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Psychological and contextual drivers of indoor air quality behaviours in a deprived urban community: Evidence from participatory research

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ABSTRACT

Indoor air pollution poses significant health risks, disproportionately affecting deprived communities that often face higher levels of exposure. This study, conducted as part of the WellHome project, employed a longitudinal design and a participatory research approach, directly involving 110 residents of a deprived urban area in West London in indoor air quality research. It tested an adapted Health Belief Model (HBM), tailored to indoor air quality behaviours, to examine how perceived vulnerability, perceived severity, self-efficacy, perceptions of indoor and outdoor air quality, and contextual cues to action relate to behavioural changes aimed at improving indoor air quality. It also assessed whether these factors predicted behaviour change over time, and explored patterns across various household behaviours, such as cooking, cleaning, heating, smoking, personal care, home fragrance use, window opening, and air purifier use. Results show that self-efficacy, perceived severity, perceptions of indoor and outdoor air quality, and cues to action were significantly associated with behaviour change, while perceived vulnerability was not. Notably, the influence of self-efficacy on behaviour increased over time, underscoring its role in sustaining long-term change. Visible cues, such as mould and damp, emerged as strong contextual triggers for action. Among the behaviours assessed, changes were most frequently reported in window opening, cooking, and cleaning, although a clear increase in change over time was only observed for cooking and heating. These findings suggest that a participatory approach can be effective in promoting healthier indoor environments in vulnerable communities.

1. Introduction

1.1. Background

Air pollution is a major global health threat and a leading environmental health risk in the UK [1]. While outdoor air pollution has historically been the primary focus of research and public concern, indoor air pollution has recently gained wider attention [2]. The World Health Organization [3] estimates that indoor air pollution is responsible for 3.2 million deaths annually. Given that adults and children spend approximately 80–90 % of their time indoors, prolonged exposure to indoor air pollutants within homes, workplaces, and schools poses a significant but frequently overlooked health risk [4,5].

The health consequences of indoor air pollution can be wide-ranging and severe. Exposure has been linked to severe health conditions, including respiratory diseases such as asthma and cardiovascular conditions such as stroke [3,6,7]. In children, prolonged exposure is specifically associated with an increased risk of asthma, wheezing, and allergic conditions [8,9]. These risks are further compounded in deprived communities facing structural disadvantage such as substandard housing and a higher prevalence of pre-existing health conditions [10,11].

Individual behaviours within the home contribute significantly to exposure to air pollutants [12]. Understanding what drives individuals to take protective actions such as changing cooking or heating practices to reduce emissions is essential for designing effective public health interventions [13–15]. The complexity of behavioural change requires an understanding of both psychological and contextual factors that shape how people act in specific situations [16,17].

However, moving from outdoor to indoor environments presents significant challenges to public health research and regulation [18]. Homes are private spaces where individuals engage in their daily

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routines, such as cooking, sleeping, and cleaning. Intervening in personal choices can be contentious, particularly when interventions fail to take account of the diverse circumstances of households [7,19]. Direct engagement with households could be a more effective way to both motivate behavioural change and examine psychological and contextual factors relevant to indoor air quality [20].

In this study, conducted as part of the WellHome project [18], we used a longitudinal design and participatory research approach (PR) to engage with residents of a deprived urban area in West London. In the context of WellHome, PR provided a valuable opportunity to investigate how psychological and contextual factors shape behaviours related to indoor air quality in a setting marked by structural inequalities. At the same time, because participants were engaged over a period of several months, the project also allowed to explore whether spending time in the programme itself contributed to behavioural change. This dual focus allowed us to investigate not only psychological and contextual factors relevant to behavioural change, but also how ongoing engagement in the project was associated with such change.

1.2. Awareness and behaviours in indoor air quality

In industrialised countries, such as the UK, deprived communities often experience greater exposure to air pollutants due to factors including substandard housing, proximity to polluted sources, limited access to ventilation improvements, and a higher prevalence of pre-existing health conditions [10,11,21,22]. However, occupants are not just passive recipients of pollutants in indoor settings; rather, they actively shape their exposure through routine activities, such as cooking, cleaning, using spray products, relying on combustion-based heating, and failing to adequately ventilate indoor spaces [23,24]. For example, cooking is strongly associated with increased levels of particulate matter ($PM_{2.5}$ and PM_{10}) and nitrogen dioxide (NO_2) [12]; vacuuming is linked to elevated PM_{10} concentrations [25]; and household and personal care products, such as air freshener [26], spray cleaners, and cosmetics [27] emit volatile organic compounds (VOCs) (see also [28]).

Despite these risks, public awareness of indoor pollution sources and their health impacts remains limited [29–31], constraining individuals' ability to make informed decisions to reduce emissions and exposure. This limited awareness is reinforced by the belief that the home is a safe space compared to the outdoors, even though harmful indoor pollutants are common and often go unrecognised [32].

Research on occupants' understanding of indoor air pollution has shown that occupants often rely on sensory cues such as smell to assess the air quality in their homes (e.g., [33]). Some visible indicators of poor air quality are easily recognised, for example, mould is more widely seen as a health risk [31,34]. These cues may make the risks feel more immediate and tangible, potentially prompting individuals to take protective measures. However, most pollutants are undetectable without specialised equipment [35,36] and occupants' perception is often inaccurate [37,38]. Even when strong odours are present, such as those from cooking or candles, they are often perceived as pleasant rather than a signs of poor air quality, even by those most vulnerable to exposure [39].

Indoor air quality perceptions are also shaped by perceptions of the outdoor environment, influencing for example ventilation practices as a protective response to outdoor pollution sources [31]. While the relationship between perceptions of indoor air quality and in-home behaviours has not yet been systematically investigated, findings from studies on outdoor air quality suggest that people's perceptions can influence the actions they take. For instance, perceptions of outdoor air pollution have been associated with pro-environmental behaviours such as reducing waste, avoiding polluted areas, and donating to environmental organisations [40,41].

Given that people often assess indoor air quality using sensory cues, understanding behavioural change requires considering both perceptions of indoor and outdoor air, as well as visible signs like mould.

1.3. Psychological predictors of indoor air quality behaviour

Individual beliefs about air quality play an important role in shaping individual decisions in relating to indoor air quality. In particular, some studies have highlighted the role of beliefs about health risks and an individual's sense of agency to take action (e.g., [33,42–44]).

The Health Belief Model (HBM; [45,46]), a widely-used framework in health behaviour research, outlines how individual beliefs and cues to action shape behavioural change. According to the model, individuals are more likely to take health-related actions if they believe they are vulnerable to a health issue (perceived vulnerability), view the risk as serious (perceived severity), believe the benefits of action outweigh the barriers (perceived benefits and barriers), have confidence in their ability to take those actions (self-efficacy), and encounter cues that prompt them to act, such as information or advice (cues to action). These cues are most effective when they align with existing perceptions about vulnerability, severity, efficacy, and the balance of benefits and barriers. The model is consistent with wider social-cognitive theories, such as Protection Motivation Theory (PMT; [47]), regarding the role of people's risk perceptions, expectations, and sense of efficacy in behavioural change. The main difference is that in the HBM these beliefs are directly linked to behaviours, whereas Protection Motivation Theory links them to people's protection motivation or intention to act [48]. The HBM has been successfully applied to various health behaviours, including COVID-19 vaccine acceptance [49], cervical screening uptake [50], and diabetes self-care [51]. Emerging evidence suggests that the model may also be relevant in the context of indoor air quality [42,44,52]. For example, Veiga et al. [44] found that perceived severity of poor indoor air quality predicted intentions to adopt technologies such as air purifiers in German and Portuguese samples. In the US, Wong-Parodi [42] identified self-efficacy as a key predictor of behavioural intentions to reduce indoor air pollution. Similarly, Huang et al. [52] found that perceived susceptibility and severity were associated with protective behaviours such as using air purifiers, anti-haze screens, and green plants in China. Furthermore, several studies suggest that sensor-based air quality information can help promote behavioural change through these psychological pathways (e.g., [53,54]).

Despite growing interest in household air quality-related behaviours, several gaps remain. First, relatively few studies have applied established psychological frameworks to behaviours within the home environment. While Durand et al. [55] used the Theory of Planned Behaviour (TPB) to examine window-opening intentions, and Shi et al. [56] combined TPB and Norm Activation Theory (NAT) to study $PM_{2.5}$-reduction behaviours in Chinese urban areas, such studies remain scarce. Second, many existing studies suffer from methodological limitations, including small sample sizes and short study durations (e.g., [42,57–59]), making it difficult to assess long-term behavioural adaptation. Third, research has often focused on single behaviours, such as reducing combustion activities [60] or improving ventilation [61], rather than examining multiple behaviours together.

1.4. The present research

The present study developed and applied an adapted version of the HBM to investigate the psychological and contextual predictors of behavioural change related to household air pollution. This adapted model retained the core constructs, i.e., perceived vulnerability, perceived severity, perceived self-efficacy, and cues to action, while introducing two key extensions (see Fig. 1).

First, it incorporates subjective perceptions of both indoor (IAQ) and outdoor air quality (OAQ) as additional predictors. These perceptions are particularly relevant in the home context, where individuals often rely on personal impressions rather than objective measurements to assess air quality. As previously discussed, many indoor pollutants are

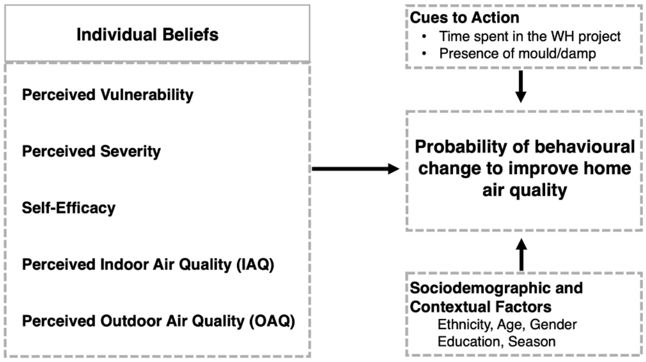

Fig. 1. The adapted Health Belief Model (HBM).

invisible and odourless, meaning that subjective beliefs play a disproportionate role in shaping behavioural decisions. Second, the model expands the notion of cues to action, placing greater emphasis on those arising from the participatory research setting and the physical home environment. In this study, two such cues are examined: participation in the WellHome project and the presence of visible mould or damp. While participation may heighten awareness and motivation to act, mould and damp function as concrete and recognisable signals of poor indoor conditions, potentially prompting remedial behaviour. Together, these additions aim to provide a more context-sensitive understanding of household decision-making in relation to indoor air quality.

The primary objective was to test the adapted HBM in the context of a deprived urban community in London (*Objective 1*). Specifically, we hypothesised that individuals are more likely to adopt behaviours to improve indoor air quality when they feel personally affected by its consequences (perceived vulnerability), perceive indoor air quality as a serious health risk (perceived severity), and feel confident in their ability to take action (self-efficacy). We also expected that those who perceive both indoor (IAQ) and outdoor (OAQ) air quality as good, are less likely to take action. Additionally, we hypothesised that individuals are more likely to adopt behavioural changes the longer they have been engaged in the project, and that the presence of visible mould and damp serves as a cue to action to improve indoor air quality.

The study further addressed two secondary objectives. *Objective 2* was to examine whether the influence of the adapted model's psychological constructs on behaviour change varied over time, as participants progressed through the WellHome programme. *Objective 3* was to explore patterns of behavioural change more broadly, including identifying which specific behaviours were most likely to shift during the course of the study.

2. Method

2.1. Study design

As mentioned in the introduction, this study used a Participatory Research (PR) approach to work alongside residents over time to explore the factors motivating their indoor air quality behaviours. PR approaches offer a promising way to engage individuals in the behavioural change process, as they involve working closely with those affected by a particular issue to explore concerns and co-develop responses [62,63]. By fostering shared decision-making between researchers and participants, PR helps ensure that research is culturally appropriate, inclusive, and locally relevant [64].

The WellHome project consisted of two monitoring periods ('campaigns') over an 18-month period [18], each lasting four weeks and scheduled three to six months apart (Fig. 2). The longitudinal design ensured that each household participated in one monitoring period during the spring-summer season and another during the autumn-winter season, to account for seasonal variations in indoor and outdoor air quality. The survey used in this study was administered from September 2022 to June 2024.

Air quality sensors and passive samplers, used to measure chemical, microplastic, and biological contaminants, were installed in participants' homes at the start of each campaign. At this point, participants were also asked to complete a detailed survey on air-quality-related beliefs and behaviours (Time 1 and Time 3). The sensors and samplers were retrieved at the end of each four-week campaign, at which time participants completed a shorter follow-up survey on the same topic (Time 2 and Time 4). This resulted in a total of four questionnaire responses for each household, i.e., two comprehensive surveys at the start of each campaign (Time 1 and 3) and two shorter follow-up surveys at the end (Time 2 and 4). In addition, participants completed a set of other questionnaires [18], including one on the home environment that included questions about the presence of mould and damp, the types of fuel used, and the types of windows in the home. The present study drew on data from questionnaires on beliefs and behaviours and from the home environment questionnaire. Throughout the WellHome project, participants were invited to participate in several engagement and involvement activities, including science festivals, educational sessions for children, workshops and interactive panel discussions, among others [65]. These initiatives were designed to engage and involve the community with the project and to raise awareness of the wider topic of indoor and outdoor air pollution [18]. Participants could choose to engage with as many activities as they wished, or participate more passively by only interacting with the community ambassadors within their networks or with the researchers during the home visits.

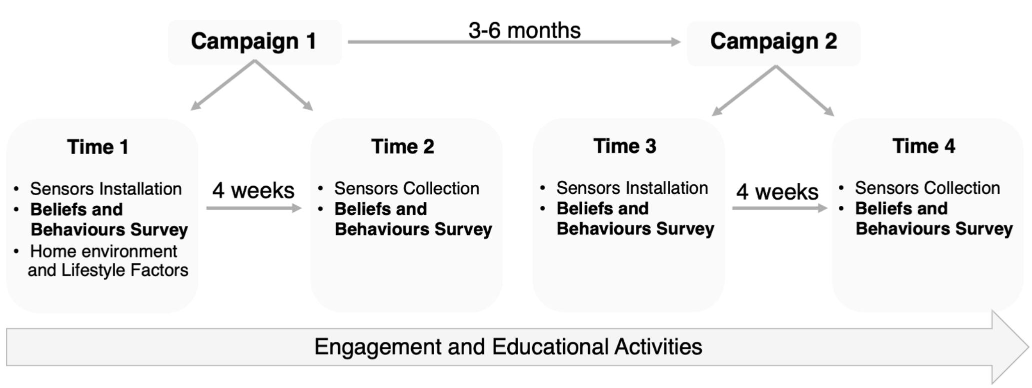

Fig. 2. Design of the WellHome project.

2.2. Study participants

Participants were recruited from an ethnically diverse and socio-economically disadvantaged area of West London near the Imperial College White City Campus. Engagement was conducted in partnership with the Imperial College London White City Engagement Team (WCET) and local organisations, including Nova [66] and Bubble and Squeak [67], alongside other community groups within the WCET network. To support recruitment, ten WellHome Ambassadors were appointed from the local community. Eligible participants were adults (18+) who were primary householders, able to provide informed consent, and living in the study area. Households with children aged 5–17 years with asthma or allergies, particularly from minority ethnic backgrounds, were prioritised.

A total of 110 households were recruited, reflecting a broad range of ethnicities and educational backgrounds. Written consent was obtained from all adult participants, with verbal consent available when needed to accommodate varying literacy levels. Age-appropriate assent materials were provided for children under 18. Participants received £100 in compensation, and translation support was offered when required. The sample characteristics are presented in Table 1.

2.3. Measures

Participants were offered the opportunity to complete the questionnaire in five different languages (English, Amharic, Arabic, Somali, and Tigrinya) which reflected the most commonly spoken languages in our sample. However, only one participant completed the questionnaire in a language other than English, choosing Somali. Each participant completed a longer questionnaire prior to each installation visit and a shorter questionnaire before each collection visit.

As part of the wider project, participants completed several other health questionnaires and took part in repeated home visits, including sensor installation and maintenance, while also participating in engagement activities, which made their overall participation demanding (see [18]). The main questionnaire used in this study (i.e., the beliefs and behaviours questionnaire) was designed to limit burden, with some constructs (e.g., self-efficacy) measured using single items from the outset. However, after feedback at Time 1 from participants that the survey was still too long, it was further shortened at two of the four waves to support retention. Within this participatory longitudinal design, using single-item indicators represented a pragmatic trade-off between measurement quality and respondent burden [68]. In the shorter version, key constructs, such as perceived vulnerability and perceived severity, were assessed using a single-item measure. This paper focuses on the measures included in both the longer and shorter versions of the questionnaire (i.e., only the single items).

Table 1
Sample characteristics (n = 110).

Category	n	%
Gender		
Female	86	78.2
Male	24	21.8
Ethnicity		
Black, Black British, Caribbean or African	49	44.5
White	33	30
Asian or Asian British	12	10.9
Mixed or multiple ethnic groups	11	10
Other ethnic group	5	4.5
Education		
Primary education	3	2.7
Secondary education	10	9.1
A-levels	20	18.2
Bachelor’s degree	42	38.2
Postgraduate degree	33	30
Prefer not to say	2	1.8
Age		
18–24	2	1.8
25–34	10	9.1
35–44	65	59.1
45–54	27	24.5
55–64	5	4.5
65–74	1	0.9

The questionnaires were developed to assess the adapted HBM [45, 46] (see Fig. 1). Constructs measured included perceived vulnerability, perceived severity, self-efficacy, perceived indoor air quality (IAQ), perceived outdoor air quality (OAQ), and two cues to action, with behavioural changes to improve home air quality as the main outcome variable. Participants had the option to add notes on how they had changed each behaviour. Over 90 % did not provide comments, and the few responses received did not include new or detailed information (e.g., “I open windows more often”). These comments were therefore not included in the analysis.

Behavioural changes to improve home air quality was assessed by asking participants: “In the past month, have you made any changes to improve the air quality in your house?”. Response options included “Yes, I have,” “No, but I plan to,” and “No, and I don’t plan to.” Those who responded “Yes, I have” were then asked: “What changes have you made to improve the air quality in your home?”. Participants selected from a predefined list covering changes related to cooking, heating, cleaning, personal care, smoking, home fragrance use, window opening, and air purifier use. Those selected were recorded as changes within their respective categories. For instance, cooking could include using an extractor fan or avoiding high-temperature frying; heating could involve switching from gas to electric or reducing use; cleaning could mean choosing fragrance-free products or using fewer sprays; personal care could involve limiting aerosols; smoking could mean smoking outdoors or quitting; home fragrance use could involve reducing candles or air fresheners; window opening could refer to ventilating rooms more often; and air purifier use could involve starting to use one or running it more regularly.

Perceived vulnerability was assessed using a custom item: “To what extent do you believe you and your family are personally impacted by poor indoor air quality?” Responses were recorded on a 5-point scale ranging from (1) Not at all affected to (5) Extremely affected.

Perceived severity was measured using a single item adapted from Poortinga et al. [69]: “How serious do you think the health consequences of poor indoor air quality are?” Responses could be provided on a 5-point scale ranging from (1) Not at all serious to (5) Extremely serious.

Self-efficacy was measured using an item adapted from Wong-Parodi et al. [42]: “How confident are you that you can take actions to improve the air quality in your home?” Responses could be provided on a 5-point scale ranging from (1) Not at all confident to (5) Extremely confident.

Perceived indoor air quality (IAQ) and *perceived outdoor air quality* (OAQ) were both measured using single items adapted from Hofflinger et al. [70]: “How do you rate the quality of the air in the following places?” (referring to both their home and London overall). Responses could be provided on a 5-point Likert scale from (1) Very poor to (5) Very good.

Cues to action was assessed separately using two measures: First, *time* in the WellHome project, tracked as a continuous variable spanning from Time 1 to Time 4, corresponding to the four survey waves completed in different months and years during the installation and collection visits. Second, the *presence of mould and damp* in the home was assessed at Time 1 through the question: “Are you aware of any signs of mould or damp in your home?” with response options (1) Yes or (0) No.

Covariates included gender, education, age, ethnicity, and season. These variables were included as potential confounders. For instance, women tend to spend more time on indoor domestic activities [71]; awareness of indoor air pollution is generally higher among those with higher education levels [72]; there may be generational differences in how risks related to air pollution are perceived [73]; minority ethnic households in England have been shown to experience higher indoor PM 2.5 than White households [22]; and season can influence behaviours such as window opening and heating [74]. Gender was classified as (1) Female or (0) Male. Education and age were treated as continuous variables. Education ranged from (1) lowest to (5) highest level. Participants who selected "Prefer not to answer" ($n = 2$) were coded as missing values. Age ranged from 0 ("18–24") to 5 ("65–74"), with higher values indicating older age. Ethnicity was grouped into two categories: (1) White and (0) Other ethnic background (including Black, Black British, Caribbean or African; Asian or Asian British; Mixed or multiple ethnic groups; and Other ethnic group). Season was included as a categorical variable, coded as four categories: (1) Winter, (2) Spring, (3) Summer, and (4) Autumn, based on the month in which the survey was completed at each visit. Summer was used as the reference category.

2.4. Analytical approach

Reliability of the single-item measures: Before conducting the main analyses, we assessed test-retest reliability of the individual items using a linear mixed-effects model with a random intercept for participant ID. This approach estimates the Intraclass Correlation Coefficient (ICC) as the proportion of total variance attributable to stable between-person differences. Unlike ICC methods based on ANOVA (e.g., [75]), which exclude participants with any missing data, the mixed-effects model uses all available observations and accounts for within-person variability across time. This offers a more flexible framework for estimating reliability in longitudinal data [76]. For constructs that included multiple items at both Time 1 and Time 3 (perceived vulnerability and perceived severity), we examined the correlations between the single-item and multi-item measures to assess convergent validity.

The resulting ICCs indicated moderate reliability [77] for all single-item measures. Specifically, the ICC was 0.56 for extent of perceived vulnerability, 0.53 for perceived severity, 0.55 for self-efficacy, 0.64 for perceived indoor air quality and 0.61 for perceived outdoor air quality. These ICCs suggest that between-person differences account for a substantial proportion of the variance in each predictor, while still allowing for within-person fluctuation over time. This moderate level of stability is appropriate for our analytic focus in this study. Furthermore, the correlations between the single-item measures and the corresponding multi-item constructs (perceived vulnerability and perceived severity) demonstrated moderate to strong convergent validity [78] with coefficients ranging from 0.43 to 0.63 ($p < .001$). These findings indicate that the single-item measures align well with their respective multi-item counterparts, reinforcing their validity. The survey items used in this analysis are reported in the Supplementary Materials, Table S1. The correlation matrix used for the convergent validity is provided in Supplementary Materials, Table S2.

Power analysis: To assess the statistical power of the models, we conducted simulations using the *simr* package [79]. We tested a range of fixed effect sizes (0 to 0.8 log odds) across sample sizes ranging from 70 to 110. The results indicated that, with a sample size of $n = 110$, the study provided at least 80 % power to detect effect sizes in line with the odds ratios observed in our analyses. These simulations were based on the actual data structure, including missing data and repeated measures, ensuring that power estimates reflect realistic conditions. Details on the power simulations are available in the Supplementary materials.

Main Data Analyses: All analyses were conducted in R, primarily using the *glmer()* function from the *lme4* package [80]. A generalised linear mixed-effects modelling (GLMM) approach was used, suitable for binary outcomes (i.e., behavioural change: 1 = present, 0 = absent). This method allowed us to analyse all behavioural outcomes within a single integrated framework, rather than running separate models for each behaviour. The mixed-effects structure enabled us to account for multiple observations per participant, improving the reliability and stability of continuous predictor estimates. This reduces standard errors and increases the precision of parameter estimates [81,82]. All models controlled for key sociodemographic and contextual covariates: age, gender, education, ethnicity, and season.

To test the adapted HBM across all behavioural categories (*Objective 1*), we included fixed effects for perceived vulnerability, perceived severity, self-efficacy, perceived indoor and outdoor air quality, and two cues to action (time in the project and presence of mould and damp; Model 1). Time in the project was modelled as a continuous predictor (from Time 1 to Time 4), while presence of mould and damp was binary (0 = absent, 1 = present). All continuous predictors, including perceived vulnerability, perceived severity, self-efficacy and perceptions of indoor and outdoor air quality, were scaled to facilitate model convergence and interpretation. Each predictor was retained for each measurement wave rather than averaged across time points.

To examine whether key psychological factors interacted with time in the project (*Objective 2*), we followed the same analytical approach as in Objective 1, but added interaction terms between *time* and each of the three psychological predictors: perceived vulnerability, perceived severity, and self-efficacy (Model 2). The plot_model() function from the *sjPlot* package [83] was used to compute marginal effects. Predictions were obtained on the logit scale from the fitted model and subsequently transformed into probabilities using the inverse logit function plogis(). Both Model 1 and Model 2 included two random intercepts: one for participant ID (to account for individual baseline differences) and one for behavioural category (to account for variability across behaviour types).

To explore patterns of behavioural change over time (*Objective 3*), we conducted a two-part analysis. First, baseline differences in the likelihood of behavioural change across behaviours were examined by extracting random intercepts for each behavioural category from the adapted HBM (Model 1; see Objective 1). These random effects captured differences in the likelihood of change relative to the model's global intercept, while accounting for individual-level and covariate effects. Second, an additional multilevel logistic regression model (Model 3) was run to assess time trends across behaviours. The dependent variable remained the same (1 = presence of change, 0 = absence of change), and the fixed effects included an interaction between time (continuous) and behavioural category (categorical), in addition to the predictors from Model 1 (e.g., self-efficacy, perceived vulnerability, perceived severity, perceived IAQ/OAQ, mould/damp, and covariates). Participant ID was included as a random intercept to control for repeated measures.

In this model, air purifier use (selected alphabetically) served as the reference category. The main effect of time represents change over time for this reference, while interaction terms indicate how other behaviours differ from this trend. Since this structure limits direct interpretation of time effects across all behaviours, we conducted post-hoc analyses using the *emmeans* package [84]: (1) emmeans() was used to estimate predicted probabilities for each behaviour over time, and (2) emtrends() was used to test whether the slopes of predicted probabilities significantly differed from zero. A schematic summary of the analytical approach is provided in Table S3 of the Supplementary Materials.

The full correlation matrix of the predictors used in the analysis is shown in the Supplementary Materials (Figure S1).

3. Results

3.1. The adapted Health Belief Model (Objective 1)

Table 2 shows that a stronger belief in negative consequences of indoor air pollution (perceived severity) and higher confidence in one's ability to address indoor air pollution (self-efficacy) were both associated with a greater probability of behavioural change over the period of the study (see Table 2). However, contrary to expectations, perceived vulnerability was not significantly associated with the probability of behavioural change (*Objective 1)*. Perceived indoor air quality (IAQ) and perceived outdoor air quality (OAQ) were also significantly associated with a greater probability of behavioural change. The findings further show a significant effect of the 'time spent in WellHome project' cue of action, indicating that longer participation in the WellHome project was

Table 2
Odds ratios from the adapted HBM in logistic regression (Model 1).

Predictors	Odds Ratios	95 % CI	p
(Intercept)	0.03	0.00 – 0.15	.001
Perceived Vulnerability	0.88	0.73 – 1.05	.145
Perceived Severity	1.2	1.00 – 1.44	.044
Self-Efficacy	1.21	1.03 – 1.41	.019
Perceived IAQ	0.82	0.68 – 0.99	.04
Perceived OAQ	0.83	0.70 – 0.99	.036
Time spent in WellHome	1.37	1.14 – 1.64	.001
Presence of Mould/Damp	2.45	1.21 – 4.96	.013

Note. The model controlled for gender, education, age, ethnicity, and season. IAQ = indoor air quality; OAQ = outdoor air quality.

associated with greater probability of behaviour change. The presence of mould and damp was identified as the predictor with the largest standardised effect on behaviour change, indicating that visual cues strongly influence how individuals manage their indoor environment.

Age ($OR = 1.30$, 95 % CI [0.88, 1.92], $p = .188$), gender ($OR = 0.84$, 95 % CI [0.40, 1.77], $p = .645$), and ethnic group ($OR = 0.81$, 95 % CI [0.42, 1.55], $p = .517$) were non-significantly associated with behavioural change; and there were no seasonal differences: autumn ($OR = 1.76$, 95 % CI [0.82, 3.81], $p = .149$), spring ($OR = 0.95$, 95 % CI [0.58, 1.56], $p = .850$), and winter ($OR = 0.92$, 95 % CI [0.53, 1.61], $p = .771$). Individuals with higher levels of education were less likely to adopt behavioural changes ($OR = 0.73$, 95 % CI [0.55, 0.98], $p = .035$).

In this model, fixed effects explained 8.5 % of the variance (Marginal $R^2 = 0.085$), fixed and random effects together explained 47.2 % of the variance (Conditional $R^2 = 0.472$), showing that including individual differences and behavioural category differences significantly improved the model's explanatory power.

3.2. Effects of adapted HBM factors on behaviour change over time (Objective 2)

Table 3 show that only the interaction between time and self-efficacy was statistically significant (*Objective 2*). Fig. 3 further presents the predicted probability of behavioural change as a function of self-efficacy at each time point, with all other variables in the model held constant. The results indicate that self-efficacy became a progressively stronger predictor of behavioural change as the project advanced. Among individuals with high self-efficacy (SD = +2.39), the predicted probability of behavioural change increased from 3 % at Time 1 to 16 % at Time 4. In contrast, participants with low self-efficacy (SD = −2.50) showed consistently low probabilities, remaining between 2 % and 3 % throughout. These findings suggest that while self-efficacy had little effect at baseline, its influence grew steadily over time.

No significant interaction effects were found for perceived vulnerability or perceived severity. The main effect of self-efficacy was no longer significant once interaction terms were added, whereas the main effect of perceived severity remained significant throughout. Perceived vulnerability remained non-significant, consistent with the results from the main model. These findings suggest that self-efficacy became an increasingly important predictor of behavioural change over time, while the effect of perceived severity remained stable across time points.

Table 3
Odds ratios from the adapted HBM in logistic regression with interaction effects (Model 2).

Predictors	Odds Ratios	95 % CI	p
(Intercept)	0.02	0.00 – 0.14	<0.001
Perceived Vulnerability	0.72	0.49 – 1.05	.090
Perceived Severity	1.59	1.09 – 2.30	.015
Self-Efficacy	0.89	0.65 – 1.21	.455
Perceived IAQ	0.80	0.66 – 0.97	.027
Perceived OAQ	0.83	0.70 – 0.99	.040
Time spent in WellHome	1.38	1.15 – 1.66	.001
Presence of Mould/Damp	2.45	1.19 – 5.02	.014
Time x Vulnerability	1.08	0.94 – 1.24	.266
Time x Severity	0.89	0.77 – 1.01	.078
Time x Self-Efficacy	1.14	1.02 – 1.29	.027

Note. The model controlled for gender, education, age, ethnicity, and season. IAQ = indoor air quality; OAQ = outdoor air quality; Time = Time spent in WellHome.

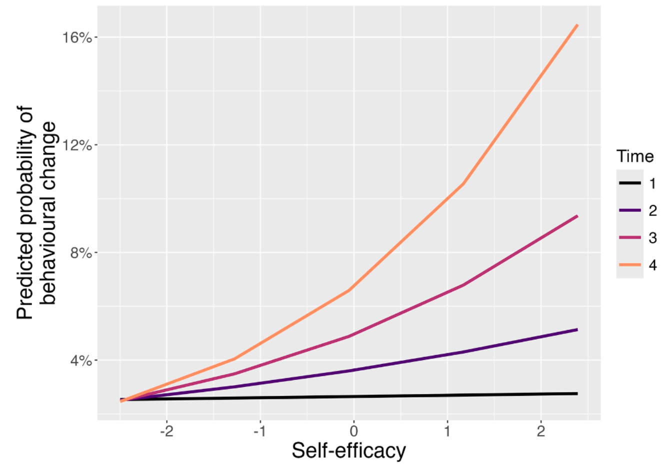

Fig. 3. Predicted probability of behavioural change by self-efficacy for four time points.

Regarding the effects of sociodemographic variables and season, these were consistent with those observed in Model 1. Fixed effects explained 8.7 % of the variance (Marginal $R^2 = 0.087$), fixed and random effects together explained 47.2 % of the variance (Conditional $R^2 = 0.472$).

3.3. Probability of behavioural change across and over time (Objective 3)

Fig. 4 presents the random intercepts for different behaviours, indicating their baseline likelihood of change. The results show that behaviours related to window opening, cleaning, and cooking were more likely to change over the course of the project compared to others (Objective 3). Smoking behaviour exhibited the lowest likelihood of change.

Fig. 5 displays the predicted probabilities of behavioural change for each behaviour across four time points, based on estimates from Model 3. Among all behaviours, cooking at Time 4 exhibited the highest predicted probability of change (probability = 0.22, 95 % CI [.128–.356]),

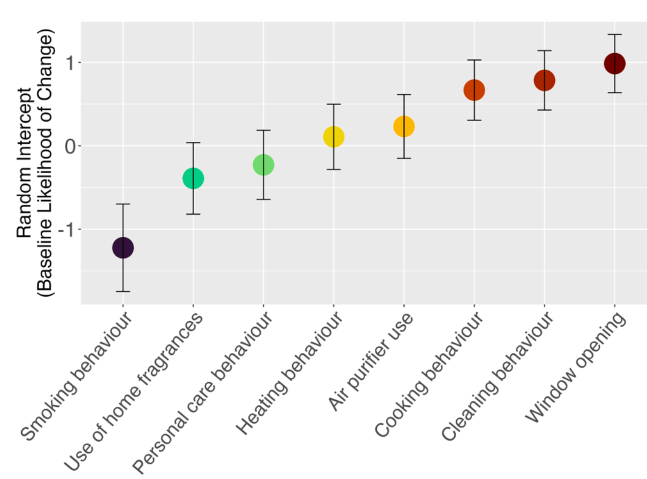

Fig. 4. Random intercept estimates for behavioural categories (Model 1).

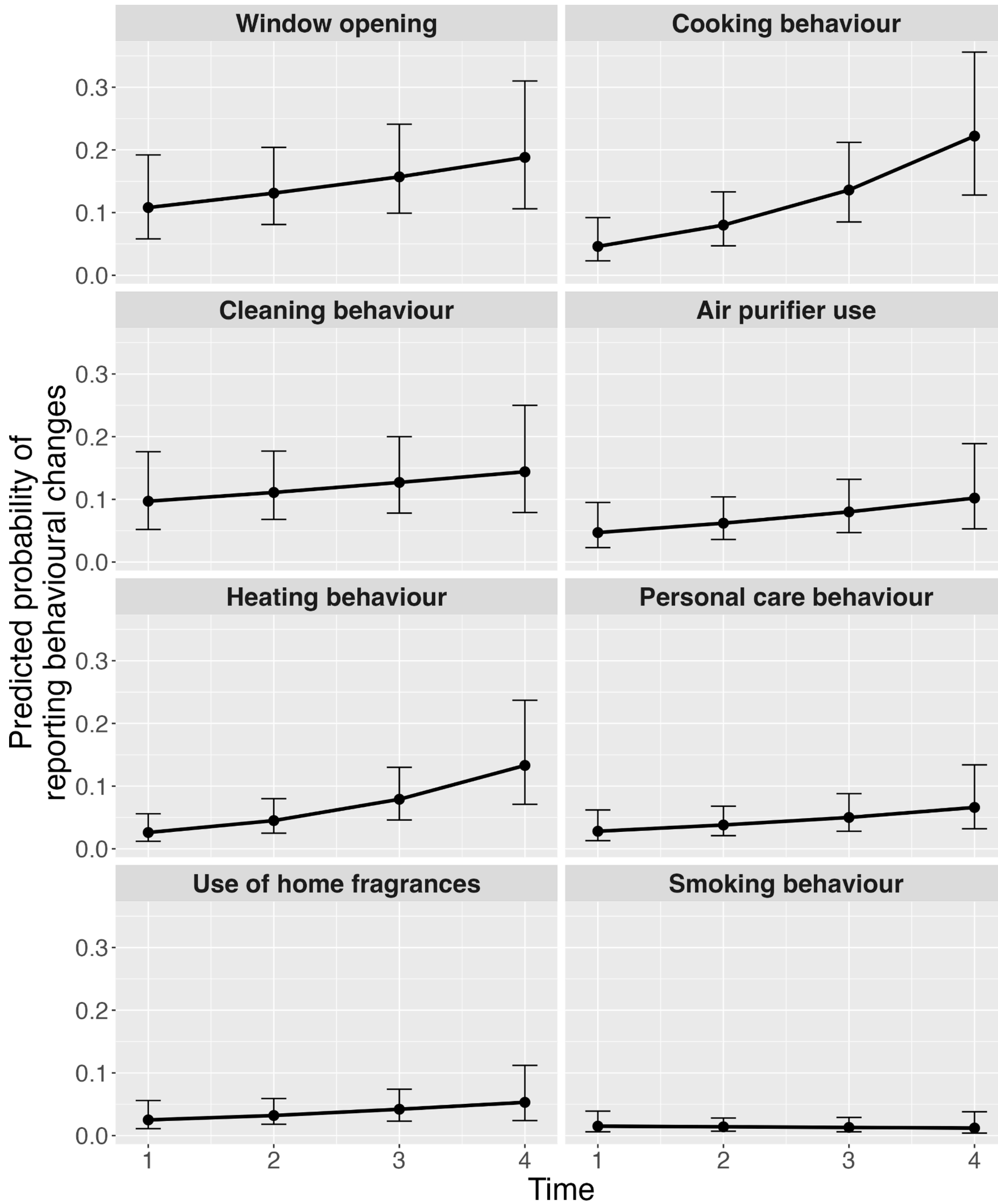

Fig. 5. Predicted probabilities of behaviour reporting at each time, with 95 % confidence intervals (Model 3).

followed by window opening at Time 4 (probability = 0.19, 95 % CI [.106–.31]), window opening at Time 3 (probability = 0.157, 95 % CI [.099–.241]), and cleaning at Time 4 (probability = 0.144, 95 % CI [.079–.25]). In contrast, smoking consistently showed the lowest predicted probabilities of change across all time points, with the lowest estimate at Time 4 (probability = 0.012, 95 % CI [.004–.038]).

Fig. 6 presents the estimated slopes derived from Model 3, representing change over time in the predicted probability of reporting each behaviour. It shows that only cooking and heating behaviours show a statistically significant increase over time in the probability of change. The full fixed-effect results from Model 3 are provided in the Supplementary Materials (Table S4). The complete table of predicted probabilities for all behaviours across time points, which reflects the data shown in Fig. 5, is available in the Supplementary Materials (Table S5). The complete table of estimated slope of time for each behaviour, which reflects the data shown in Fig. 6, is available in the Supplementary Materials (Table S6).

4. Discussion

4.1. Summary of results

The study is part of the West London Healthy Home and Environment Study, also known as WellHome [18], which employed a participatory research approach to engage a deprived urban area in West London with indoor air pollution. The primary aim of this paper (*Objective 1*) was to

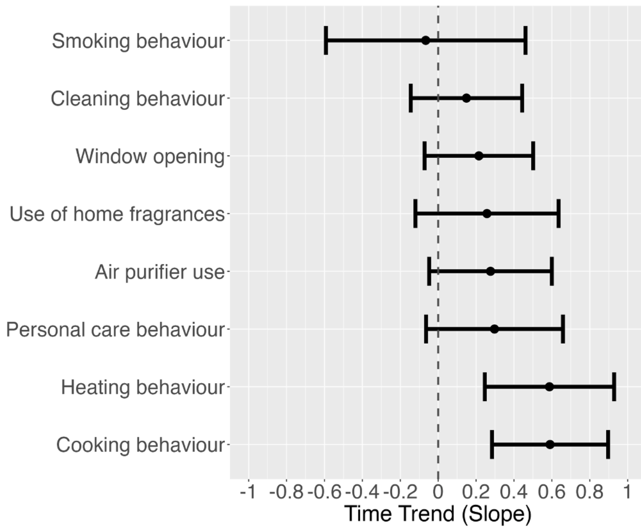

Fig. 6. Estimated slopes representing change over time in the predicted probability of reporting each behaviour (Model 3).

test an adapted version of the Health Belief Model (HBM), to investigate predictors of behavioural changes related to household air pollution. The secondary aims were to investigate the impact of perceived vulnerability, perceived severity, and self-efficacy on behavioural changes at different time points (*Objective 2*), and to investigate which behaviours were most likely to change overall and over time (*Objective 3*).

The results for Objective 1 show that perceived severity of the health consequences and self-efficacy were positively associated with behavioural changes. Perceived vulnerability, the belief of being personally affected by poor indoor air quality, was however not significantly associated with behaviour change. These findings align broadly with existing HBM literature in other contexts (e.g., [49,51]), and with studies employing related models in similar domains [42,44,52]. The results further show a negative association between perceived air quality (both indoor and outdoor) and behavioural change. Consistent with previous research [40,41], individuals who perceived air quality as poor were more likely to take action, underscoring the motivational role of perceived risk.

Two distinct cues to action were identified as significant predictors of behavioural change. First, the 'time spent in WellHome' cue was positively associated with behavioural change, suggesting that increased exposure to the participatory elements of the study contributed to greater engagement and awareness. This finding highlights the value of longitudinal, participatory research approaches in facilitating gradual but sustained changes in behaviour, particularly in underserved communities where trust-building and ongoing interaction may be key to impact [85].

Second, the 'mould and damp' cue emerged as the strongest behavioural predictor overall. This tangible and visible sign of poor indoor air quality likely served as an immediate and salient trigger for household action, consistent with previous research showing mould to be a powerful motivator (e.g., [31]). However, such cues represent late-stage indicators of exposure, raising concerns about the delay between problem onset and behavioural response. By the time mould becomes visible, indoor air quality may already be severely compromised, increasing health risks. This underscores the importance of early-warning systems, such as real-time indoor air quality monitors, which could empower households to take preventative action before visible signs emerge [53].

The results relating to *Objective 2* revealed that the influence of self-efficacy on behavioural changes strengthened over time. This suggests that self-efficacy may become increasingly important as individuals are repeatedly exposed to information or prompted to reflect on their behaviours. However, this effect was limited to individuals with higher self-efficacy, who showed a marked increase in the predicted probability of engaging in behaviour change across time 2, 3 and 4. In contrast, those with low self-efficacy remained consistently unlikely to act. One possible explanation is that individuals with higher self-efficacy were more responsive to cumulative exposure to information or experience during the WellHome project. This pattern highlights self-efficacy as a critical enabling factor for behavioural change in the context of indoor air quality. However, to our knowledge, this is the first study to explore the dynamics of self-efficacy in the context of behavioural change aimed at reducing indoor air pollution over time.

For *Objective* 3, we found that some behaviours, such as window opening, cooking, and cleaning, were more likely to change than others, independently of time. Moreover, some behaviours were more or less likely to change at different time points, with cooking behaviour showing the highest probability of change at Time 4. Finally, when examining the probability of change over time - whether behaviours increased, decreased, or remained stable - only cooking and heating showed a statistically significant increase. These patterns likely reflect which behaviours participants found easier [86] or clearly linked to indoor air quality.

For cooking and heating behaviours, the likelihood of reporting a change increased progressively across the four time points, suggesting that continued participation in the project may have progressively increased participants' awareness [39]. These behaviours may not be immediately recognised as contributors to indoor air pollution, and participants may have been less aware of their consequences at the outset. Through ongoing involvement in the project, participants may have acquired the knowledge and the confidence needed to reconsider and eventually change these routines. For example, through the project's engagement activities and regular contact with researchers and ambassadors.

Simpler or more intuitive behaviours, such as window opening and cleaning, were quickly adopted and remained stable throughout the project. Smoking had the lowest probability of changing. This likely reflects how different smoking is from the other behaviours in this study. Smoking is a highly habitual, nicotine-dependent behaviour with low unaided quit rates (around 3–5 % per year; [87]). Participants might already have been aware of its health risks, so taking part in WellHome may not have added much new awareness. In addition, many households may already have avoided or restricted indoor smoking, leaving less scope for further change than for other behaviours.

Finally, we found that higher education was associated with a lower likelihood of behavioural change. Although UK data are limited, studies from other countries suggest that awareness of indoor air pollution is higher among those with more education (e.g., [72]).These individuals may already engage in behaviours that support better air quality, leaving less room for improvement. In contrast, those with lower education may have been less aware initially and more likely to change. Future research should further investigate this relationship, ideally using representative UK samples to better understand how education influences awareness and behaviour.

4.2. Theoretical contributions

The current study advances understanding of the psychological and contextual factors associated with behavioural changes aimed at improving indoor air quality in the home. The results show that perceived severity and self-efficacy, rather than perceived vulnerability, are the main psychological predictors of reported change. This pattern is in line with previous research showing that perceived vulnerability is the weakest and most inconsistent predictor among the different HBM constructs [44,88] and extends that observation to household air quality behaviours. By incorporating perceptions of indoor and outdoor air quality and contextual cues within a single framework, the study shows how psychological beliefs and contextual factors work together to support household air-quality behaviours [17,53].

The study's sample was drawn from a deprived urban community in West London with significant health inequalities. Given that deprived communities often experience greater exposure to air pollutants [10,11,22], the present study also contributes to understanding behavioural responses to indoor air pollution in a context of environmental and social disadvantage.

4.3. Practical implications

Key practical implications from the present study are that information on indoor air quality should focus both on the severity of the health risks and on building people's confidence in their ability to take action against indoor air pollution; and that mould and damp serve as visible cues indicating poor indoor air quality and frequently prompt individuals to act. Communication campaigns and policymakers should therefore focus less on simply raising awareness of the dangers of mould and more on concrete actions that households can take to prevent mould from developing in the first place.

The study demonstrated that participatory research can be an effective approach for fostering ongoing engagement of communities with the topic. However, the participation process did not have the same effect on all behaviours over time. Although several behaviours were likely to change at different points during the project, further analysis revealed that only cooking and heating showed a significant increase in the probability of change over the participation period.

Furthermore, the study shows that participatory programmes, such as the WellHome project, may support relevant behavioural changes and could potentially strengthen the effect of self-efficacy in these processes.

4.4. Limitations of the research and future research

The current study has several limitations that should be acknowledged, many of which also highlight opportunities for future research. First, although the study employed a longitudinal design, the analyses were observational and lacked a control group. As a result, causality cannot be established with certainty. Future research could address this by incorporating a comparator group to strengthen causal inference.

Second, not all constructs from the original HBM were included in the survey. In particular, perceived benefits and perceived barriers were omitted to minimise respondent burden and due to uncertainty about which items would be most relevant. As a result, the model tested in this study was incomplete. Future work should aim to incorporate the full range of HBM constructs to provide a more comprehensive understanding of behavioural motivation. It may also be valuable to examine potential interaction effects between constructs, for example, whether perceived vulnerability becomes a stronger predictor when perceived severity is also high [89].

Third, behavioural change was assessed through self-reported measures, which are subject to recall bias and social desirability effects. Moreover, due to project time constraints and the timing of sensor calibration, we were not able to assess whether reported behavioural changes actually produced the desired improvements in indoor air quality (i.e., by examining sensor data). It is therefore possible that some reported changes were not optimal for reducing pollution, for example opening windows during peak traffic near busy roads or switching to 'natural' home fragrances that still emit pollutants. While self-report is often necessary in studies involving private household behaviours, future research could strengthen measurement validity by including a more detailed behavioural baseline and exploring the use of objective data collection methods, such as sensors, to track behaviours like window opening or air purifier use [90]. Future research should also examine the long-term sustainability of the behavioural changes reported in this study. Longitudinal studies with longer follow-up and repeated behavioural measures would help to determine whether these actions are temporary responses to the intervention context or become embedded practices.

Fourth, key psychological predictors were measured with single-item indicators, and convergent validity could only be evaluated for perceived vulnerability and severity. Results should therefore be interpreted in light of the specific questions asked and the restricted measurement of these constructs. The use of single items was a pragmatic choice in a demanding participatory longitudinal study and helped maintain ecological validity in a real-world community setting. However, future work should, where feasible, use multi-item scales to provide a more detailed and robust assessment of these constructs.

Fifth, participants did not have the option to indicate that some behaviours were not applicable to them, although some behaviours may not have been relevant to all participants. For instance, behaviours such as smoking (among non-smokers) or using an air purifier (e.g., if participants could not afford one) were not applicable to certain individuals, potentially limiting the number of respondents able to report a change.

Finally, the study was conducted within a socioeconomically disadvantaged and ethnically diverse population in West London. While this context provides important insights into communities disproportionately affected by poor indoor air quality, the findings may not be generalisable to other settings. Future studies should replicate and extend this work in a range of populations and environments to test the robustness and applicability of the adapted HMB more broadly.

5. Conclusions

This study advances understanding of the psychological and contextual factors that support behavioural changes to improve indoor air quality in the home. The findings demonstrate that individual beliefs, particularly perceived severity rather than perceived vulnerability, play a crucial role in motivating behaviour change. Immediate environmental cues, such as visible signs of mould and damp, also act as important contextual triggers for action, although relying solely on such cues may delay interventions until after exposure has occurred. Participatory research emerged as an effective approach to engage communities, contributing to changes in behaviours and increases in self-efficacy over time.

Notably, the probability of behaviour changes over time increased significantly predominantly for cooking and heating behaviours, underscoring that the likelihood of behaviour change varies across behavioural domains. Self-efficacy became a stronger predictor of behaviour change in successive waves of the study, highlighting the time-dependent nature of its influence.

Taken together, the results show the importance of addressing both individual-level psychological factors and broader contextual influences when designing interventions. Incorporating proactive engagement, behaviour-specific information, and accessible monitoring tools could enhance the timeliness and effectiveness of efforts to improve indoor air quality, particularly in vulnerable communities.

Data availability

The dataset and R code used for the analyses are available on the OSF project page: https://doi.org/10.17605/OSF.IO/5JZCG.

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CRediT authorship contribution statement

Francesca Ausilia Tirotto: Writing – review & editing, Writing –

original draft, Visualization, Investigation, Formal analysis. **Diana Varaden:** Writing – review & editing, Investigation. **Frank J Kelly:** Writing – review & editing, Funding acquisition. **Wouter Poortinga:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.buildenv.2025.114089.

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