are commonly used in occupational settings and were modified for use with our system. Formaldehyde concentrations in indoor environments may vary with time. These badges will measure the average concentration over the measured time period because they respond linearly to the cumulative exposure. We requested that the badges display a greater intensity of color change for a lower range of formaldehyde exposure concentrations more common in residential environments. We also requested adjustments to the layout of the badges to be more easily read with the app and to incorporate a calibration area that does not change color. We also evaluated a modified version of the ChromAir® badges (referred to as "version 2" of the badge), but selected the SafeAir® badges for use with our system due to increased precision and a lower detection limit.

2.2. Prototype app development

The first steps of app development were to create a back-end image processing method to measure formaldehyde concentration based on substrate color change, and a front-end user interface for the app. The required functionalities included: create multiple tests, take badge image via camera before and after badge exposure, convert badge image into color change ratio and calculate the concentration result, save multiple tests containing badge images and formaldehyde concentration results, request test data and user experience feedback from users and incorporate relevant changes.

2.2.1. Prototype

The first step of app design was creating the framework of our prototype. To facilitate organizing multiple tests, the main layout was designed with a master-detail two-panel structure: table view and detail view. The table view contains all existing tests with titles and dates, and the detail view displays the whole process of a badge test, including user input parameters, images taken by the camera, and access to data upload surveys.

Our design strategy was closely related to the functional requirements and utilized object-oriented design, which is the process of planning a system of interacting objects. The object-oriented design structure was focused on the badge test, and for each test, we included the unique ID, title, date, images as inputs, and result as output. For memory efficiency, the test objects were stored in JSON format and images were referred by path in the internal storage.

The main functional requirements fall into two categories: test management and image processing. As shown in Fig. 2, the app allowed the user to create a new test by inputting the test title, and the start time was recorded after taking the "before" image. Afterward, the user has access to view all existing tests via the table view and check details by clicking a test in the list. For camera setup, the original plan was to use the default camera embedded with the smartphone. However, default parameters vary by phone manufacturer and model, and many of the smartphone cameras in different systems are rather restrictive in the customizable function settings (e.g. ISO level, aperture control). Thus it is challenging to realize homogeneity in terms of colors and lighting sensitivity across different smartphone cameras in different systems. Therefore, in our app, we experimented with taking images with different parameters on different phones, and selected a set of the most common parameters each for Android and IOS systems to minimize variation (see Lighting Experiments section below). Our mathematic model uses the calibration patch on the badge to account for environmental variation, and thus we expect the differences in camera parameters can be partially addressed. For details on the mathematical model used, please refer to the supporting information (Fig. S1). Briefly, color change is measured by the color change ratio of lightness by comparing the color changing area to the calibration (non-changing) patch. Lightness is a relative value (unitless) and is computed from standard RGB images with fixed value ranges. Normally the lightness of the actual environment is measured through the magnitude of the analogue electrical pulses of the light sensor chips (with units $W{\cdot}m^{-2}{\cdot}sr^{-1}$ where sr refers to steradian). However the digitization process of the smartphone built-in camera quantifies these pulses into the unitless RGB values. Therefore the lightness values represent the magnitude of the lighting condition in a relative sense (up to a scale). The "color change ratio" in our model takes advantage of the fact that the reaction and calibration patch undergo the same light illumination and by dividing these values, their units can be cancelled.

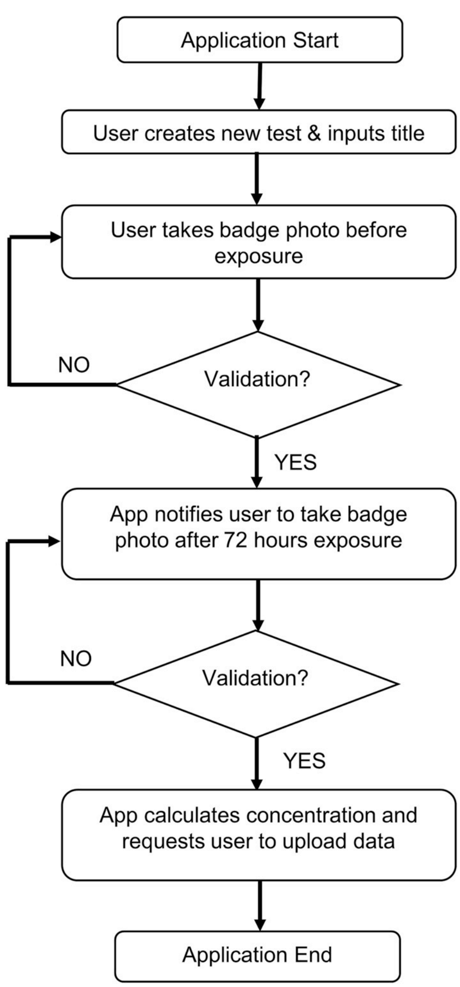

Fig. 2. Flow within app. Note that the research version also contained a mandatory consent form upon the application start. If the user did not consent, then the application would end.

2.2.2. User interface design

The initial user interface for the detail page contained multiple functionalities, such as taking a photo of the surroundings of the test, taking pre-exposure ("before") and post-exposure ("after") images, and uploading data to a survey platform (Qualtrics). Surveys were intended to engage users in creating a database of formaldehyde exposure information, and these included a survey about personal health and a survey about environmental characteristics of the sampling location. A unique non-identifiable code is automatically copied to user phone's clipboard when leaving the app and can be pasted into the ID field in the survey, which allows multiple survey and formaldehyde test entries to be linked together without additional personal identifying information.

2.3. Quantification of color change

2.3.1. Integration of user warnings

We identified key conditions that could lead to erroneous readings throughout app development (Table 1). For each condition, we analyzed images taken under both suitable (no error) and unsuitable (may cause an error) conditions. The parameter associated with each error, such as lightness or saturation, was chosen based on the value with the most substantial difference between conditions. Boundaries for warnings were selected to be about halfway between extreme points measured in suitable and unsuitable conditions.

2.3.2. Lighting experiments

We also conducted lighting experiments to determine limits on lighting conditions in the indoor environment for accurate calculation of illumination values for the badge. When developing this application, we needed to take clear images with no shadows and correct color composition. We also tested the accuracy of the automatic camera settings on the iOS and Android phones and compared to alternative settings. To do this we purchased different types of lightbulbs and a desk lamp, setting up the lamp 30.5 cm from the badge with the lampshade horizontal to avoid shadows covering the badge. The types of lightbulbs purchased were: 25 W Soft White, 40 W Clear, 40 W LED, 50 W Soft White, 60 W Crystal Clear and 60 W LED Soft White.

Table 1
SmART-Form app warning list. Boundary levels are listed in Table S1.

Warning Type		Condition[a]	Solution Suggested to User
Overexposure		Average lightness > 0.8	Retake the badge photo with less light
Low-light		Average lightness < 0.4	Retake the badge photo with more light
Badge Contamination		Lightness ratio > 1.0	Redo the test with a new badge
Blue tint due to high relative humidity		Average saturation < 0.4	Redo the test with a new badge
Short exposure time	Exposure time < 12 h	Wait for 72 h of total exposure	
Below detection limit	Concentration < 20 ppb	Concentration too low to detect	
Above detection limit	Concentration > 120 ppb	Concentration higher than detectable limit	

[a] Lightness refers to the lightness values of the converted HSI (Hue, Saturation, intensity) space from RGB, unitless.

We photographed the color grid paper under three different manual camera settings and auto adjust. Four settings (Table S2) were tested using special color grid paper (Fig. 3). After each image was taken, they were imported into Matlab and cropped by reaction area and calibration area. These cropped bitmaps from the orange and yellow blocks were converted into the HSI (Hue, Saturation, and Intensity) color model [23]. We found that the color-changing reaction of the badge changes the color lightness. Lightness is correlated with the intensity value of the HSI transformation, so we then calculated the ratios of the means of color intensity (I) of each image. We used the color grid paper instead of the actual badge because the printed color will not change, thus providing a good reference to determine the influence caused by the camera settings.

2.3.3. Algorithm

The mathematical model is based on the color change ratio (illumination or lightness) between the calibration patch and the chemical badge. Fig. 4 highlights the areas in green and red, respectively. These two blocks of bitmap were cropped and calculated for the mean value of the color intensity I, and the ratio = I(red)/I(green). We confirmed a linear relationship between exposure (formaldehyde concentration in ppb·hr) and the color change ratio.

2.4. Calibration

Calibration was performed by subjecting the badge sensor to several known concentrations of formaldehyde maintained in a 50 L small-scale environmental chamber (0.5 m by 0.4 m by 0.25 m, Fig. S2). The test system included a pressurized clean air supply and a Dynacalibrator containing a permeation tube at a constant temperature and flow rate to provide the desired formaldehyde generation rate (Fig. S3). Different concentrations in the chamber were obtained by adjusting the total airflow rate through the chamber, and were verified by air sampling with DNPH cartridge followed by HPLC analysis (Table 2). We conducted 6 different tests (Table 2), each with three badges of the two types (six total) inside the chamber. Each test had many images taken over the time period that the badge was exposed. For each test, a set of three badge sensors were placed inside the chamber (Fig. S4), and their color change was measured over time. Images were taken before the badges were placed in the chamber, after exposure inside the chamber over the different time periods through a pane of glass, and after they were removed from the chamber by using the mobile phone app

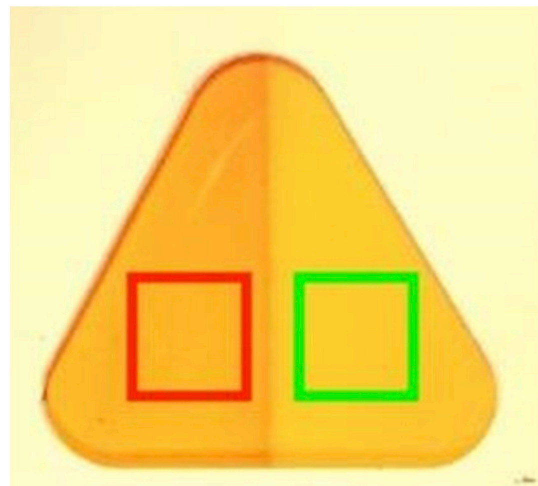

Fig. 4. The cropped badge image from the SmART-Form application camera. The calibration patch noted in green and the color-changing area is noted in red. Each block contains 50 × 50 pixels in the 250 × 250 cropped badge image. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Fig. 3. Color grid paper used to evaluate lighting conditions. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Calibration test conditions. All tests were conducted at 23 ± 0.5 °C for 72 h. The "Low Concentration" test was extended to measure continued color change. The "VOC co-exposure" test was used to simulate a realistic indoor condition with VOC emissions from a piece of particleboard placed inside the chamber.

Test name	Formaldehyde Concentration (ppb)		Co-exposure conditions		Relative humidity
	Target	Actual (HPLC)	Acetaldehyde (ppb, HPLC)	VOCs	
High Concentration	100	109	0	No	50 ± 5%
Medium Concentration	50	68	0	No	50 ± 5%
Low Concentration	25	18	0	No	50 ± 5%
Acetaldehyde co-exposure	50	68	26	No	50 ± 5%
VOC co-exposure	50	54	18	Yes	50 ± 5%
High relative humidity	50	67	0	No	75 ± 5%

(Huawei Mate 8 Android 7.0 and iPhone 6s iOS 11.2) and a high resolution digital camera (Casio Exilim- F1). Data were analyzed to obtain the mean color change ratio of the three badges as a function of the amount of cumulative exposure (i.e., concentration multiplied by the cumulated exposure time, (E= C× T): CCR $= f(E) = f(C \times T)$, where CCR is the color change ratio, E is total exposure, C is formaldehyde concentration, and T is time. Given this calibration curve, the concentration can be determined from the color change ratio and exposure time. The uncertainty of the badge response was quantified by the standard deviation of the color change ratio measured by the three badge sensors. Taking images through the glass had a small effect on the measured values, so the mathematical model was adjusted for this "glass effect" by comparing images taken without the glass (out of the chamber) and through the glass (in the chamber) at the same time point, both before and after testing.

2.5. Beta testing

We conducted a user test of the app's beta version to ensure that the SmART-Form app is useful for and accessible to interested members of the public. We followed the principles of user-centered design [24]. We asked participants to download and use the app with an image of an exposed badge, and to provide feedback on the app's design, clarity, and functionality. Participants provided feedback to study staff through a survey in Qualtrics with questions about whether or not they had trouble at each step of the app, from initial downloading through survey completion, and were asked for general feedback and suggestions. We recruited beta test participants through: (1) email solicitation of people who had participated in the initial feasibility assessment study, (2) social media solicitation of an environmental community science network, (3) solicitation on the project website. Recruitment targeted both a national network of citizen scientists with high technological literacy and a community environmental group in a small city in southern Georgia with average to low technological literacy. One purpose of the beta test was to evaluate image collection on different smartphone systems. Another core component of the beta test was to investigate whether or not the intended flow of the app, including exiting the app in order to provide health and environmental data through a secure browser-based platform Qualtrics, was intuitive, confusing, or caused technical challenges for users.

The user feedback portion of the beta test was conducted through an analogous survey on Qualtrics. The survey was available from September 2017 to May 2018. Feedback was then integrated into app design. To support improvements, a user interface consultant was hired to provide guidance, as the usability of the app is of fundamental importance. This study was approved by the Ohio State Institutional Review Board (IRB).

2.6. Field test

Following incorporation of the beta test feedback, we conducted a field test of the new system in 17 homes. The main objective of this field test was to confirm feasibility of the app and badge system. We recruited participants for a community-based case study in Waycross, GA. This community was selected due to enhanced community interest in environmental exposures due to local concerns. We targeted three neighborhoods with low to medium income levels. Postcards with study information were mailed to residents in advance, and a study team member and community leader then visited homes to allow residents to test the system. The system was tested in 17 homes, with 20 unique sampling events. In seven events, a single image of a single exposed badge was collected. In six events, multiple images of a single exposed badge were collected. In seven events, images of multiple co-located badges were collected. This study was approved by the Ohio State Institutional Review Board (IRB).

2.7. Statistical analysis

Statistical analysis of the calibration data was conducted in SAS, version 9.4 and Microsoft Excel. Formaldehyde concentrations were evaluated as ppb·hr and badge color change was evaluated as the color change ratio of the color changing area to the calibration area (referred to throughout as the color change ratio). The method detection limit was calculated as 3 times the standard deviation of blank readings. Blank badges were defined as those that had just been opened and not yet exposed to any air. In a separate analysis, we also exposed badges to air containing no formaldehyde and did not observe measurable color change. The standard deviation of all the data was calculated by comparing the actual formaldehyde concentration to the calculated formaldehyde concentration based on the color change ratio and our mathematical model. Cross-contamination of acetaldehyde and VOCs were evaluated using the GENMOD procedure in SAS by considering the interaction term based on grouping reading based on presence or absence of acetaldehyde and using the "no intercept" option.

For the field test data, we calculated the mean and standard deviation of both 1) images taken of the same badge and 2) images taken from co-located badges. The relative standard deviation is also reported.

3. Results

Our testing of the badges demonstrated the ability of smartphone cameras to accurately determine changes in lightness (color change) associated with formaldehyde exposure under controlled laboratory conditions. Some variability in initial field testing of our badge and smartphone system indicates the need for additional, larger field tests that include side-by-side sampling with an established sampling and analysis method such as DNPH cartridge sampling followed by HPLC analysis.

3.1. App development

The app user interface (Fig. 5, Fig. 6) was developed and refined using a collaborative development model to allow both measurements of the color change of the badges and access to surveys that can be made publicly available (Figs. 3 and 4). Modifications were made to the user interface throughout the app design process (Table 3), resulting in improved usability and flow (Figs. 5 and 6).

3.2. Necessary user warnings and education

3.2.1. Integration of user warnings

The image output relies on the camera settings and the lighting conditions, and it is important to reduce the possibility of overexposure or low lighting conditions. To avoid such test errors, we identified a list of warnings to test and subsequently notify the user to instruct them on the appropriate use of the app (Table 1).

The values in Table 1 were determined from a series of experiments on the badges. Different experimental conditions were tested, and boundaries for warnings were selected to be about halfway between extreme points measured in suitable and unsuitable conditions.

For instance, we noted that high relative humidity conditions above about 75–80% will interfere with the color change of the badge and can potentially cause erroneous readings in the app. Fortunately, under these conditions the badge also develops a blue/purple tint that is detectable in the image. We incubated badges at various relative humidity conditions to determine when an interfering blue color appeared on the badge. The lowest saturation value detected in suitable conditions was 0.80 and the highest saturation value detected in unsuitable conditions was 0.52. Therefore, we selected 0.6 as the boundary for activation of this warning. We also subjected badges to long-term, high-temperature storage conditions to produce contamination and quantified detection

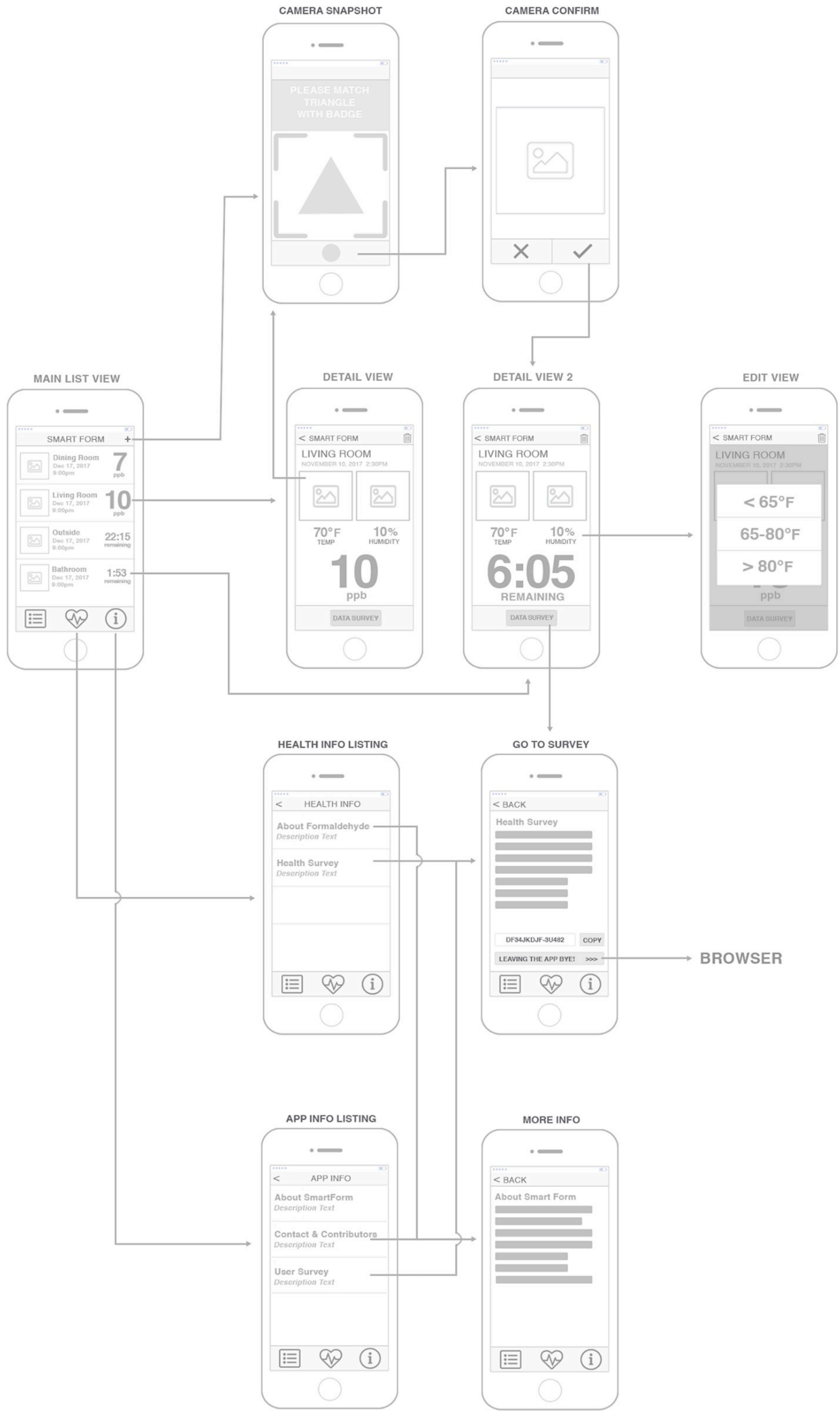

Fig. 5. Final wireframe.

with the app.

For exposure time, we selected a 72 h period to balance detection capabilities with user time and consistency in the color-changing area of the badge. The badge can theoretically be read at different times that allow for sufficient color change (at least about 12 h), but those parameters were not validated here. Taking an image in a very short amount of time (for instance, 5 min) will result in an artificially high value by dividing by a very small time value due to the algorithm used, and thus we also wanted to prevent this error. We also placed a limit on the reported values so that high and low values will be reported as > 120 ppb and < 20 ppb, respectively. This range represents the calibration range above the method detection limit. Values above 120 ppb may have also experienced saturation on the badge, but this needs further evaluation to confirm.

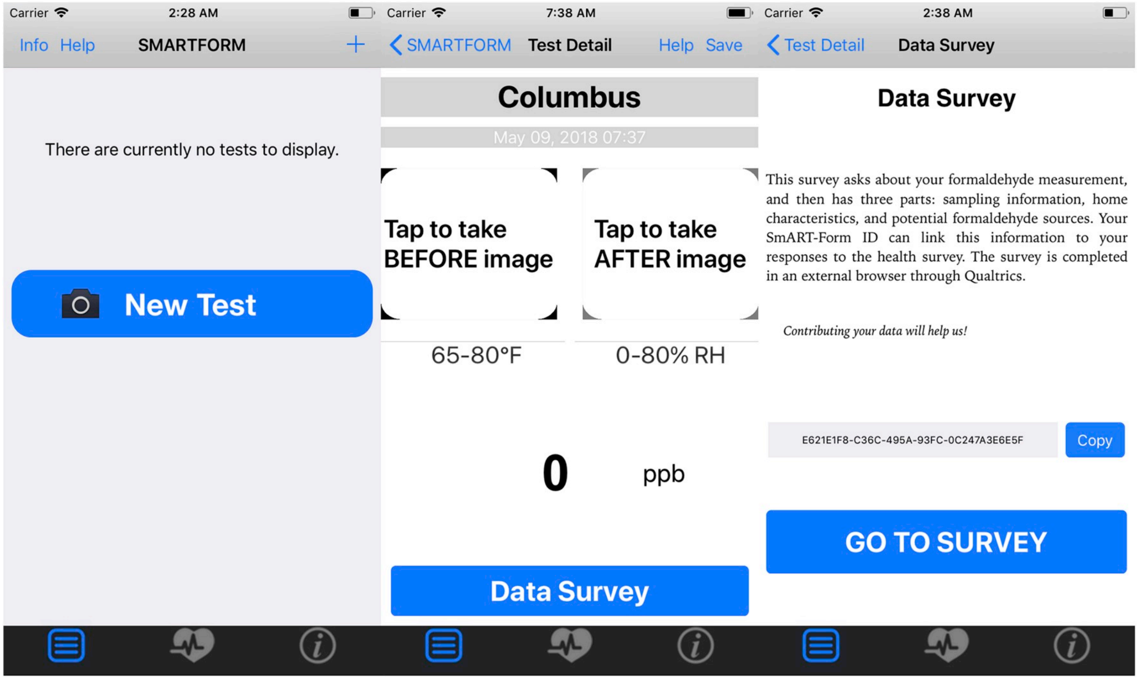

Fig. 6. Screenshots from the app. The first screen is the test display screen. Each test will bring the user to the test detail page (second screenshot). The third screen is accessed via the "data survey" link and will send the user to the external survey after clicking the "go to survey" link.

3.2.2. User education

We integrated a formaldehyde information sheet into the app, with the intention of providing necessary information to users to interpret their results and take appropriate action if necessary. The informational page lists typical formaldehyde concentrations and potential sources and remediation strategies.

3.2.3. Camera parameters and lighting conditions

Our results at different lighting conditions and camera settings informed our decisions related to app design. Overexposure was a challenge that could potentially result in inaccurate readings, but fortunately, we could prevent these inaccuracies by incorporating warning messages into the app. Under our experimental conditions with a close light source 30.5 cm from the badge, the ratio of color intensity between "orange" and "yellow" is quite stable with different camera settings under 25 W, while the results of 60 W show more variations (Fig. S5). In our setup, the 25 W or 40 W non-LED light bulb worked best (Fig. S6), and we were able to determine the optimal bounds for lighting conditions. The variations are possibly caused by overexposure as well, so the ideal camera settings should eliminate such overexposure. We also determined that it was necessary to use fixed camera settings as opposed to automatic settings, which vary by phone. We selected White Balance: 4000 K, ISO: 200, Exposure Duration: 1/60s or 1/125s depending on external lighting conditions, to avoid any overexposure (Table S2). Other uncontrolled camera settings may cause small differences in image quantifications, especially under extreme lighting conditions. However, we expect the system to perform well under most "normal" indoor lighting situations. We incorporated error messages into the app to alert the user if lighting conditions exceed acceptable bounds, allowing them to take a better picture for more accurate results.

3.3. Calibration

The results of color change ratio as a function of exposure time, CCR = f(t), for the three different levels of formaldehyde concentrations under the same temperature (23 °C) and relative humidity (50% RH) are shown in Fig. S8. A total of 216 individual readings were used to calibrate the system. The badge sensors did not appear to suffer from saturation up to the 72 h tested. The sensors of the low concentration test showed only minimal color change at 72 h because this was close to the limit of detection. In order to test the limit of sensor under the low indoor concentration level, we extended the test of the low concentration test to 360 h until it reached the saturation state. The results show that the function CCR = f(t) shows the trend of linear relation for all the three levels of formaldehyde exposure conditions (Fig. S8). The results also show that the color change of version1 (SafeAir®, Morphix Technologies, Virginia Beach, Virginia) of the badge sensor is more sensitive to the formaldehyde exposure than version2 (ChromAir®, Morphix Technologies, Virginia Beach, Virginia).

The results of high relative humidity test are plotted in Fig. S9. Under high RH condition, the CCR value increased instead of decreased with time, indicating a RH interference. This was partially due to a blue/purple tint that occurs under this condition. The CCR at the high

Table 3
Comparison of app layouts before and after refinement.

Initial Version	Final Version
Two layouts, with many features located on test page	Three layouts, move surveys to additional page
Simple list view, only titles and dates	Add intuitive color signs and result information
Three ambiguous steps to take photos	Remove capability to take image of surroundings, highlight the two before/after steps
Evenly distributed user interface spaces for all elements	Assign weighted space to each element
Simplified camera process, hard to handle	Redesign camera function, show badge icons

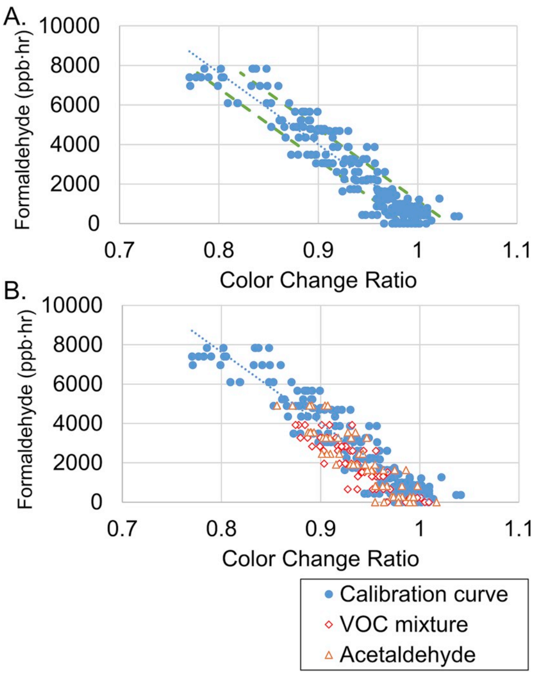

Fig. 7. Calibration of the app. A. The best-fit line to the data was $y = -36301x + 36671$ ($R^2 = 0.8811$ and $P < 0.0001$) and is shown in small blue dots. Standard deviation lines (dashed outer lines) are shown in green around data. The standard deviation of the data was equivalent to 10.9 ppb at 72 h of exposure. B. Co-exposure to acetaldehyde or a VOC mixture did not interfere with measurement ($P = 0.93$, $P = 0.07$, respectively). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

RH also varied with time or exposure amount, but in a non-linear fashion. It is therefore recommended not to use the current sensor at high RH, and a warning was integrated into the app that detects this blue/purple color.

Fig. 7 shows the exposure as a function of CCR and time for all the tests conducted at 23 C and 50% RH without potential contaminants, including a linear correlation function that was implemented in the app. Illumination (lightness) from the color change was associated with formaldehyde concentration ($R^2 = 0.8811$, $P < 0.0001$).

We calculated the method detection limit to be 20 ppb at 72 h. We also placed an upper limit of 120 ppb detection due to concerns about saturation of the reaction area beyond what was tested. The standard deviation of the data was calculated to be equivalent to 10.9 ppb if measured at 72 h of exposure. Assuming a normal distribution, we expect 68% of the measured values to fall within 10.9 ppb of the true value at 72 h of exposure, and 95% of the data will be within 21.8 ppb of the true value.

The data in Fig. 7 are from the Android system, and a similar graph with nearly equivalent linear model resulted from the DLSR camera images. The iPhone that was used in testing developed an artificial blue tint only when images were taken through the glass that interfered with analysis, and thus the Android results were used for all versions of the app. Further testing indicated that Android and iOS systems yielded similar results within error limits when imaging the same badge under appropriate lighting conditions ($P = 0.70$). We do not expect the blue tint to interfere in future use of the app on iOS systems because 1) it appeared to be limited to the phone used and 2) we do not expect users to be taking images through glass under normal circumstances.

We also tested the badges under two additional conditions at the mid-concentration level to examine the possible interface effect of the co-existence of acetaldehyde, which is another major VOC contaminant in buildings, and other VOCs from the composite wood product source such as a particleboard. The results were not statistically different with and without co-exposure to acetaldehyde ($P = 0.93$) or with and without co-exposure to a VOC mixture from the particleboard ($P = 0.07$) (Fig. 7B). We note that the p-value for the VOC mixture is low. While we collected 60 data points for this test, it is possible that some low-level interference is present that could be seen if more data had been collected. This could be evaluated further in future field tests.

Table 4
Beta test results. A total of 10 people consented to the survey and completed at least one question.

Question	Yes (n)	No (n)	No response (n)
Did you have trouble opening the app?	0	10	0
Did you have trouble taking images?	0	9	1
Did you have trouble taking survey?	6	3	1
Was any part confusing?[a]	2	6	2
Were you able to get a formaldehyde concentration?	8	0	2
Did you receive an error taking survey?	3	1	6

[a] Comments indicated confusion was related to survey access or questions.

3.4. Beta testing

We received 10 responses to our beta test survey that both consented and completed at least one question on the survey. Four users reported their age with a mean age of 33 years. We received three other responses where users did not consent to participate, and we are unable to determine how many people in total attempted the beta test. Users rated the usability of the app at the time of testing with a mean of 8.1 on a 1 (difficult) to 10 (easy) scale. Users cited “ease of use,” “simple use,” and “clean layout and intuitive” as the main strength of the app (Table 4). The biggest challenge occurred with accessing the survey. Importantly, beta testers reported a bug that impeded the Unique ID assigned to their app from being automatically copied to the Qualtrics survey, which is essential for contextual data collection while protecting personally identifiable information. Because of this issue, many users had difficulty submitting their feedback within the beta test survey and 9 additional beta testers emailed feedback directly to research team members. Other more minor technical glitches included compatibility with down market and older phones. These glitches were addressed to ensure the app functioned properly.

Another suggestion received from three beta testers and others who reviewed the app was the need for more clear instructions, both with an overview instruction page and step-by-step instructions for each phase. The user interface was substantially transformed following beta testing to address the app's clarity by adding instructional pages, improving the screen layout to emphasize key information, utilizing familiar icons, and ensuring more intuitive user pathways.

Overall, the app and beta test had global appeal. There were 136 app downloads from September 2017 to May 2018, although a small but unknown number of those included from the study team. Country of download included the United States, India, South Korea, South Africa, Mexico, China, Italy, Canada, United Kingdom, Turkey, Afghanistan, Brazil, Czech Republic, Chile, Germany, Japan, Namibia, Malawi, Niger, Taiwan, Ukraine, and Russia.

3.5. Field test

We tested the novel formaldehyde detection system at 17 homes in southern Georgia, with 20 unique sampling events. We obtained multiple images of an exposed badge (six events) to test the variation in calculated formaldehyde concentration from an individual badge. We also obtained images of co-located badges (seven events) to test the consistency of badge exposure results. Finally, we obtained a single image of a single exposed badge (seven events) as part of a larger study

Table 5
Field test formaldehyde concentration data for sites with multiple images or co-located badges within the quantification limits of the system. The number in the badge name indicates the site and a letter indicates that badges were different, co-located badges. Analyses in the table with just one badge name indicate a comparison of multiple images collected from the same badge. Analyses in the table with multiple badge names indicate that one image from each badge was compared. In the lighting conditions column, "similar orientation" refers to badges placed in equidistant radial locations around a light source. "Different orientation" refers to badges places in a line with the light source on the right side of the line, so badges were different distances away from the light source. We note that lighting conditions warnings were not included in the app used to conduct some of these tests.

Analysis	Site	Badge	Number of images compared	Average Formaldehyde Concentration (ppb)	Formaldehyde Concentration Standard Deviation (ppb)	Formaldehyde Concentration Relative Standard Deviation (%)	Lighting conditions
A	3	3	3	71	9.6	14	Similar orientation
B	4	4	2	85	1.4	2	Similar orientation
C	6	6	2	61	4.9	8	Similar orientation
D	8	8a	2	35	4.5	13	Different orientation
E	8	8b	2	47	13	27	Different orientation
F	8	8c	2	49	10	42	Different orientation
G	8	8a, 8b, 8c	3	37	2.1	6	Standard orientation
H	8	8a, 8b, 8c	3	50	17	33	Different orientation
I	9	9	2	92	6.4	7	Similar orientation
J	10	10a	2	62	3.5	6	Different orientation
K	10	10b	2	57	1.0	2	Different orientation
L	10	10c	2	56	3.5	6	Different orientation
M	10	10a, 10b, 10c	3	56	2.8	5	Standard orientation
N	10	10a, 10b, 10c	3	50	3.4	6	Different orientation
O	10	10a, 10b, 10c	3	130[a]	8.2	6	Natural light; Different orientation;
P	14	14a, 14b, 14c	3	61	9.8	16	Light impacted by shadows
Q	14	14a, 14b, 14c	3	80	7.2	9	Natural light; light impacted by shadows
R	15	15a, 15b, 15c	3	58	16	28	Light impacted by shadows
S	19	19a, 19b, 19c	3	68	4.6	7	Similar orientation

[a] Above quantification limit.

to test whether the system quantification limits are appropriate for residential exposure and how environmental and health factors may relate to residential formaldehyde exposure.

Of the 20 sampling events, 15 collected data that was within the quantification limits of system (20–120 ppb formaldehyde); one sample was below detection limits, and four were above quantification limits. The four sampling events that surpassed the quantification limit occurred in two homes, with one reading taken after 72 h badge exposure, and a second reading taken with new badges after 48 h. For these homes, the upper quantification threshold is too low for accurate readings, but is sufficient to indicate there is significant formaldehyde exposure occurring in the homes. Both homes had detectable odors. For the majority of homes samples (14 of 17), the system quantification limits were appropriate. Only data within the quantification limits of the system were further analyzed for system precision.

Where multiple images of the same badge were obtained, the orientation of the badge to the light source may be a key factor driving variation in calculated formaldehyde exposure (Table 5). For image pairs taken with similar orientation of the badge to the light source, standard deviations ranged from 1.4 to 9.6 ppb, with relative standard deviations (RSDs) of 2%–14%. For image pairs that were taken with one image in a standard orientation and one in a different orientation, standard deviations ranged from 1.0 to 20 ppb, with RSDs of 2%–42%. This includes image pairs of two sets of co-located samples, which ranged from 1.0 to 3.5 ppb (2%–6% RSD) in one lighting setup, and from 4.5 to 20 ppb (13%–42% RSD) with a different lighting setup.

Where images of co-located badges were obtained, the formaldehyde concentrations calculated from multiple badges with similar orientations to light sources were more precise than images of a single badge with different orientations (Table 5). When three co-located badges were arranged with the standard orientation, the standard deviation of their calculated values ranged from 2.0 to 4.6 ppb (1%–7% RSD). At two locations, the threesome of badges were arranged in an additional formation with a variable orientation to the light source. With these alternate orientations, the standard deviations were 3.4 and 17 ppb, as opposed to 2.8 and 2.1 ppb, respectively (6% and 33% versus 5% and 6%, respectively). There were two sets of co-located badges with higher standard deviations, of 9.8 and 16 ppb (16% and 28% RSD), however images of these sets were taken with complex lighting conditions that likely included shadows. Formaldehyde concentrations calculated from images of co-located badges under consistent lighting conditions were as precise as formaldehyde concentrations calculated from images of a single badge under similarly consistent lighting conditions. Thus, any imprecision due to badge variation was not observable in the field test beyond the imprecision introduced by image capturing.

For two sampling events, images were collected under indoor lighting conditions and natural lighting conditions. In both of these instances the images taken under natural lighting conditions calculated significantly higher formaldehyde concentrations, but the extent to the formaldehyde elevation varied. At location 14, the images taken under natural light calculated a formaldehyde concentration that was 19 ppb higher compared to calculated from images taken under indoor light (80 vs. 61 ppb, 130% higher), while at location 10 the images taken under natural light calculated a formaldehyde concentration that was > 64 ppb higher than that calculated from the same badges under indoor light (> 120 vs. 56 ppb, 220% higher). We have now adjusted the app to contain lighting condition warnings based on these results.

4. Discussion

We have developed a novel measurement system for formaldehyde in the indoor environment. Our current results indicate that this system can provide accurate results and is amenable to use by citizen scientists and concerned members of the general public, as well as visiting nurses and researchers [14,25]. Our initial small field test indicated some variability in measurement, and our system would benefit from more extensive field testing in the future. Eventually, this technology, which is openly-licensed and open sourced (https://github.com/publiclab/SmART-Form), can be expanded to detect additional compounds of concern in the indoor environment. Integration into a smartphone app also provides an important venue for user education.

Formaldehyde is present in most indoor environments [1,8,26,27], and is notoriously difficult to measure. The contaminant is too volatile to effectively adhere to many common sorbents, and also requires derivitization for detection by gas chromatography/mass spectrometry. Ubiquitous presence also increases the possibility for ambient contamination during sampling.

4.1. Challenges

Uncontrolled lighting conditions present the greatest challenge for use of this system. The user warning about ambient lighting conditions is critical to successful use of the app. Shadows, overexposure, multiple light scattering, and low light are situations that could affect the reading of the badge. Previous work has considered these challenges in applications of surface material and optical property measurement. Normally, measuring the albedo of a surface requires a lab-based reflectance measurement [28,29], with a single light source and an object with known shape (i.e. a perfect sphere) in a dark room. In a natural or indoor environment, surface albedo measurement requires physical-model based disturbance correction (e.g. atmosphere and light scattering) with *in situ* information such as scene geometry (walls, tables, etc. in the room) or humidity/weather conditions [30–32]. In our system, we know that the badge is a flat surface, while the environment and its lighting are unpredictable. We designed the badge to include a calibration patch, where we assumed that this portion in the smartphone image encodes variants of the environment. Using this, we are able to approximate the albedo computation through calculating the ratio of lightness of the reaction and calibration areas. We also integrated warnings to the user within the app to account for some of these conditions, but potential still remains for introduced error, which was observed in our field test when taking images of the badge with a different orientation to a light source. The mathematical light reflectance model we used in our algorithm is a simple linear color change ratio between the calibration patch and the reaction patch. This is based on the assumption that the indoor environment contains only homogeneous and ambient light. Although the calibration patch is able to capture most of the environment lighting, this model is not able to account for complex and often non-linear lighting environments and non-standard image-taking practices, such as non-orthogonalized view, concentrated light sources, and inhomogenous shadows. In this work, our capability is limited to a standard and commercial product for designing a more capable calibration patch accounting for more complex lighting environment, which could be attempted in future work. Future enhancements of the system can focus on further improving mathematical models used for color calculation, and improving and systematizing conditions under which images are taken.

We also noted that the formaldehyde levels measured in our field test were, on average, slightly higher compared to those found in some other studies but still within a similar range [26,27,33–37]. It is unclear whether this is due to systemically higher formaldehyde levels in this particular community with environmental concerns, or if other co-contaminants not considered in the chamber study may inflate values. A future side-by-side field test with the DNPH measurement method would help to identify the reason for these levels and also potentially indicate additional improvements for the system.

The standard deviation of our data was 10.9 ppb if the badge has been exposed for 72 h and the image is taken with a standard orientation to the light source. For example, this means that a reading of 35 ppb is 68% likely to have a true value between 24 and 46 ppb, and a reading of 85 ppb is 68% likely to have a true value between 74 and 96 ppb. It is always desirable to obtain a more precise reading. However, the accuracy and precision available here is most likely acceptable to citizen scientists or concerned citizens who want to quickly determine the general range of their formaldehyde exposure with an inexpensive and easily-accessible method. This device is best used as a screening tool to determine if their exposure is high or low, and can inform decisions about further testing or potential remediation.

Colorimetric badges have well-established limitations that will also impact the use of this system. This includes dependence on temperature, relative humidity, and pressure/air flow in the ambient environment [38,39]. Another general limitation is the interpretation of color change intensity by the human eye [38], which we are able to overcome with the use of the smartphone app. These well-established limitations should be weighed against the benefits of using this system for measurement, including ease of use and low cost.

4.2. Future use and interventions

This system is not as precise as the gold-standard DNPH cartridge sampling and HPLC analysis method [40], but it does serve as an important screening tool for formaldehyde in the environment. By comparison, the DNPH cartridge method has a reported coefficient of variation of 1.02% and a method standard deviation of 0.71 $\mu g/m^3$ (approximately 0.57 ppb) [41]. Such extreme precision is not necessary in all situations, especially when other factors such as ventilation changes or occupant activity may alter formaldehyde levels over different periods of time. An interested user will need to weigh cost, usability, accessibility, and accuracy/precision when deciding which measurement tool to employ. In some cases, the smartphone-based system described here may provide the best combination of these factors, and also provides additional information to the user related to interpretation of results and options for remediation. After utilizing the SmART-Form system, the user can decide to either 1) pursue more expensive/difficult but more precise testing, 2) conduct additional tests with the SmART-Form system, 3) do nothing, or 4) take remedial action to reduce exposure. More precise and more expensive/cumbersome methods can be employed if desired. Additionally, future improvements can potentially increase precision in future iterations of this system. Future work based on the results of the field test should include instruction to guide the user to orient the badge to the lighting source in a standard fashion, and to capture images of the badge under indoor lighting conditions instead of under natural light. These additions should preempt errors introduced by image capture variables.

The use of a smartphone for measurement of environmental exposures presents a novel opportunity for user education and engagement. Increasing viability of low-cost and easy-to-use monitoring systems is already changing the current paradigm of air quality monitoring, according to the U.S. Environmental Protection Agency and others. The historical monitoring model relied on highly expensive and complex instruments with limited input from the public on where they are deployed and limited access of the data once collected. A new paradigm is variously influenced by citizen science, participatory civic engagement, and the popularity of 'quantified self' technologies and is seen to bear the possibility of bringing communities and members of the general public into closer dialog with scientists about air quality. This can enhance source compliance monitoring and yield more robust understandings of personal exposures [42,43]. Most of the "next generation" air quality monitors are electronic real-time sensors that pose ongoing calibration and drift issues, and are *relatively* inexpensive (150 USD or more) but still too expensive for the communities that bear the highest burdens of environmental exposure. Even highly motivated and scientifically literate users are finding that they are "drowning in data" due to the large volumes of data produced by real time sensors [44,45]. For smartphone colorimetric systems, the analytical technology is already owned by 77% of the U.S. population (with higher rates in some Asian, Middle Eastern, and European countries), allowing a truly accessible price point with badges costing approximately 5 USD and the app being free. Further, these badges represent discrete averages of exposure that are more easily understandable, meaningful, and actionable for the general public than thousands of real-time data points. Information in the app can also assist users in result interpretation and decision-making related to remediation.

Fortunately, there are interventions available that can reduce formaldehyde exposure once it is detected. These include primarily source removal or avoidance, but may also involve increasing ventilation rates [1]. Future work might explore how occupants respond to detecting high levels of formaldehyde with this app, and if they are likely to take action to reduce their exposure.

4.3. Limitations

Limitations of our system include potential error introduced due to uncontrolled and potentially untested lighting conditions, including different orientations of the badge and camera to the lighting source while capturing an image for calculation. We expect our system to function properly under most indoor lighting conditions and provide a warning to the user when lighting conditions are outside of system requirements. We also plan to provide instructions on badge and camera orientation in future work. However, it is still possible that shadows or other untested conditions could affect results. We tested the badges under various lighting conditions, but the lightbulbs in our test were placed close to the badge (30.5 cm) and this will generally not reflect the typical light distance in a given room. Thus, the bulbs used are reported here for reproducibility, but may not indicate the bulbs that are necessary to use in a room where the light source is placed further away from the badge.

Error in the final reading could potentially be reduced with future badge enhancements such as by controlling the position in which the user takes the image, taking multiple images from which to calculate the final value, and further refining our mathematical model. We tested and did not see interference from co-exposure to acetaldehyde or other compounds present in pressed wood products. However, it is also possible that other untested compounds, such as acetone or ammonia, may cause interference in the color change of the badge. Our system is not able to be used under conditions of elevated relative humidity, above about 75–80%, which causes an artificial blue tint to the color changing area of the badge. Additional work needs to be done to ensure sufficient communication of measurement precision and error within the app. Further development and testing of this technology may be able to overcome some of the limitations listed here.

4.4. Strengths

Strengths of this study include the development of a novel screening tool to use a smartphone and color-changing badge to measure formaldehyde concentration in the air. This system was developed in conjunction with end-users across the spectrum of technological literacy to expand potential use. We found a strong correlation between exposure to formaldehyde and color change in the badge as read by the smartphone camera. Thus, the badge is useful as an inexpensive indicator that formaldehyde is present and detectible, while additional modification is required to enhance the precision of the quantitative results. Given the wide range of plausible values from each reading, and levels of uncertainty, we recommend use by well-informed users, professionals, or paraprofessionals with risk communication training to interpret results and recommended actions until greater quantitative precision can be achieved. However, information in the app can also assist with interpretation of results and user education. This app is currently available for download on both Android and iOS devices. This system can be further improved upon to provide results that are more precise in the future. Our system makes formaldehyde measurement more accessible to community scientists and other interested users and also provides a new opportunity for both scientific engagement and education.

5. Conclusions

Here, we developed a novel system for smartphone-based formaldehyde measurement for testing of residential formaldehyde levels. This new method can expand measurement options for a range of future users and potentially also be applied to additional compounds of interest. This current system is best used as a screening tool to determine the general level of formaldehyde in an environment when cost, usability, and accessibility are the most important considerations. We expect that future improvements to this and similar systems can improve precision. The use of a smartphone encourages engagement of community scientists and concerned citizens, and also provides an additional opportunity for education about formaldehyde exposure. This platform can also be used by researchers in epidemiological studies as well as medical providers conducting home visits for vulnerable populations, such as people with asthma. Finally, this system can be used to respond to future widespread concerns that might occur related to formaldehyde exposure.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2018.11.029.

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