TBM

ORIGINAL RESEARCH

Assessing reinforcing versus aversive consequences in a real-time secondhand smoke intervention

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Cite this as: *TBM* 2021;11:1558–1566
doi: 10.1093/tbm/ibab004

Abstract

Few studies have examined the relative effectiveness of reinforcing versus aversive consequences at changing behavior in real-world environments. Real-time sensing devices makes it easier to investigate such questions, offering the potential to improve both intervention outcomes and theory. This research aims to describe the development of a real-time, operant theory-based secondhand smoke (SHS) intervention and compare the efficacy of aversive versus aversive plus reinforcement contingency systems. Indoor air particle monitors were placed in the households of 253 smokers for approximately three months. Participants were assigned to a measurement-only control group ($N = 129$) or one of the following groups: 1.) aversive only (AO, $N = 71$), with aversive audio/visual consequences triggered by the detection of elevated air particle measurements, or 2.) aversive plus reinforcement (AP, $N = 53$), with reinforcing consequences contingent on the absence of SHS added to the AO intervention. Residualized change ANCOVA analysis compared particle concentrations over time and across groups. Post-hoc pairwise comparisons were also performed. After controlling for Baseline, Post-Baseline daily particle counts ($F = 6.42$, $p = 0.002$), % of time >15,000 counts ($F = 7.72$, $p < 0.001$), and daily particle events ($F = 4.04$, $p = 0.02$) significantly differed by study group. Nearly all control versus AO/AP pair-wise comparisons were statistically significant. No significant differences were found for AO versus AP groups. The aversive feedback system reduced SHS, but adding reinforcing consequences did not further improve outcomes. The complexity of real-world environments requires the nuances of these two contingency systems continue to be explored, with this study demonstrating that real-time sensing technology can serve as a platform for such research.

Keywords

Contingency management, Secondhand smoke, JITAI, Real-time data, Operant theory

Implications

Practice: Systems that continually use aversive contingencies to present immediate feedback in response to individuals' smoking behavior, both with and without the addition of reinforcing contingencies, can reduce in-home secondhand smoke outcomes.

Policy: Policy makers interested in protecting household members, particularly children, from secondhand smoke exposure should consider the use of real-time feedback systems.

Research: Future research can increase the precision of behavior science by leveraging real-time, streaming technology to investigate how aversive/reinforcing contingencies and other operant constructs function in real-world settings.

INTRODUCTION

Modifiable health behavior is a leading cause of morbidity and mortality in the USA [1, 2], which implies that significant gains to public health can be achieved with effective behavior-altering systems. However, many interventions demonstrate small, short-lived effects [3], partially due to a focus on between-individual characteristics rather than on dynamic, within-person factors [4]. Interventions are often deployed at infrequent, pre-determined occasions and are not sensitive to participants' idiosyncratic changes over time. Furthermore, they are frequently assumed to produce relatively permanent outcomes, which is incompatible with the everyday experience of behavior that continually varies with time, context, and other factors. Real-time tools such as smartphones and internet-of-things devices have the potential to shift behavioral interventions toward a framework that is better equipped to affect, and possibly maintain, change by facilitating just-in-time, adaptive interventions (JITAIs) [5]. JITAIs pair intensive data collection with analytic systems capable of real-time implementation and adaptation, allowing interventions to react on an ongoing basis to participants' behaviors, environmental setting, and unique recorded history.

An area poised to benefit from transitioning to JITAIs is secondhand smoke (SHS) exposure, which is responsible for over 41,000 deaths and $5.6 billion in costs each year in the USA [6], with a recent study showing that greater than 4 in 10 children aged 3–11 years in the USA are exposed [7]. Interventions aimed at reducing SHS exposure have typically relied on infrequent and imprecise measurements of indoor smoking, occasionally deployed with delayed feedback, which has resulted in modest effect sizes [8, 9]. In an effort to improve these outcomes, the Project Fresh Air (PFA) JITAI was conducted in homes where children plus an adult tobacco smoker(s) resided. Within PFA, in-home SHS exposure was continuously measured with air particle monitors and contingent, aversive feedback (i.e., lights and tones) was delivered immediately after the detection of a suspected exposure event. In select homes, reinforcing feedback for attenuated air particle levels was also presented. PFA significantly reduced average air particle concentrations, time with elevated particle concentrations, the number of particle events, indoor air-nicotine levels, and self-reported indoor cigarette and cannabis smoking [10, 11].

The ongoing exposure to an aversive feedback contingency within PFA was developed to align with previous calls to optimize mobile technology interventions by rooting them in behavior models that are dynamic, regulatory, and adaptable based on an individual's behavior and context [12]. The contingency approach is emblematic of operant theory, which posits that the occurrence of a behavior in a given context is governed by the contingent consequences of previous instances of the same behavior in similar contexts. Contingencies can be either *reinforcing* or *aversive*, depending on whether they lead, respectively, to a higher or lower probability of a behavior being emitted under similar conditions in the future. When implementing an operant JITAI, either type of contingency, or a combination of both, can be incorporated into the design; but the optimal balance between these two approaches remains to be determined. Within non-JITAI settings, the effects of reinforcing versus aversive contingencies have been widely studied in non-humans [13–18], digital agents [19, 20], and humans [21–25]. For humans, aversive contingencies have generally been found to more effectively regulate behavior [21, 23, 24], but in certain domains, particularly for complicated tasks, the combination of reinforcement and punishment was optimal [21, 22, 25].

Until recently, it has been challenging to arrange contingencies in the free-living world, which has limited our ability to assess reinforcement versus punishment in a natural context. As demonstrated by the aversive lights/tones feedback implemented within PFA, innovations in mobile technology have made it easier to arrange real-world contingencies, which imbibe JITAIs with the potential to serve as critical platforms to conduct operant experiments. From this perspective, this paper describes the development and deployment of a reinforcement plus aversive contingency within the PFA study and contrasts its performance relative to aversive-only and measurement-only contingencies. Understanding the comparative ability of these approaches to change behavior will aid practitioners in optimally designing future interventions.

METHODS

Overview of project fresh air

Full details of PFA have been published elsewhere [10, 11]. Briefly, 298 homes with at least one adult smoker and at least one child under 14 were enrolled. Two Dylos DC1700 air particle monitors were installed, one in the room nearest to where most smoking occurred and the other in the child's bedroom; only the monitor in the main smoking room was used in this study. The monitors were calibrated to count particles ranging from 0.5 to 2.5 μm in diameter, which is consistent with SHS as well as non-tobacco aerosol sources [26]. The monitors measured air particle concentrations every 10 s and were installed in homes for an average of 3 months. The intervention was broken into three phases, delineated by four home visits from PFA coaches. While the study design specified that home visits should occur at 1-week intervals, scheduling conflicts and technological issues led to variance in the duration of the three phases.

Homes were block randomized using a block size of two into either an *intervention* condition or a measurement-only *control* condition. Intervention homes were stratified into two phases: (a) *baseline*—a period during which feedback was disabled and (b) *post-baseline*—a period during which feedback was activated. The feedback consisted of mildly aversive visual and auditory stimuli programmed to be provided in response to elevated air particle measurements. In its default state, the monitors displayed a green light emitting diode (LED). The LED turned yellow and an aversive tone was presented when air particle measures exceeded 15,000 counts; if the measurement exceeded 30,000 counts, the LED transitioned to red and a second, more aversive tone was presented. The aversive lights remained on until air particle measures returned to below 15,000 counts. As described in the next section, for select homes the aversive feedback contingency was supplemented with a reinforcement contingency.

Operationalizing feedback contingencies

Aversive only

The aversiveness of the two monitor tones was established in a previous study [27]. The yellow/red LEDs were considered a conditioned stimuli since they were not aversive in their own right, but drew this characteristic from their common association with everyday items such as traffic lights. The homes that were exposed to only the aversive contingency were denoted as *Aversive Only* (AO). To aid with retention and to offset participant burden, the AO homes were provided with a gift card (up to $20 or $40 in value, depending on enrollment period) for attempting to implement SHS reduction strategies.

Aversive plus reinforcement (AP)

As outlined in the Introduction, previous studies indicated that the combination of aversive and reinforcement contingencies may be optimal for complex tasks (such as reducing SHS), so a second intervention component that added a reinforcement contingency to the aversive lights/sounds was introduced. *Aversive Plus* (AP) homes were simultaneously exposed to the same auditory/visual contingencies as the AO homes, as well as reinforced for extended periods of attenuated air particle levels. This added process is known as the differential reinforcement of other behavior (DRO) because it reinforced any behavior that did not produce indoor air particles. The DRO contingency operated on functional units designated as *valleys*, which were defined as consecutive measurement instances with air particle concentrations below 15,000 counts (see Fig. 1). This name was chosen to contrast *peaks*, observations above 15,000 counts that activated the aversive feedback. Once a valley duration exceeded a pre-specified, home-specific *valley duration threshold* (e.g., 1 hr), participants began accruing monetary compensation on a gift card, up to a $40 value. Monetary accrual continued until the valley ended, either due to the exceedance of the 15,000 counts threshold or the end of a trial phase. Reinforcement magnitude was calculated (see details below) independently during each of the three intervals that were delineated by the four coaching home visits and was provided at the next coaching visit.

Calculation of AP reinforcement threshold

Due to a large variance in the frequency of indoor smoking among enrolled participants, a one-size-fits-all reinforcement approach was not feasible. Instead, the valley duration threshold was individualized for each home as follows: the unique household distribution of valley durations over the baseline phase was calculated, after omitting valleys with a duration less than 3 min, since they were unlikely to be associated with smoking. From the computed distribution, the 65th percentile was selected as the valley duration threshold. Figure 1 illustrates a schematic of the valley duration threshold determination and valley reinforcement procedures for a single home. Appendix 1 details the selection of the 65th percentile and 3-min exclusion as system parameters.

Conditioned reinforcer system

A key characteristic of the aversive contingency in PFA was a very small delay between the generation of air particles and the feedback presentation, with visual and auditory stimuli delivered immediately upon the detection of sufficiently elevated air particle concentrations. This feature is known to increase the degree to which consequential stimuli affect future behavior [28], so we sought to extend it to the AP condition by minimizing the time between the generation of a sufficiently long valley and the presentation of a reinforcing stimulus. This was accomplished by immediately presenting a solid blue LED on the air particle monitor once the valley duration threshold was reached; this LED remained lit until the air particle level again breached 15,000 counts. Participants were informed that the blue light indicated the accrual of gift card value and that the longer the blue light was present, the more monetary compensation they would receive.

Determining reinforcement value

In the AO arm, households were provided with a monetary reward of up to either $20 or $40 on a gift card when they attempted to implement SHS-reduction features that were developed with their coaches. Success/failure in this goal was based on self-reported measures that were evaluated during each coaching visit. Self-reported attempts were not

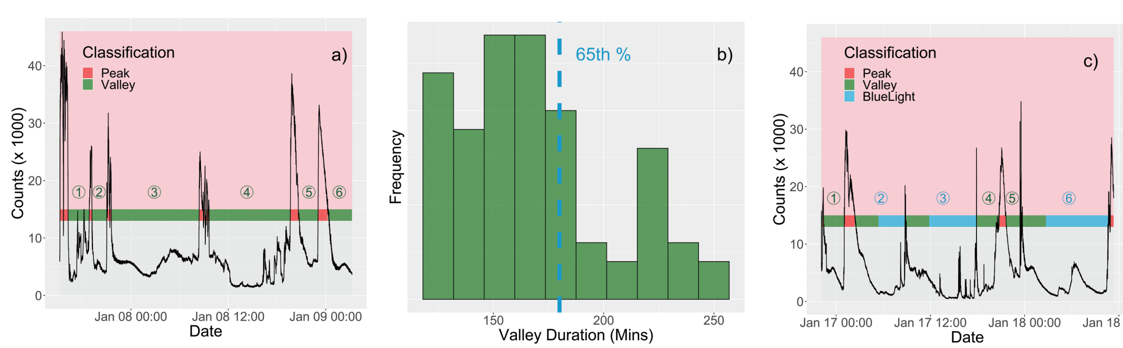

Fig 1 | Schematic of reinforcement protocol. Panel (a) illustrates baseline data, where the boundaries between peaks (denoted by red rectangles) and valleys (denoted by green rectangles) are identified. A green, encircled number denotes each of the six distinct valleys. Panel (b) illustrates the distribution of valley lengths and the calculation of the 65th percentile (180 min), which serves as the valley duration threshold in the post-baseline phase. Panel (c) illustrates the post-baseline phase. Peaks and valleys are colored as in Panel (a), but now valleys that exceed the valley duration threshold for reinforcement are shown in blue, which mirrors the blue light conditioned reinforcer that was presented during these times to indicate that gift card value was being accrued. Encircled numbers denote each distinct valley and are colored by whether the valley duration threshold was reached.

verified, as this reinforcement criterion was intentionally designed to be easily achieved in order to combat attrition. For most participants, the entire \$20/\$40 was disbursed throughout the intervention period, although approximately 15% of households did not report making an attempt to institute SHS mitigation efforts and did not receive compensation.

Monetary compensation in the AP arm was based on the percentage of total time that homes spent within sufficiently long valleys, with an aim to have the rewards mirror the AO reinforcement as closely as possible. Participants in the AP condition could earn up to \$13.33 in each of the three phases delineated by coaching sessions, with the monetary compensation in each coaching phase calculated via the following equation:

$$13.33 \cdot \frac{t_V}{t_T};$$

where t_T is the total time elapsed in the phase and t_V is the total time in valleys, including the time to reach the valley duration threshold. This value was rounded up to the nearest dollar.

Outcome measures

The following four outcome measures were used for analyses:

1. Mean daily particle counts
2. Mean daily percentage of time that particle concentrations were ≥15,000 counts.
3. Mean number of daily "particle events" (PEs), defined as instances of a rapid increase in particle levels followed by an exponential decay [11]. This measure was created to identify indoor cigarette smoking episodes, although non-tobacco sources could also lead to PEs.
4. Air nicotine, as objectively measured by dosimeters (i.e., passive devices containing an air filter designed to absorb nicotine). Dosimeters were installed at two different occasions–for 7 days at the beginning of the intervention and for 7 days at the end of the intervention. Assays were conducted by liquid chromatography tandem mass spectrometry using electrospray ionization (see Ref. [11] for full details), which provided a measure of the time-adjusted air nicotine exposure that occurred while the monitors were deployed.

Statistical analysis

To ensure equal sample sizes across conditions, homes were randomly assigned to the control/intervention groups in pairs. Control homes did not receive an intervention, so the "baseline/post-baseline" delineation for each control home was assigned to that of its corresponding intervention home. Thirty-six pilot homes were eliminated from all analyses as were nine homes that did not fully complete the study. Of the remaining 253 homes, 71 were in the AO condition, 53 were in the AP condition, and 129 were in the control condition. A summary of demographic and outcome variables for the final sample are provided in Table 1.

To compare the monetary reward in the AO and AP conditions, a Mann–Whitney U test was performed to compare the means in each group. This procedure was used rather than a t-test since the distributional assumptions of the t-test were severely violated by this variable.

Each of the four outcome variables were averaged separately during the baseline and post-baseline periods for each participating household. Averages were right-skewed for each outcome variable, so all values were log transformed. Three homes did not have any peak events or time above the 15,000 count threshold during the baseline period. To facilitate the log transform for these scenarios, the baseline average was set equal to minimum, nonzero baseline value observed over all other homes.

For each outcome, residualized change analysis was performed by fitting an analysis of covariance (ANCOVA) model with post-baseline measures as the dependent variable and study arm (i.e., AO vs. AP vs. control) as the grouping variable, after adjusting for baseline measures as a covariate. This approach accounts for postbaseline values regressing toward the mean. It is recommended when group differences across the baseline period are not expected [29], which is the case for this study since randomization had not yet occurred when baseline measures were collected; this assumption was assessed via analysis of variance (ANOVA). Subsequent to ANCOVA analyses, pairwise comparisons of study groups were performed via post hoc Holm-corrected t-tests of the estimated marginal means.

RESULTS

The mean valley duration threshold for homes in the AP condition was 1.47 days (standard deviation = 1.42 days, median = 0.97 days) with a minimum value of 54 minutes and a maximum value of 6 days. (Valley duration thresholds were not calculated for the AO/control conditions, since they were not required for intervention procedures.) Figure 2 illustrates a histogram of valley duration thresholds for all AP participants, which indicates that the distribution was skewed right with roughly half of the homes having reinforcement duration thresholds that were less than 1 day. The wide variance in valley duration thresholds demonstrates the necessity of the household individualization procedures that were implemented.

The mean total monetary reward provided to participants was \$25.43 in the AO group and \$30.66 in the AP group. A Mann–Whitney U test indicated that this difference was not significant (W = 1,719.5, p = .48).

Figure 3 illustrates changes in mean outcome variables from baseline to post-baseline, stratified by study condition. ANOVA analysis indicated that group differences at baseline for daily particle counts ($F_{2,250}$ = 1.09, p = .034), % of time >15,000 counts ($F_{2,250}$ = 0.69, p = .51), daily particle events ($F_{2,250}$ = 0.66, p = .51), and air nicotine ($F_{2,248}$ = 1.29, p = .28) were not significant, meaning the ANCOVA assumption was met. Table 2 illustrates the results of ANCOVA and post hoc pairwise analyses for each outcome variable. With the exception of air nicotine, ANCOVA indicated that, after controlling for baseline measures, there was a statistically significant difference in postbaseline measures due to study group. Subsequent post hoc analyses indicated that the differences between the control group and both the AO and AP groups were statistically significant in nearly every case; but the differences between the AO and AP groups were not statistically significant.

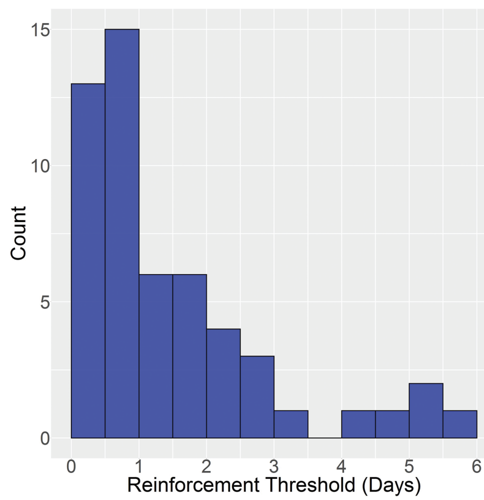

Fig 2 | Histogram of valley duration thresholds for AP homes.

DISCUSSION

This study demonstrated the use of real-time technology to implement a precise contingency that reinforced the absence of air particles consistent with SHS. This contingency was deployed in conjunction with another that provided aversive consequences in response to the generation of SHS. Both contingencies made use of near-immediate feedback and were present on a continual basis over the duration of participants' enrollment in the study. Previous SHS interventions introduced behavioral contingencies by, for example, encouraging household members to enforce home smoking bans [30] and/or having coaches provide feedback to participants [9]. Partially due to limitations in technology, these interventions were implemented without real-time feedback and continuous measurement of the target behavior, both of which are expected to improve intervention efficacy. The current study represents a considerable increase in the precision of arranging reinforcing/aversive contingencies and in the frequency with which these contingencies were encountered by families in the experimental condition.

To the best of our knowledge, this is the first study to examine the *continual* presentation of aversive feedback versus aversive plus reinforcement feedback in a real-world environment. As a result, our findings help appraise the degree to which

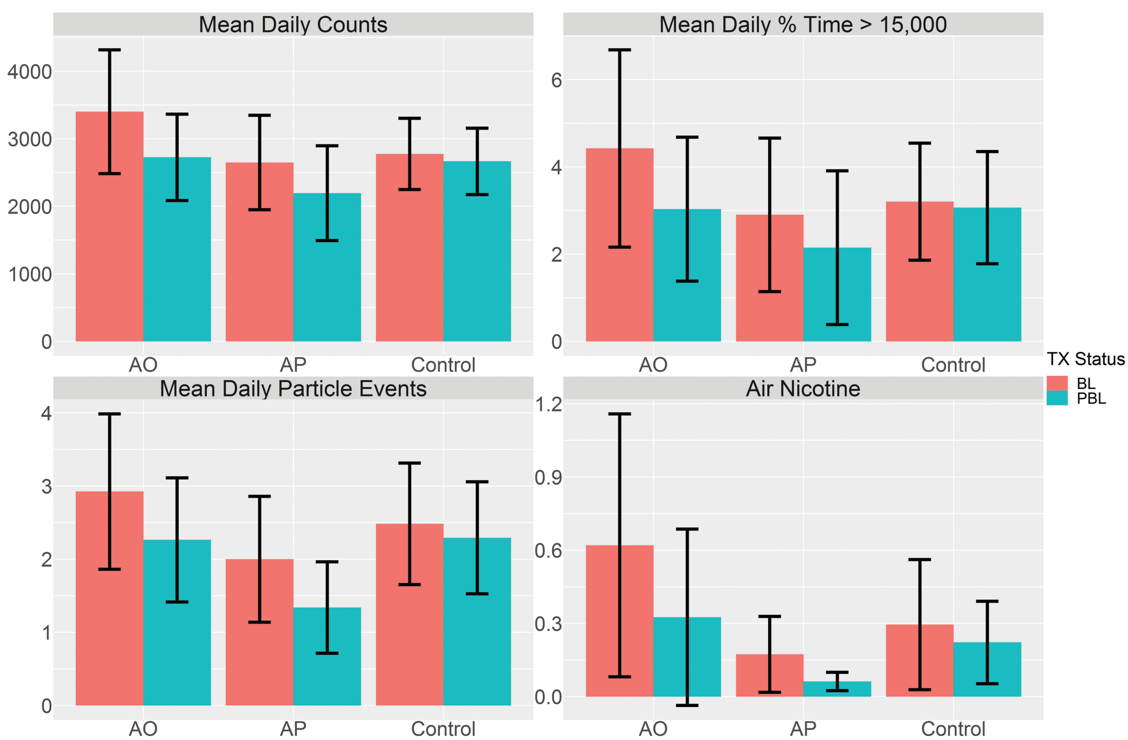

Fig 3 | Changes in mean outcome variables from baseline (BL) to post-baseline (PBL), stratified by study condition. Error bars indicate 95% confidence interval.

Table 1 | Sample characteristics, stratified by incentive condition

	All (*n* = 253)	AO (*n* = 71)	AP (*n* = 53)	Control (*n* = 129)
TC age, years	4.3 (3.8)	4.6 (4.0)	3.7 (3.7)	4.11 (3.31)
TC gender, % female	123 (48.6)	31 (0.44)	28 (0.53)	64 (0.50)
TC race/ethnicity				
Black	31 (0.12)	9 (0.13)	8 (0.15)	14 (0.11)
Hispanic	126 (0.50)	36 (0.51)	30 (0.57)	60 (0.47)
White	48 (0.19)	17 (0.24)	8 (0.15)	23 (0.18)
Other	48 (0.19)	9 (0.13)	7 (0.13)	32 (0.25)
TP age, years	33.1 (8.8)	32.6 (8.4)	32.9 (9.2)	33.4 (8.9)
TP gender, % female	241 (0.95)	70 (0.99)	48 (0.91)	123 (0.95)
TC race/ethnicity				
Black	38 (0.15)	9 (0.13)	11 (0.21)	18 (0.14)
Hispanic	98 (0.39)	28 (0.39)	22 (0.42)	48 (0.37)
White	67 (0.26)	20 (0.28)	12 (0.23)	35 (0.27)
Other	50 (0.20)	14 (0.20)	8 (0.15)	28 (0.22)
Household income				
<\$10,000	46 (0.18)	18 (0.25)	8 (0.15)	20 (0.16)
\$10,000–29,999	82 (0.32)	26 (0.37)	16 (0.30)	40 (0.31)
\$30,000–49,999	54 (0.21)	10 (0.14)	9 (0.17)	35 (0.27)
\$50,000–69,999	23 (0.09)	3 (0.04)	9 (0.17)	11 (0.09)
>\$70,000	22 (0.09)	6 (0.08)	7 (0.13)	9 (0.07)
Not reported	26 (0.10)	8 (0.11)	4 (0.08)	14 (0.11)
Mean daily counts, *n*	2,924 (3247)	3,400 (3940)	2,648 (2594)	2,775 (3058)
Mean daily time > 15,000 counts, %	3.5 (8.1)	4.4 (9.7)	2.9 (6.5)	3.2 (7.8)
Mean daily Particle events, *n*	2.5 (4.4)	2.9 (4.6)	2.0 (3.2)	2.5 (4.8)
Air nicotine, μg/m^3	0.4 (1.7)	0.6 (2.3)	0.2 (0.6)	0.3 (1.5)

Values are mean (standard deviation) for continuous variables and count (proportion) for categorical variables. All values were collected during the baseline phase.
AO aversive only contingency; *AP* aversive plus reinforcement contingency; *TC* target child; *TP* target parent.

Table 2 | Results of ANCOVA and post hoc pairwise analyses for the four outcome variables

	ANCOVA		Post hoc contrast by estimate marginal means		
	F	*p*	Group	*t*	*p*
Mean daily counts	6.42	.002	CTL-AO	2.67	.02
			CTL-AP	3.12	.006
			AO-AP	0.62	.54
Mean daily % time > 15,000 counts	7.72	<.001	CTL-AO	2.85	.009
			CTL-AP	3.48	.002
			AO-AP	0.80	.424
Mean daily particle events	4.04	.02	CTL-AO	1.62	.21
			CTL-AP	2.73	.02
			AO-AP	1.13	.26
Air nicotine	1.53	.22	CTL-AO	1.11	.54
			CTL-AP	1.63	.32
			AO-AP	0.51	.61

Bold font indicates $p < .05$.
AO aversive only contingency; *AP* aversive plus punishment contingency.

previous operant research, which has typically been conducted in clinical environments and/or used discrete contingencies, generalizes to other settings. Our results also demonstrate that outcomes beyond those explicitly targeted by the intervention (e.g., air nicotine), can be affected by real-time feedback and monetary rewards.

Participants exposed to both an aversive contingency and the combination of an aversive plus reinforcing contingency had improved air quality relative to a measurement-only control condition. However, in contrast with previous research on complex behaviors, the addition of the reinforcing contingency did not improve upon the effectiveness of the aversive contingency. Since arranging continually active feedback systems in real-world environments is a novel and challenging field, the inability of reinforcement to improve outcomes may be reflective of imperfections in the study design, rather than a definitive behavioral phenomenon. For instance, we do not know if participants discriminated the activation of the reinforcement LED, so we are unsure of how powerful the LED was as a conditioned discriminative stimulus. This is especially true considering that no stimulus was provided when payment was actually presented to participants. Additionally, the reinforcement magnitude was modest, with a maximum value of $40 over 3 months, which may not have been sufficient to produce behavioral changes beyond those that were prompted by the aversive feedback system. Over this time period, participants were likely exposed to a bevy of competing, and probably stronger, contingencies that moderated intervention effects. These could include well-established chains of behavior that regularly produce tobacco smoking, an unwillingness of all household members to collaborate on SHS reduction, and/or aversive consequences associated with nicotine withdrawal. Previous research has demonstrated that increasing monetary rewards for addicted individuals can combat competing contingencies [31], but we lacked the resources to explore this option. If future studies with a more robust reinforcement system also find that exclusively using aversive feedback is sufficient to affect behavior, it should also be noted that punishment/aversion is often not attractive to clinicians, since it can produce undesired side effects including counter-aggression [32].

Much work remains to tease apart the benefits and shortcomings of reinforcement versus aversive contingencies, but this paper critically demonstrates that technology-enabled JITAIs can serve as a platform to pursue such research. Both JITAIs and operant principles characteristically focus on objective, observable measures of behavior and context, which allows axiomatic principles to be faithfully incorporated into study designs. This increases *theoretical fidelity*, defined as the degree to which a design adheres to established theory, which has been shown to improve intervention outcomes [33]. Other dimensions of operant behavior beyond reinforcement/aversive feedback can also be investigated within JITAIs, as shown in [34]. For instance, contingency schedules could withhold feedback for a subset of triggering events or reinforcement magnitude could be varied. Furthermore, the intensive data generated by JITAIs allows analyses to examine within-person responses to interventions at a much more precise level of detail than was previously achievable (e.g., see Refs. [35, 36]). This development has the potential to significantly advance the science of behavior change and shift the paradigms on which interventions are conducted toward a focus on ecological factors that can more easily be observed and manipulated.

This study also portends changes in the conceptualization of study designs. Our methodology explicitly attempted to control for the effect of reinforcement magnitude by providing similar monetary rewards to each participant. However, as the science and technology of JITAIs matures, it may be beneficial to abandon this approach in favor of a single case design logic that attempts to implement optimal consequences for each participant. Mobile technology's precision is well-suited to tailoring interventions in this way and one can imagine future studies where reinforcement magnitudes are increased or decreased for participants who do not initially respond to an intervention. Such studies could make use of frameworks such as the Sequential Assignment Multiple Randomized Trial approach [37], to guide the systematic assessment and modification of participants' intervention strategies in response to performance.

Several limitations were present in this study. The magnitude of the reinforcing/aversive stimuli provided to participants was likely small relative to those that sustain in-home smoking; therefore, their ability to affect in-home smoking behavior may be limited. This point notwithstanding, prior research has demonstrated that a subset of homes had improvements in air quality associated with the activation of the feedback system [35, 36]. The reinforcement system sometimes failed, delaying or eliminating monitor feedback; also coaching sessions were often rescheduled or cancelled. The valley durations used to determine the onset and amount of reinforcement likely included time intervals during which participants were sleeping or not home, resulting in rewards that were not exclusively contingent upon changing indoor smoking/particle generation behavior. Auditory feedback did not accompany the reinforcing visual stimulus (i.e., blue LED), as was done for the aversive stimuli; therefore, reinforcing feedback may have been more difficult to perceive. Elevated air particle measurements may have been due to sources that participants could not control, such as a neighbor smoking or vehicular traffic. Furthermore, the AP condition was developed midstream, once the trial had begun, so this study was not explicitly designed or powered for testing AO/AP contingencies and the AO/AP sample sizes were not equal. As a result of the small statistical power, moderating variables were not considered in our analyses.

To address the shortcomings outlined above, future studies should consider the following enhancements: (a) alarm systems that exclusively react to tobacco/cannabis smoke, (b) a more salient stimulus when monetary rewards are being earned (e.g., mobile phone push notifications), (c) the immediate presentation of a reward once the valley duration threshold has been met, (d) increased reinforcement magnitude, (e) increased sample sizes to properly power the study, and/or (f) a reinforcement only arm.

In conclusion, this manuscript highlights the ways in which the incorporation of real-time sensors into health interventions provides a platform for assessing principles of operant theory. Ideally, this will lead to synergistic systems where previously developed theoretical constructs inform health promotion trials and the findings from these studies clarifies the generalizability of these constructs to real-world scenarios. The overall effect will be a more precise science of behavior change that will lead to a healthier society.

Acknowledgments

Funding: Research reported in this publication was supported by the National Heart, Lung, and Blood Institute of the National Institutes of Health (NIH) under award number R01HL103684. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH. This work was also supported by a Tobacco-Related Disease Research Program award (31KT1501).

Compliance with Ethical Standards

Conflict of Interest: The authors declare that they have no conflict of interest.

Author Contributions: V.B., J.B., S.C.H., and M.H. conceptualized the study. N.E.K., and B.N. supervised the collection of the data and the maintenance of real-time feedback tools. V.B., B.N., and M.A.A. conducted statistical analyses. All authors assisted with the drafting of the paper.

Ethical Approval: All procedures performed were in accordance with the ethical standards of the San Diego State University Institutional Review Board and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

APPENDIX 1. SENSITIVITY ANALYSIS FOR REINFORCEMENT THRESHOLD PERCENTILE SELECTION

In order to determine a reasonable percentile value to be used in the calculation of the valley duration threshold, a sensitivity analysis was performed on a subset of 25 AO homes that had been enrolled in the trial prior to the establishment of the AP arm. For these trials, the reinforcement values were calculated using the above protocol with thresholds calculated using the 5th through 95th percentiles, in increments of 5. The calculation was performed separately for each intervention stage. Figure 4 illustrates the proportion of reward values totaling \$0–\$3, \$4–\$9, and \$10–\$13 for each percentile under consideration. Because the effectiveness of the reinforcement was not yet known, one criterion for percentile selection was that there should be a relatively large number of high rewards (\$10–\$13) to ensure that reinforcement values would be relatively close to the \$40 available in the AO arm. A second criterion, though, required the percentile to be stringent enough to allow for an appreciable amount of improvement via the AP conditions. The 65th percentile appeared to best satisfy these criteria. Approximately 2/3 of the

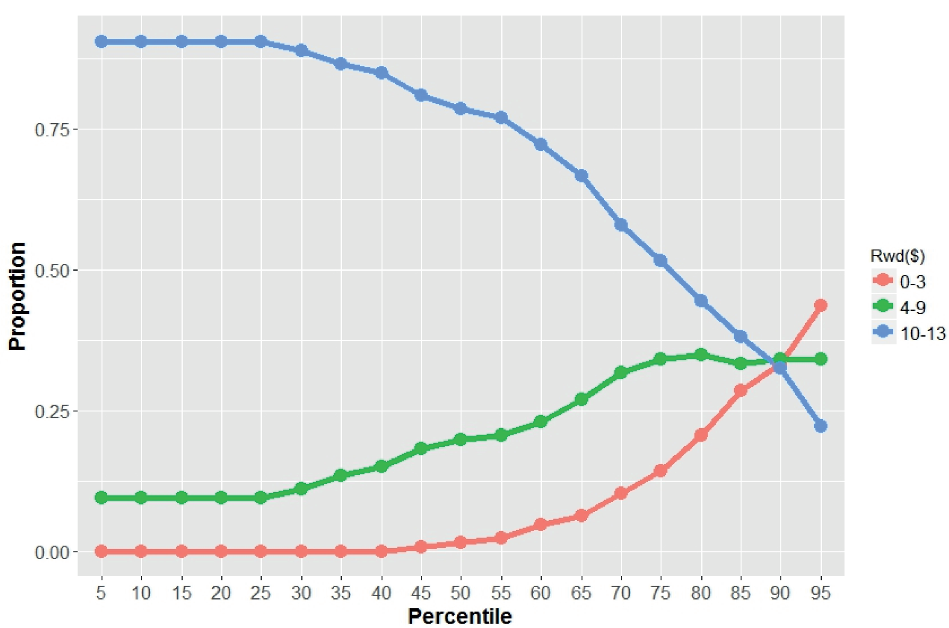

Fig 4 | Results of sensitivity analysis for the selection of the reinforcement percentile parameter. Using 25 homes from the AO arm, the reinforcement value was calculated for the different reinforcement phases under the protocol outlined in the text. This figure illustrates the proportion of reinforcement value ranging from \$0–\$3, \$4–\$9, and \$10–\$13 for various percentiles.

reinforcement values were in the \$10–\$13 range, leaving 1/3 of the reinforcement intervals eligible for large improvements. As a result, the 65th percentile was selected for the reinforcement protocol.

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