Investigating the probability of behavioural responses to cold thermal discomfort

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Abstract

In buildings, occupant behaviour is recognised as a major contributing factor to energy demand and in particular to heating consumption. To achieve thermal comfort within the heating season, people report to use heat in very different ways; for example behaviours include switching on the heating system, putting on warm clothes, drawing curtains, changing rooms, making a hot drink and using a hot water bottle. While research has focused on subjective accounts using interviews, diaries and questionnaires, little is known about the frequency and probability of these behaviours. Using a mixed-method approach, this paper reports on the results of a field study in dwellings using wearable and environmental sensors. The analysis investigates the probability of these behavioural responses as a function of seven independent variables; (1) external and (2) internal monitored temperature, (3) probability of heating being on or off, (4) time of the week, (5) time of the day, (6) the three categories of the predictive thermal comfort model, and (7) the three categories of the adaptive thermal comfort model. Results show that participants were more likely to increase their clothing and activity level as internal temperature decreased, although there was no significant change in activity level throughout the course of a day. Methodologically, this paper demonstrates the effectiveness of different statistical tools in analysing occupants' behaviours. Substantively, this paper emphasises the need for future research to gather objective data on what people do.

Keywords: Adaptive Behaviours, Occupant Surveys, Ubiquitous Sensors, Behaviour Analysis, Thermal Comfort

1. Introduction

A recent report by the Energy Technologies Institute (ETI) focusing on smart system and heat in the UK [1] has shown that *"people do very different things to get comfortable when they are at home"*. This variability in behaviour responses presents a real challenge in the prediction of energy demand and occupant's comfort [2] [3].

To date most thermal comfort studies have focused on occupants' modelled and reported thermal sensations [4]. Little is known about what occupants actually do to alleviate cold thermal discomfort. This gap in knowledge may be one of the explanatory factor of building performance gap [5]. Behavioural adaptive strategies may manifest as intentional actions or habits. At home it is assumed that people have access to diverse coping strategies, including adjusting the output of the heating system, shielding from draught, changing location within the home, increasing activity level, wearing more clothes, having a warm drink or food, and implementing localised behaviour adaptation strategies (e.g. hot water bottle) [6] [7] [8] [9] [10]. The empirical studies that ascertained these adaptive behaviours have employed qualitative research methods such as interviews. The recent study by Burris, et al. [11] was aiming to gain an understanding of how and why occupants create comfort at home. Here 'comfort' touches many themes, including thermal, surroundings, physical, entertainment, food, state and visual stimuli. With regards to thermal behaviours, participants reported in the interviews, the following comfort-making elements: *"turning on/off the heating system, using a fireplace, adapting clothing level, or bathing"*. Another study by Tweed, et al. [10] reports on thermal comfort practices and energy consumption in five dwellings in South Wales. Interestingly the study carried out a mixed-method approach with series of audio tours and telephone surveys. The householders developed a range of strategies, including additional clothing, covers, hot drinks, interacting with the heating system (thermostatic radiator valves, thermostat set-point, timers, manual controls), zoning system and portable heaters. The study concluded that occupants reported very different thermal comfort ideals and ways to achieve those. The results of these field studies are very insightful in identifying the range of cold thermal discomfort behaviours although crucially these are reported behaviours; little is known about the probability of actual behaviours.

As these studies are focusing on reported accounts, they have employed qualitative research methods such as questionnaires, interviews, focus groups and pen-and-paper diary. In contrast, actual behaviours may be uncovered using ethnographic methods such as observations and automated diaries. The observation of occupants may be carried-out directly by the researcher; however there is a strong risk of observer-bias as the occupants may alter their behaviour to 'please' the researcher [12]. Observation can also be carried-out using a piece of equipment such as a wearable logger or audio recording equipment. This method is often employed in behavioural medicine [12]. A portable camera may record pictures when triggered by changes in movement, temperature and light intensity [13]. The output will be time-stamped, and therefore duration and frequency of particular behaviour can be estimated. The analysis will then be able to report on the probability of behaviours as function of specific predictors. For these reasons, automated visual diaries were applied in the empirical study reported in this paper.

The question remains, which factors may influence behavioural responses to cold thermal discomfort, or in other words what are the predictors to consider in the study? Recent ethnographic studies in the UK have focused on practices what one may adopt. Interestingly people may chose to turn on the central heating to dry clothes rather than keeping warm [14]. Social pressure may also play a role, for example older people may turn-on their heating system when inviting guest at weekend [15]. These behavioural adaptations may be carried out consciously or unconsciously by the occupants [7]. Adaptive behaviour and practices may be influenced by external environmental conditions, socio-economical constraints, other occupants and the physical context, including the level of control an occupant has over the surrounding environment [7]. To address some of these influencing factors, this study will focus on seven predictors. These may be grouped into two strands, described as follows:

- Predictors that may relates to the adaptive approaches [7], including: external temperature, time of the week, time of the day and adaptive thermal comfort model categories;
- Predictors that may relates to the predictive approaches [16], including: internal temperature, probability of heating being on or off and predictive thermal comfort categories.

The aim of this study is to investigate the probability of behavioural responses to cold thermal discomfort. The paper is organised as follows. The applied data collection, processing and analysis methods are described in Section 2. In Section 3, results of the field study are described, and then discussed in Section 4. Finally practical implications are reviewed and conclusions are drawn in Section 5.

2. Methods

To investigate the probability of behavioural responses to cold thermal discomfort, this study introduces a mixed-method framework drawn from psychological and thermal comfort studies. A field study was carried out in nineteen homes with twenty participants over two winter-seasons; from the 27^{th} of January to the 17^{th} of March 2012 (7-weeks, part 1), and from the 26^{th} of October to the 19^{th} of December 2012 (8-weeks, part 2). External environmental conditions were retrieved from local weather stations using an open-source database [17]. The recordings were taken every 30-minutes. During the two studied periods, external temperatures (T_{ext}) were below the degree-day threshold of 15.5°C for 99.6% of the time, and low enough to require space heating [18]. Each home was monitored for a minimum period of 10-consecutive days, to include a period of 'adaptation' of 1-day and a monitoring period of 5-weekdays and 2-weekend days for each participant.

This study was based on a convenience sample. Participants were recruited through a call for participation sent out to the University College London's mailing lists. Recipients of the email were encouraged to share the announcement within their networks. No incentive was offered. The sample frame was based on three physiological criteria; gender, age and weight. As defined by ISO 8996:2004 (Annex C) [19], these variables have a direct influence on the estimation of metabolic rate, which is the most influential variable in the PMV predictive model as a recent study employing global sensitivity analysis found [20]. Clothing is the second most influential variable. Although convenience-sampling was used, participants were selected to ensure a 'spread' of the 3-primary criteria. The sample consisted of N=20 participants, with an equal number of males and females. The age range was 20 to 64 years old, the weight range was 45 kg to 95 kg, and the BMI range was 19 to 29.4. No participants reported having health conditions that may affect their thermal responses. Participants lived in different location within the South-East of England, mostly focus within Greater London.

This study relies on a small sample of participants; theoretical criteria (i.e. age, weight and gender) were applied rather than population representative criteria due to fieldwork constraints, in particular limited access to resources, and the time constraint of the project. Participants were observed at different times of day, and in different contexts - at home alone or socialising. The aim of this study is to develop a method to investigate the probability of behavioural responses to cold thermal discomfort in a free-living environment. The research is concerned with the refinement of a method about the way people respond, rather than a large sample size. To this effect, an in-depth investigation was undertaken, qualitative and quantitative information was collected through a mixed-method framework, using questionnaires, semi-structured interviews, visual diaries and environmental monitoring. Although the number of participants was small, the amount of data collected was very large, in particular the output from the wearable sensors.

2.1. Data collection

In this study the data collection sequencing included 3-parts described as follows. During the first part, the researcher visited the participants in their homes. Participants were given information sheets, consent forms, had an induction of monitoring equipment and completed two questionnaires addressing socio-demographic informations, building characteristics, and thermal comfort assessments. Both questionnaires used questions from established templates, including the English Housing Survey [21] and ISO 10551:2001 (Annex B) [22]. Finally the state of the windows (open/closed) was noted and mean air velocity (v_a) was measured in each room using Testo 425; this hot-wire anemometer has an accuracy of $\pm$ $(0.03 + 0.05v_a)$ m/s. Results from these field tests showed that windows were closed and air velocity was below 0.1 m/s in all cases. Although window opening was not monitored throughout the study, it was assumed an air velocity of 0.1 m/s, as previous studies highlight that during winter little window operation occurs [23].

Monitoring took place during the second part of the data collection sequencing, and included environmental monitoring and automated visual diaries. Ambient air temperature (T_a) and relative humidity (RH) were monitored using Onset HOBO U12-012 dataloggers with respective accuracy of $\pm$ 0.35°C and $\pm$ 2.5%, and a logging frequency set at 5-minutes interval. As it was hypothesised that the residential environments may be heterogeneous with both vertical stratification and horizontal temperature differences, three set of 4-dataloggers were fastened to wooden poles, and positioned at 0.1m, 0.6m, 1.1m and 1.7m from the ground to comply with the requirements set by ISO 7726:2001 [24]. The wooden poles were located in different rooms, close to participants typical activity and away from sources of direct light and heat. For example, if a participant reported to often be seated on a chair with one side close to a radiator, the sensors were placed next to but on the other side of the chair. If the sensors were monitoring radiant temperature then the sensors should have been positioned between the chair and the radiator. Concurrently to the environmental monitoring, participants wore a SenseCam during periods spent awake at home (Vicon Motion Systems, Microsoft, UK) [25]. Of similar size to a small badge, the SenseCam was worn around the neck. This device recorded ambient air temperature, light intensity, 3-axis acceleration, and a visual diary at a minimum of 1-minute interval. The SenseCam's temperature sensor was a Nat Semi LM75 with an accuracy of ± 2°C. The SenseCam's camera was a 119° wide-angle lens triggered when changes in sensors input occurred.

Finally during the third part of the data collection sequencing, the researcher visited the participants' homes a second time to collect the equipment and complete a semi-structured interview with the participant. As inductive research, these interviews enabled reported behavioural responses to cold thermal discomfort to be identified. Open-ended questions encouraged discussions, focusing on typical responses to thermal discomfort, associated thresholds and influencing factors.

This study gathered different type of data, which may be summarised as follows:

- Subjective and qualitative data from the semi-structured interviews;
- Subjective and quantitative data from the questionnaires;
- Objective and qualitative data from the visual diaries;
- Objective and quantitative data from the various monitoring sensors (temperature, relative humidity, air velocity, light intensity, and 3-axis acceleration).

2.2. Data processing

These diverse types of data required different analysis methods, ranging from content analysis and image processing, to descriptive and inferential statistics. This paper is focusing the analysis of the objective data as described above; in particular three dependant variables (1) participants' responses to thermal discomfort identified in the semi-structured interviews and the visual diaries, (2) participants' clothing levels and (3) activity levels ascertained from the monitoring. Examples of pictures from the visual diary are shown in Figure 1. As described in Gauthier and Shipworth [26], content analysis was used to review the transcripts of the semi-structured interviews. Results show that participants reported responses to cold thermal discomfort were of six -types: ‘turning on the heating’, ‘closing curtains or windows’, ‘putting on item(s) of clothing’, ‘changing body position, location within a room or room’, ‘having a warm drink, or food’, and ‘using a hot-water-bottle or having a warm bath’. These six-types of reported responses were then used to categorise the results of the SenseCam’s visual diary. Automated segmentation was employed as image processing technique [26]. Following the analysis of the visual diary only three behaviours were observed with N>15 during the course of the study, including ‘putting on item(s) of clothing’ (*clothing*), ‘changing body position, location or room’ (*activity*), ‘having a warm drink, or food’ (*food&drink*). Following the methods described in Gauthier and Shipworth [26], participants’ clothing insulation (I_{cl}) and activity level (M), as defined in ISO 7730:2005 [16], were estimated using SenseCam’s sensors output, indoor environmental monitoring and questionnaires’ results (body height and weight). (I_{cl}) was estimated from the monitored surface temperature of clothing and ambient air temperature; while (M) was estimated from participants’ monitored acceleration, weight and height. It is important to note that participants may engage with these behaviours for reasons independent to their states of thermal discomfort. The method developed in this study enables to uncover what people do, but not directly why. By reviewing the relationships between environmental, temporal and standards variables and the observed behaviours, this paper may suggest some inferences.

2.3. Data analysis

Having define the three dependent variables to be investigated, the paper establishes the frequencies of occurrence and relationship of these behaviours as a function of either (1) external temperature (T_{ext}), (2) internal temperature (T_{int}), (3) probability of heating being on or off ($H_{on \oplus off}$), (4) time of the

Figure 1: Sample of three pictures from the visual diary showing three different behaviours (1) 'putting on an item of clothing', (2) 'changing room' and (3) 'having a warm drink'.

week ($t_{week \oplus weekend}$), (5) time of the day (t_{24h}), (6) the three categories of the predictive thermal comfort model (C_{PMV}) [27], and (7) the three categories of the adaptive thermal comfort model (C_{ADP})[27]. For the purpose of this analysis, T_{ext} was retrieved from local weather stations at building sites in the city (T_{ext}=6.2±4.3 °C) [17]. T_{int} was estimated as the standing position living room temperature by averaging across sensors at three heights (0.1m, 1.1m, and 1.7m), this takes into account potential thermal variations in height (T_{int}=18.5±2.7 °C) [24]. $H_{on \oplus off}$ was estimated from internal temperature measurements using the method described in Huebner, et al. [28], with T_{int} averaged over 30-minutes epoch, amounting to 48-measurement points per day. This resulted in a binary string with 0 for heating being 'off' and 1 for heating being 'on'. $t_{week \oplus weekend}$ was determined as another binary string with 1 for 'week days' and 0 for 'weekend days'. t_{24h} reprensents the time of day, set as a 24-hours sequence. C_{PMV} includes the recommended predictive categories I, II and III, as described in BS EN 15251:2007, with Category I for $|PMV| < 0.2$, Category II for $|PMV| < 0.5$, and Category III for $|PMV| < 0.7$ (where PMV is the Predictive Mean Vote). Finally, C_{ADP} includes the adaptive categories I, II and III, as described in BS EN 15251:2007, with Category I for ±2, Category II for ±3, and Category III for ±4.

2.4. Summary

The paper consider three dependent variables and seven independent variables. The outcome variables are defined as (1) participants' observed responses (Bev), (2) participants' clothing insulation (I_{cl}) and (3) activity level (M). The predictor variables are defined as (T_{ext}), (T_{int}), ($H_{on \oplus off}$), ($t_{week \oplus weekend}$), (t_{24h}), (C_{PMV}) and (C_{ADP}).

3. Results

The results of the field study are reviewed in the following two sections. First the frequency of the observed responses from the visual diaries will be analysed, then the monitoring results of participants' clothing and activity levels will be investigated.

3.1. Observed responses

The first part of this analysis uses binary logistic regression with the observed behaviours (*clothing*, *activity*, and *food&drink*) as categorial outcome variables. This regression analysis is applied to two predictors, (T_{ext}) and (T_{int}).

Table 1: Logistic regression analysis of observed behaviours.

Outcomes	**Predictors**	β	**SE** β	**Chi Square**	***df***	**p**	**Odds Ratio**
clothing	T_{ext}	-0.048	0.054	0.77	1	0.38	NA
	T_{int}	0.018	0.096	0.04	1	0.85	NA
activity	T_{ext}	-0.003	0.007	0.16	1	0.69	NA
	T_{int}	-0.026	0.013	4.00	1	0.045*	0.97
food & drink	T_{ext}	-0.010	0.017	0.33	1	0.56	NA
	T_{int}	-0.03	0.03	1	1	0.31	NA

Note: Significance level set at 0.05. NA = not applicable.

Results show that (T_{ext}) and (T_{int}) were not significant predictors to any of the observed behaviours, with the exception of (T_{int}) on (*activity*), see Table 1. In that case, the odds ratio was 0.97 with a 95% confidence interval of 0.95 to 0.99. As the odds ratio was lower than 1, when (T_{int}) increased the odds of (*activity*) occurring decreased. This suggests that participants were more likely to change body position, location within a room or room when (T_{int}) decreased. Nagelkerke's R^2 of 0 indicated a very weak relationship between the predictor (T_{int}) and outcome (*activity*) although significant. Further analysis reviewed the ranges and variances of (T_{ext}) and (T_{int}) for the three observed behaviours. As shown in Table 2, the ranges in (T_{ext}) and (T_{int}) are similar for the three observed behaviours. Furthermore, there is no statistically significant difference in (T_{ext}) between observed behaviours as determined by one-way ANOVA (F(2,1245)=0.383, p=0.682), and there is no statistically significant difference in (T_{int}) between observed behaviours as determined by one-way ANOVA (F(2,1245)=0.112, p=0.894). In summary participants may change their clothing levels, location or food intake at similar external and internal temperature levels.

Table 2: Summary of the statistical characteristics of (T_{ext}) and (T_{int}) for the three observed behaviours

Observed behaviours	**Variables**	**Mean**	σ	**Minimum**	**Maximum**	**Range**
clothing	T_{ext}	5.3	3.8	-2	12	14
	T_{int}	19	2.8	13.4	23	9.6
activity	T_{ext}	6.1	4.3	-5	15	20
	T_{int}	18.7	2.5	12.1	24.8	12.7
food & drink	T_{ext}	6	4.5	-3	15	18
	T_{int}	18.7	2.3	13.3	23.9	10.6

The second part of the analysis investigates the relationship between (*clothing*), (*activity*), and (*food&drink*) as outcome, and (t_{24h}) as predictor using probit regression analysis. Results summarised in Table 3 show that there is a significant relationship between (t_{24h}) and both change in (*clothing*) and (*food&drink*) intake. However there is no significant relationship between (t_{24h}) and (*activity*). Participants tended to change their clothing level in the morning (22% probability of change between 9 and 10am) and in the evening (17% probability of change between 10 and 11pm). With regards to (*food&drink*) intake, the distribution is trimodal, with peaks at 8am, 1pm and 8pm. Both changes in (*clothing*) and (*food&drink*) intake may relate more to daily rhythm rather than responses to cold thermal discomfort.

Table 3: Probit regression analysis of observed behaviours.

Outcomes	**Predictors**	**Chi Square**	***df***	**p**	**Log likelihood**
clothing	t_{24h}	35.51	21	0.025*	-137.1
activity	t_{24h}	15.79	21	0.782	-4,679.9
food & drink	t_{24h}	39.89	21	0.008*	-1,208.7

Note: Significance level set at 0.05.

The third part of the analysis focuses on relationship between ($t_{week \oplus weekend}$), ($H_{on \oplus off}$), (C_{PMV}) and (C_{ADP}) as predictors, and *observed behaviours* as outcomes (including 'putting on item(s) of clothing' (*clothing*), 'changing body position, location within a room or room' (*activity*), 'having a warm drink, or food' (*food&drink*)). This analysis reviews the frequencies of occurrence that fall into each categories. Here the outcomes and the predictors are categorical variables with two categories, forming 2x2 contingency tables. To alleviate the risk of Type I error, this analysis uses chi-square test with Yates's continuity correction. The results summarised in Table 4 show that:

- There is no significant difference in the occurrence of observed behaviours between weekdays and weekend day. Participants' work patterns may have had an influence on this result as 45% of the participants worked full time, 35% worked part-time and 20% did not work. As a group, participants may have had similar patterns during weekday and weekend day. Further analysis showed participants were slightly more likely to be at home during a weekend day (57%) than a weekday (43%). To conclude changes in observed behaviours may be more related to daily rather than weekly rhythms.

- There is no significant association between heating being on or off and whether or not observed behaviours occurred, with the exception of (*activity*) ($\chi^2(1)=6.32$, $p<0.05$). This seems to represent the fact that, based on the odd ratio, the odds of (*activity*) occurring were 0.85 (0.75, 0.97) times smaller if there was heating than if there was no heating.

- There was no significant association between being within or outside of the three PMV categories and whether or not observed behaviours occurred, with the exception of (C_{PMV}III) and (*activity*) ($\chi^2(1)=5.03$, $p<0.05$). This seems to represent the fact that, based on the odd ratio, the odds of (*activity*) occurring were 1.17 (1.02, 1.34) times higher if within (C_{PMV}III) than if outside (C_{PMV}III). This suggests that participants were more likely to change body position, location within a room or room if within (C_{PMV}III).

- There is no significant association between being within or outside of the three adaptive model categories and whether or not observed behaviours occurred.

In summary, participants were more likely to change (*activity*) when there was no heating and when (T_{int}) decreased. Participants change in (*clothing*) levels and (*food & drink*) intake have a significant relationship with 'time of day'.

Table 4: Analysis of observed behaviours using chi-square test with Yates's continuity correction.

Outcomes	**Predictors**	**Sample size**	**EF**	**Chi Square**	***df***	**p**	**Odds Ratio**
clothing	$t_{week \oplus weekend}$		Yes	5.53e-25	1	1	-
	$H_{on \oplus off}$		Yes	0.02	1	0.90	-
	C_{PMV}I	2	No	-	-	-	-
	C_{PMV}II	3	No	-	-	-	-
	C_{PMV}III	4	Yes	0.07	1	0.79	-
	C_{ADP}I	4	No	-	-	-	-
	C_{ADP}II	4	No	-	-	-	-
	C_{ADP}III	4	No	-	-	-	-
activity	$t_{week \oplus weekend}$		Yes	0.47	1	0.49	-
	$H_{on \oplus off}$		Yes	6.32	1	0.012⋆	0.85
	C_{PMV}I	126	Yes	0.03	1	0.86	-
	C_{PMV}II	252	Yes	3.16	1	0.08	-
	C_{PMV}III	319	Yes	5.03	1	0.024⋆	1.17
	C_{ADP}I	28	Yes	1.17	1	0.28	-
	C_{ADP}II	39	Yes	1.57	1	0.21	-
	C_{ADP}III	54	Yes	0.80	1	0.37	-
food & drink	$t_{week \oplus weekend}$		Yes	1.73	1	0.19	-
	$H_{on \oplus off}$		Yes	0.02	1	0.88	-
	C_{PMV}I	15	Yes	3.26	1	0.07	-
	C_{PMV}II	36	Yes	1.56	1	0.21	-
	C_{PMV}III	46	Yes	1.83	1	0.18	-
	C_{ADP}I	6	No	-	-	-	-
	C_{ADP}II	10	No	-	-	-	-
	C_{ADP}III	17	Yes	0.08	1	0.78	-

Note: Sample size, defined at the number of changes in observed behaviours that occurred within each categories for both PMV and ADP. EF, defined as the expected frequencies greater than 5. Significance level set at 0.05.

3.2. Monitored clothing insulation and activity level

To follow the analysis of observed behaviours from the visual diary, the study focused on the results of the dataloggers as monitored clothing insulation level (I_{cl}) and activity level (M). In this analysis, the outcomes are defined as (I_{cl}) and (M), both are continuous and non-normally distributed variables. The predictors are divided into three groups, (1) (T_{ext}) and (T_{int}) as continuous and normally distributed variables, (2) (t_{24h}) as discrete variable with 24-intervals, and (3) ($t_{week \oplus weekend}$), ($H_{on \oplus off}$), (C_{PMV}) and (C_{ADP}) as discrete variables with 2-categories.

The first part of this analysis considers (I_{cl}) and (M) as non-normally distributed outcome variables and investigates their relationships with (T_{ext}) and (T_{int}) using regression. In order to obtain a normally distributed sample for (T_{ext}) and (T_{int}), there is two options to transform or to 'bootstrap' the data. As the sample size is very large (>15,000), the study first identified and removed outliers for (I_{cl}) and (M) using z-score (significance level set at 0.05), and then transformed the data using square-rooting. This transformation was used as the size of the residuals progressively increased as values of (T_{ext}) and (T_{int}) increased. Further tests were undertook to review any fixed effect. It was found that participants had a significant effect on (T_{ext}) and (T_{int}), as the variations of (T_{ext}) and (T_{int}) between different participants were smaller than the variation within each participants. Post-hoc analysis using F-Test compared regression models with and without participants' fixed effect, results show that the fixed effect models were better choices ($p<0.05$). The results of the regression analysis with participants' fixed effect are summariesed in Table 5.

Table 5: Regression analysis of clothing (I_{cl}) and activity (M) level with participants' fixed effect.

Outcomes	**Predictors**	β	**SE** β	**R**	**F-statistics**	***df***	**p**
(I_{cl})	T_{ext}	-5e^{-4}	4.6e^{-5}	0.08	121	17,158	$< 0.001^{\star}$
	T_{int}	-2e^{-3}	8e^{-5}	0.18	585	17,158	$< 0.001^{\star}$
(M)	T_{ext}	2e^{-4}	1e^{-5}	0.10	363	33,660	$< 0.001^{\star}$
	T_{int}	-8e^{-5}	2e^{-5}	0.02	16	33,660	$< 0.001^{\star}$

Note: Significance level set at 0.05.

Results summarised in Table 5 show that (T_{ext}) and (T_{int}) are both significant predictors of (I_{cl}) and of (M). As the coefficients are very small, a degree change in (T_{ext}) and (T_{int}) would have a small impact upon (I_{cl}) and of (M). (T_{ext}) can account for 8% of the variation in (I_{cl}), while (T_{int}) can account for 18% of the variation in (I_{cl}). In summary participants' clothing insulation level was statistically significantly influenced by both internal and external temperature. As internal and external temperature decreased, participants tended to increase their clothing insulation levels. With regards to activity level, results show that (T_{ext}) can account for 10% of the variation in (M), while (T_{int}) can account for 2% of the variation in (M). Participants' activity level was significantly influenced by both internal and external temperatures. As internal temperature decreased, participants tended to increase their activity levels, although the relationship between (T_{int}) and (M) is very weak.

The second a part of the analysis investigates the variations of (I_{cl}) and (M) throughout the day (t_{24h}) using single factor designs ANOVA with repeated measures. An error term was added to reflect the fact that there is an 'hour of day' effect nested within each participants. As per the regression analysis, outliers were identified and removed, then (I_{cl}) and (M) data were transformed using square-rooting. Results summarised in Table 6 show that there is a significant effect of hour of the day on clothing insulation level, but there was no effect on activity level.

Table 6: Analysis of the variation in clothing (I_{cl}) and activity (M) level throughout the day using ANOVA.

Outcomes	**Predictors**	df_{hour}	$df_{residuals}$	**F-statistics**	**p**
(I_{cl})	t_{24h}	20	189	1.91	0.014*
(M)	t_{24h}	21	237	0.93	0.55

Note: Significance level set at 0.05.

The third part of the analysis investigates the relationship between (I_{cl}) and (M) as outcome and the categorical variables ($t_{week \oplus weekend}$), ($H_{on \oplus off}$), (C_{PMV}) and (C_{ADP}) as predictors, using Mann Whitney U-test. The results summarised in Table 7 show that (I_{cl}) and (M) differ significantly between 'Week day' (I_{cl} Mdn=0.77clo, M Mdn=1.32met) and 'Weekend day' (I_{cl} Mdn=0.76clo, M Mdn=1.30met), although both effects are negligible and the difference in median values are very small. This indicates that participants were significantly more active and were wearing more clothing during weekday. While heating was on, (I_{cl}) (Mdn=0.77clo) did not differ significantly from (I_{cl}) while heating was off (Mdn=0.77clo). However (M) while heating was on (Mdn=1.35met) differ significantly from (M) while heating was off (Mdn=1.29met), this effect and the difference in median values are small. This suggests that participants were statistically slightly more active when the heating was on. Metabolic rate increased by just under 0.1met, which is the difference between sleeping and reclining (ISO 8996:2004, Table B.3) [19]. With regards to PMV, results show that (I_{cl}) and (M) differ significantly between falling 'within' or 'outside' of the three PMV categories, with the exception of (I_{cl}) and (C_{PMV}III). In all cases the effects are small to negligible. Participants' clothing levels were lower inside the PMV thresholds, whereas activity levels were higher. This may suggest that participants increased their activity rather than their clothing level to fall within the predictive comfort boundaries, although environmental variables' levels should also be reviewed. Finally results show that (I_{cl}) does not differ significantly for (C_{ADP}), with the exception of (I_{cl}) and (C_{ADP}I) but in this case the effect is negligible. In contrast (M) differs significantly for all (C_{ADP}), and the effects are small (C_{ADP}III) to large (C_{ADP}I). Participants activity levels were significantly higher inside the ADP thresholds, this suggests that participants increased their activity levels to fall within adaptive comfort boundaries.

Table 7: Analysis of clothing and activity level using Mann Whitney U-test.

Outcomes	**Predictors**	**Sample size**	**Mdn** $_{wk/on/in}$ **in clo**	**Mdn** $_{wd/off/out}$ **in met**	**W**	**p**	**R**
I_{cl}	$t_{week \oplus weekend}$		0.77	0.76	40,887,000	$< 0.001^\star$	-0.03
	$H_{on \oplus off}$		0.77	0.77	43,053,000	0.58	$<$-0.01
	C_{PMV}I	4334	0.71	0.78	21,550,000	$< 0.001^\star$	-0.20
	C_{PMV}II	7997	0.73	0.78	32,111,000	$< 0.001^\star$	-0.16
	C_{PMV}III	10049	0.76	0.77	38,747,000	0.054	-0.01
	C_{ADP}I	576	0.74	0.72	252,290	$0.03^\star$	-0.06
	C_{ADP}II	657	0.74	0.72	257,000	0.06	-0.05
	C_{ADP}III	1109	0.74	0.71	163,960	0.43	-0.02
M	$t_{week \oplus weekend}$		1.32	1.30	152,150,000	$< 0.001^\star$	-0.02
	$H_{on \oplus off}$		1.35	1.29	182,210,000	$< 0.001^\star$	-0.1
	C_{PMV}I	4334	1.40	1.26	45,193,000	$< 0.001^\star$	$<$-0.01
	C_{PMV}II	7997	1.38	1.25	62,392,000	$< 0.001^\star$	$<$-0.01
	C_{PMV}III	10049	1.37	1.26	57,762,000	$< 0.001^\star$	$<$-0.01
	C_{ADP}I	848	1.37	1.24	1,093,500	$< 0.001^\star$	-0.74
	C_{ADP}II	1131	1.36	1.24	1,025,000	$< 0.001^\star$	-0.57
	C_{ADP}III	1812	1.26	1.25	500,600	$< 0.001^\star$	-0.22

Note: Sample size, defined at the number of changes in monitored behaviours that occurred within each categories for both PMV and ADP. Mdn = Median. Significance level set at 0.05.

In summary, participants were most likely to increase their clothing level as (T_{int}) and (T_{ext}) decreased. Also there is a significant relationship between participants' clothing level and 'time of day'. Participants were more likely to wear higher clothing level during 'week day' than during 'weekend day'. With regards to activity level, participants were likely to be active when (T_{int}) decreased, when heating was on, and during 'week day'. Finally participants activity level was significantly higher while within PMV and ADP categories. This suggest that participants increased there activity level to fall within the comfort boundaries, thus 'activity level' may be identified as a response to thermal discomfort.

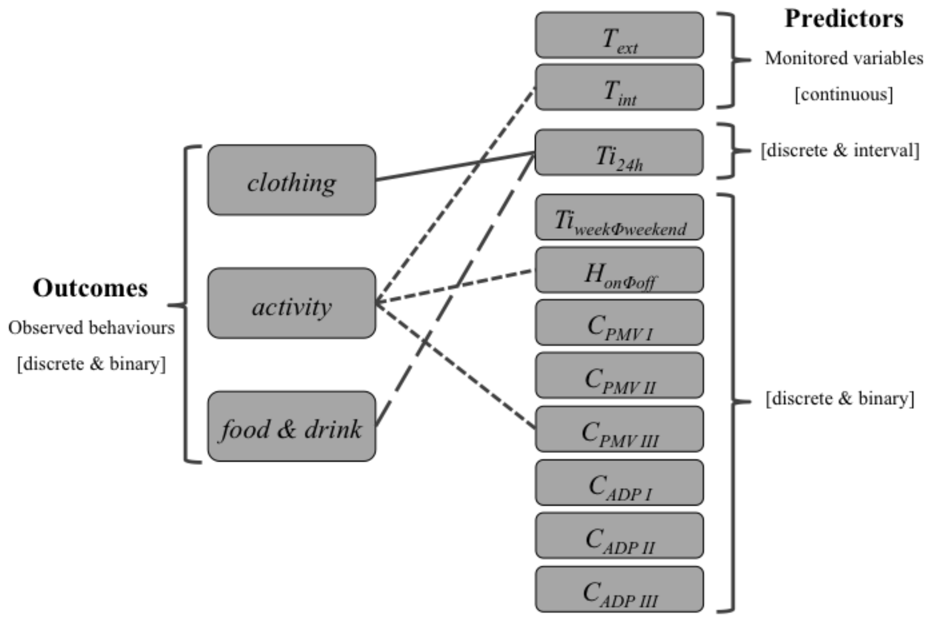
4. Discussion

4.1. Summary of the findings

Figure 2 and Figure 3 show the significant relationships found in the six statistical analysis tests; the following section will compare and contrast these results. The observed behaviours are defined as changes in (*clothing*), (*activity*) or (*food&drink*) intake; while monitored behaviours are defined as clothing insulation level (I_{cl}) or activity level (M).

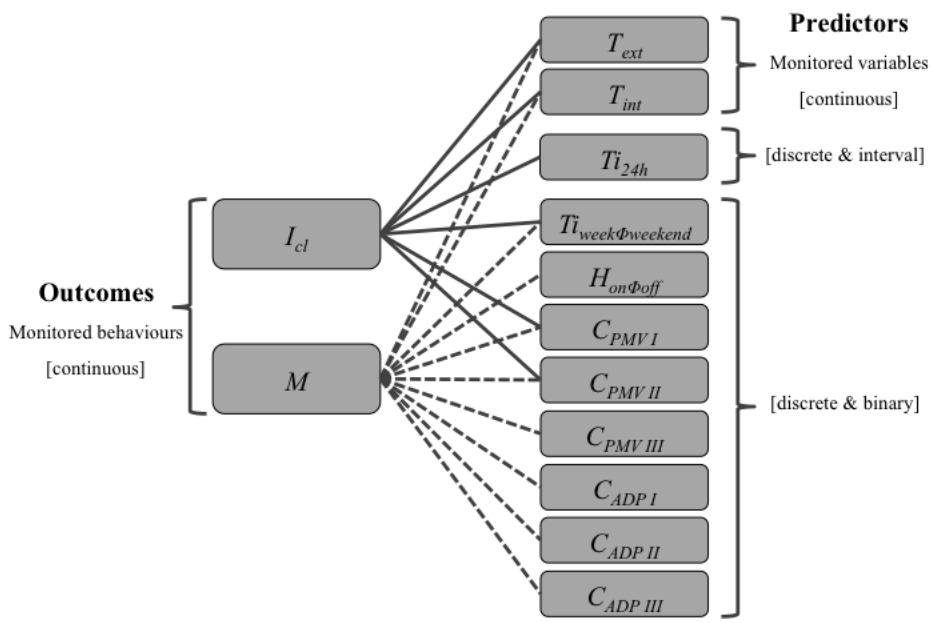
Both (*clothing*) and (I_{cl}) have a significant relationship with time of the day (t_{24h}), which may be due to daily rhythm. Reviewing variations in (*clothing*) shows that there is an increase in the change of clothing in the morning (09:00) and evening (22:00). Reviewing variations in (I_{cl}) shows that participants tend to wear higher insulation level in the morning, between 06:00 and 09:00 (Mdn=0.85 to 0.80 clo); then (I_{cl}) decreases throughout the day to 0.6 clo at 01:00 in the morning. In contrast both (*activity*) and (M) have no significant relationship with the time of the day (t_{24h}). These results show that participants tend to adjust their clothing level but not their activity level throughout the course of a day. These are interesting results and should be substantiated by future field studies with larger sample sizes and longer monitoring periods.

Figure 2: Significant relationships between the observed behaviours and the seven predictors reviewed in this study



Interestingly (*clothing*) has no significant relationship with (T_{int}), but (I_{cl}) has a significant relationship with (T_{int}). Although participants did not adjust their clothing level while (T_{int}) decreased or increased, over the course of the study they increased their clothing level as (T_{int}) decreased. These results show that clothing may not be a direct response to a decrease in temperature, there might be a delay. The previous results show that variations in clothing level is significant throughout the course of a day, it may also be more important from day to day, over the course of one week or one month.

Figure 3: Significant relationships between (I_{cl}) & (M) and the seven predictors reviewed in this study



Both (*activity*) and (M) have a significant relationship with internal temperature (T_{int}). As (T_{int}) decreased participants were more likely to change body position, location within the same room or room within their home. Furthermore as (T_{int}) decreased participants' activity level increased. These results show that participants tend to adjust their activity level with internal temperature.

With regards to the other four observed behaviours, 'turning on the heating' (number of observations=0), 'closing curtains or windows' (number of observations=2), 'having a warm drink, or food' (number of observations=198), and 'using a hot-water-bottle or having a warm bath'(number of observations=1), only (*food&drink*) had N>30. Participants' warm food and drink intake has a significant relationship with time of the day (t_{24h}), but with no other predictors. This observed effect may be due to daily rhythm, rather than responses to thermal discomfort. In particular participants did not change their (*food&drink*) intake as internal temperature decreased. Changes in frequencies and types of (*food&drink*) intake as a response to thermal discomfort will be challenging to dissociate from daily rhythms and other confounding factors such as socialising. Furthermore, it is interesting to note that participants did not interact with their heating systems. As mentioned in the interviews, one reason might be that the participants were not 'in control' of the heating in the household as other householder(s) may have been. Another reason might be that the participants did not want to interfere with the settings of the system. Having estimated when the heating was on or off ($H_{on \oplus off}$) for each participants, the review of the profiles shows dwellings with short on-off heating cycles which are most likely to be associated with constant heating and thermostatic control; while others show longer on-off heating cycles. In some cases these appear regular, suggesting programmed timers, in other dweillings they are more random and therefore more likely to be associated with manual control. The state of heating (on or off) was a signifiant predictor to change in (*activity*) and activity level (M). When the heating was off, participants increased their changes of activity, but reduced their activity level overall (from Mdn=1.35 met with the heating on to Mdn=1.29 met with the heating off). One reason might be that participants may be more static (i.e. sitting) and may change their body position more frequently (i.e. putting their hands under their legs or 'crouching down').

The current thermal comfort models rely on people's reported thermal sensations, rather than people responses to thermal discomfort. These models assume that if outside their set categories people should feel 'uncomfortable' and therefore act upon their state of discomfort. However the results of this study show that there is no relationship between observed behaviours and (C_{PMV}) & (C_{ADP}); with the exception of (*activity*) and (C_{PMV}III). Participants were more likely to change body position, location within a room or room to fall within (C_{PMV}III). In contrast the results show that there are significant relationships between monitored behaviours and (C_{PMV}) & (C_{ADP}). Participants were more likely to increase there activity and clothing levels to fall within (C_{PMV}), furthermore participants were more likely to increase there activity level to fall within (C_{ADP}). In summary (C_{PMV}) & (C_{ADP}) did not lead to a change in observed behaviours but lead to increased activity and clothing levels. To remain comfortable, participants retain higher activity and clothing levels. The methods employed in this paper enabled people's behaviours to be explored within these standard categories.

4.2. Summary of the statistical analysis methods

This study uses a mix of parametric and non-parametric tests to analyse the field study's data. The data were treated as numeric including the categorial variables, i.e. observed behaviours and predictors ($t_{week \oplus weekend}$, $H_{on \oplus off}$, C_{PMV} and C_{ADP}) represented as discrete and binary data. A common procedure was undertaken to assigned values to these categorial variables. For example, if an observed behaviour occurred the value '1' was assigned, else it was assigned the value '0'; a similar process was undertaken for the predictors $t_{week \oplus weekend}$, $H_{on \oplus off}$, C_{PMV} and C_{ADP}. (t_{24h}) was represented as a discrete and interval variable. Finally (I_{cl}), (M), (T_{ext}) and (T_{int}) were represented as continuous variables. The normality of the continuous data was assessed, as (I_{cl}) and (M) were non-normally distributed a square-root function was applied. Having determined the class of the outcomes and predictors, statistical tests were applied for each combination of variables, summarised as follows:

- (Outcomes, Observed behaviours, Discrete binary) with (Predictors, (T_{ext}) and (T_{int}), Continuous): Logistic regression
- (Outcomes, Observed behaviours, Discrete binary) with (Predictors, (t_{24h}), Discrete interval): Probit regression
- (Outcomes, Observed behaviours, Discrete binary) with (Predictors, (t_{24h}), Discrete binary): Chi-square test with Yates's continuity correction

- (Outcomes, (I_{cl}) and (M), Continuous normally distributed) with (Predictors, (T_{ext}) and (T_{int}), Continuous): Ordinary least squares regression with fixed effect
- (Outcomes, (I_{cl}) and (M), Continuous normally distributed) with (Predictors, (t_{24h}), Discrete interval) Repeated measure ANOVA
- (Outcomes, (I_{cl}) and (M), Continuous not normally distributed) with (Predictors, (t_{24h}), Discrete binary) Mann Whitney U-test

These analyses investigated the probability of behavioural responses to cold thermal discomfort in particular the significances and trends between variables.

4.3. Interval and external validity

The study employs a range of sensors to collect information, and each device may introduce measurement errors. To address this bias, it is import to review the accuracy and to test the precision of each sensor. For the environmental equipment, calibration tests were undertaken in climate chamber; results were compared to standard benchmarks [24]. Further bias might have been introduced by the positioning of sensors, in particular the height at which the environmental sensors were positioned. Consequently future studies may deploy a greater number of environmental sensors. With regards to the SenseCam, the main limitations of this method are the cost of the device, storage capacity and battery life. The study relied on four SenseCams, that were handed-out to four participants at a time. Participants were ask to recharged the device every two days overnight, as fully charged battery corresponds to 12 hours of operation [25]. With regards to storage capacity, the SenseCam could store over 20,000 pictures [25]. As an average of 7,300 pictures were taken for each participants over 10-days, future studies may extend the monitoring period. Another limitation of this method might be that participants may forget to wear the device. Having reviewed the frequency of usage and asked the participants during the final interviews if they had forgotten to wear the SenseCam, this only occurred in few instances. One reason might be that is was winter. If the participant was to go-out, the SenseCam should be taken off just before leaving the home, and placed near the entrance door or on the coat-stand. When returning home, the SenseCam should be worn again. The advice was 'coat on - SenseCam off', and 'coat off - SenseCam on'. If a similar study was conducted in the summer the frequency of 'wear' might differ. Finally further bias may be introduced by the 'observer effect'. To follow the results of the feedback interviews, the first monitoring day was not taken into account in the analysis. Although most participants reported feeling less self-conscious of wearing the SenseCam after the first few hours, the potential Hawthorne effect may continue throughout the monitoring study. Future studies may look at developing a similar device than the SenseCam but without the in-built camera.

The participants taking part in the main study were related to the University, and therefore they may have similar attitudes and lifestyles. Future studies may look at recruiting participants from an established subject pool. The research was set in people's home. This environment may allow for greater adaptive opportunities than non-domestic buildings. If a study was to be carried out in office setting, then a similar framework may be applied. The set of wearable sensors may not include a camera for privacy concerns, yet additional factors may be monitored; for example operational power of computer or lighting may enable participants' location and activity to be ascertained. The dwellings were all located in the South East of England, therefore participants may apply similar local adaptation responses. Future studies may be carried out in different regions or climate where responses may be influenced by specific geographical and cultural features. The framework develop in this study may then be used to investigate variations in local adaptation. Finally, the results of this study rely on the observed and monitored behaviours of twenty participants, therefore these results cannot be extrapolated to a population, a much larger and representative sample should be employed for this purpose. Nevertheless the methods developed to collect and analyse objective data may be deployed in future studies investigating occupants' behaviours.

5. Conclusions

5.1. New insights

The paper reviewed the variability of behavioural responses to cold thermal discomfort as a function of environmental, temporal and standard factors. Key findings include the following:

- The change and level in activity increased as internal temperature decreased. This may add to the formulation of models which include behaviour adaptation, as described by Schweiker and Wagner [29].
- Clothing thermal adaptation may not occur as an immediate response to changes in internal temperature, but as a delayed response. Future studies may be carried out over longer period of time to investigate these potential variations in clothing level.

5.2. Implications

Methodologically, this research establishes an empirical study design to investigate the probability of behavioural responses to thermal discomfort. Furthermore it demonstrates the efficacy of different statistical tools to predict the probability of occupants' behaviours to adapt to thermal discomfort.

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Due to ethical restrictions, supporting data cannot be made openly available.