TOWARDS A MULTIVARIATE TIME-SERIES APPROACH WITH BIOSIGNAL DATASETS FOR THE GLOBAL THERMAL COMFORT DATABASE

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Abstract

At the moment, the most extensive database for thermal comfort studies is ASHRAE Global Thermal Comfort Database II. It is a valuable data compilation of data from past surveys that formed the current adaptive comfort model. However, comfort research discovered the importance of new indices since then; 1. The temporal component of thermal sensation, and 2. Biosignal data correlated to thermal physiology. There are already several studies focusing on one or both indices and in the near future, the data production will speed up incrementally. This paper investigates the current database and suggests a framework to update it to include new approaches.

Introduction

Quantifying thermal comfort is a difficult task since the concept of "comfort" is not the most tangible. The static heat-balance model that was derived from Fanger's climate-chamber experiments in the 70s (Fanger, 1970) and later on the structured surveys and questionnaires conducted to establish the adaptive comfort model in the 90s (de Dear & Brager, 1998; Humphreys & Nicol, 1998) were solid efforts towards that goal.

However, both methods have had their fair share of criticism (Halawa & Van Hoof, 2012) since the performance gap was still not fully addressed, as well as the percentage of people dissatisfied was still relatively high (Li et al., 2020). In pursuit of bettering the comfort models, the last decade of studies have seen a shift towards a more dynamic understanding of comfort (van Marken Lichtenbelt et al., 2017; Vellei et al., 2021), where the missing parameter of "time" has shown itself to be relevant as not to be ignored, and new indices to include the temporal aspect of comfort are being investigated.

In more recent practices, researchers include the time component by collecting the survey data from occupants on a periodical basis with the use of using tablets, apps, and gamification projects. The resulting time-series datasets reveal that concepts like duration of exposure to a certain environmental condition (Ryu et al., 2019; Zhang et al., 2016), recent thermal history, thermal alliesthesia (Thomas Parkinson et al., 2016) are considerably relevant as well as some of the parameters that are already in consideration in the comfort models.

Another focus for the researchers that have also been a critical point of survey data, the potential psychological bias (Yetton et al., 2019), has found a response in the form of turning to the physiological domain. This has been possible in comfort research with the advancement in medical-grade reliable and wearable sensors. With the availability of these devices, several researchers have gone in the direction of collecting physiological data, to find correlations between psychologically driven responses and physiological requirements. Several publications have already attempted to create models to correlate biosignal data to survey responses (Kobas, Koth, Nkurikiyeyezu, et al., 2021; Lu et al., 2019; Nkurikiyeyezu et al., 2018; Wang et al., 2019).

As a principle, the data collection in thermal comfort-related studies includes data from the following domains: 1. Environmental data (temperature, humidity, air velocity, etc.);

2. Building/Boundary conditions data (ventilation mode, adaptive controls available);

3. Subjective feedback data (adaptive comfort questionnaires on satisfaction and preference);

4. Behavioral data (opening/closing the windows, blinds, any type of personal climatisation tools, clothing, etc.); and more recently,

5. Physiological data (demographic data, skin temperature, heart rate, respiration, sweating, neural activity, etc.).

The ASHRAE Global Thermal Comfort Database II, currently the most advanced database that comfort researchers have open access to, compiles the data from field surveys that have formed the adaptive comfort model. However, the database structure as it is, is not suitable to include these recent approaches, particularly the temporal aspect.

This paper intends to look into the existing database and suggest ways of expanding it to include datasets that are derived from the two aforementioned research focuses; 1. temporal component of thermal sensation, comfort and preference, and 2. biosignal data that is correlated to thermal physiology.

Existing thermal comfort database

The ASHRAE Global Thermal Comfort Database I, created in 98 by Richard de Dear, was the first global-scale attempt at thermal comfort data collection (de Dear, 1998). The first version of the database included survey results from 52 unique studies from 160 buildings which were collected between the years 1982 and 1997. The resulting adaptive comfort model based on this dataset had become part of the ASHRAE standard in 2004 (Földváry Ličina et al., 2018).

The second version of the database was established 20 years after, in 2018, by the Center for the Built Environment at UC Berkeley and the University of Sydney's Indoor Environmental Quality Laboratory. At the time of the publication, database II had 107,583 rows of data; of which, one row corresponds to one survey answer from one person, at the time. In total, it consists of 22,000 unique surveys (Center for the Built Environment (UC Berkeley), 2022).

Table 1 illustrates the data structure in the current database, together with the percentages of each data type that is entered (Data downloaded from ASHRAE Global Thermal Comfort Database II Query Tool (Tom Parkinson et al., 2022)).

Table 1. ASHRAE Database 2 entries

Data category	Data	Options	% entered
Metadata	Publication		98.46%
Metadata	Contributor		100.00%
Metadata	Year		99.77%
Metadata	Season	Winter, spring, summer or autumn	99.78%
Metadata	Climate		100.00%
Metadata	City		99.99%
Metadata	Country		100.00%
Metadata	Building type	Classroom, Multifamily housing, Office, Senior Center, others	96.10%
Metadata	Cooling strategy	AC, Mechanically Ventilated, Mixed Mode, Naturally Ventilated	98.86%
Metadata	Heating strategy	Mechanical heating	35.10%
Demographic data	Age		40.51%
Demographic data	Sex	F/M	62.31%
Demographic data	Height	cm	18.92%
Demographic data	Weight	kg	22.92%
Subjective feedback	Thermal sensation	-3 (cold) to +3 (hot)	97.09%
Subjective feedback	Thermal sensation acceptability	0-unacceptable, 1-acceptable	58.04%
Subjective feedback	Thermal preference	cooler, no changes, warmer	79.47%
Subjective feedback	Thermal comfort	1-very uncomfortable to 6-very comfortable	33.77%
Subjective feedback	Air movement acceptability	0-unacceptable, 1-acceptable	15.19%
Subjective feedback	Air movement preference	less, no change, more	40.32%
Subjective feedback	Humidity preference	drier, no change, more humid	11.38%
Subjective feedback	Humidity sensation	3-very dry to -3-very humid	11.66%
Comfort indices	PMV		62.03%
Comfort indices	PPD		62.03%
Comfort indices	SET		61.83%
Environmental data	Clo		92.64%
Environmental data	Met		84.05%
Environmental data	activity_10	Met 10 mins ago	8.19%
Environmental data	activity_20		9.02%
Environmental data	acitivity_30		8.14%
Environmental data	activity_60		8.92%
Environmental data	Air temperature	°C/°F	92.87%
Environmental data	Ta_h	1.1 m above the floor	26.05%
Environmental data	Ta_m	0.6 m above the floor	28.95%
Environmental data	Ta_l	0.1 m above the floor	9.71%
Environmental data	Operative temperature	°C/°F	35.29%
Environmental data	Radiant temperature	°C/°F	30.18%
Environmental data	Globe temperature	°C/°F	24.17%
Environmental data	Tg_h	°C/°F	49.27%
Environmental data	Tg_m	°C/°F	24.06%
Environmental data	Tg_l	°C/°F	21.61%
Environmental data	Relative humidity	%	90.87%
Environmental data	Air velocity	m/s	83.56%
Environmental data	Velocity_h	m/s	20.43%
Environmental data	Velocity_m	m/s	26.32%
Environmental data	Velocity_l	m/s	9.53%
Environmental data	Outdoor monthly air temperature	Monthly average	73.75%
Environmental control/Behaviour	Blind/Curtain	0-open, 1-closed	5.33%
Environmental control/Behaviour	Fan	0-off, 1-on	12.26%
Environmental control/Behaviour	Window	0-open, 1-closed	20.52%
Environmental control/Behaviour	Door	0-open, 1-closed	10.35%
Environmental control/Behaviour	Heater	0-off, 1-on	7.75%

Each row consisting of these 51 variables corresponds to a unique occupant's thermal sensation, comfort and preference under certain environmental conditions and adaptive measures, at the time of the measurement and survey-taking. However, as can be seen from the list, the two time factors have an incredibly low resolution (seasons and years), and there seems to be no way to track if the rows of data are consecutive responses from the same person, whether under static or dynamic environmental conditions.

The lack of continuity becomes further curious since the first version of the database included time and date data, as well as unique identifiers for both the buildings and the subjects (Sydney School of Architecture Design and Planning, 2022). Figure 1 shows a screenshot of the datasets from the first database.

Towards Thermal Comfort Database III

Including time data

As previously discussed, one of the main changes proposed is approaching comfort data in a time-series database.

It needs to be understood that although the database is new, the data is not. The median year of the entire data is 2003 ± 8; min and max being 1979 and 2018. This fundamentally changes the resolution of the data: The last 10 years, in particular, have seen increasing ease, affordability and availability in climate sensors with continuous logging and large internal memory/fast cloud connection, mobile devices with user-friendly UX to conduct surveys, apps that can be pre-timed for periodical questioning, wearable or non-intrusive sensors to detect physiological signals in real-time with very high temporal resolution (see Figure 2 and 3).

As mentioned in the Introduction, the comfort studies combine different data domains; from the climate, perceived comfort (subjective feedback), adaptive behaviour, and physiological responses. The native or preferred temporal resolution for each data type varies.

In most studies, climate data is stored per minute. Adaptive behaviour data usually match the climate data. Obviously, it is not feasible to acquire the subjective data on a minute basis: The frequency of repeated surveys usually varies based on the length of the study, from 15 minutes to per hour, or in the case of event-related experimental setups, before/during and/or after the event. However, the physiological data's native resolution is much higher than all of the above.

To be flexible enough to match the variety, the authors found using UNIX timecodes between the exact start and end times of each data acquisition session, on a millisecond scale. However, the problems that arose regarding the high resolution will be discussed in the following chapters.

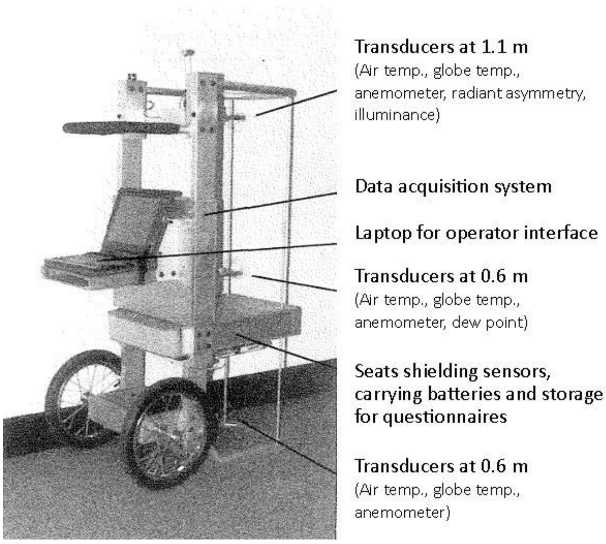

Figure 2: Mobile measurement cart that was used for indoor climatic data acquisition in 94 (de Dear & Fountain, 1994)

R. J. de Dear and M. E. Fountain. Dry Season, 1992. ASHRAE's RP-702 Air Conditioned (HVAC) building study in Townsville											
Basic Identifiers							Thermal Questionnaire				
BLCODE		AGE		YEAR	DAY			PRXY_TSA		MCI	
	SUB		SEX			TIME	ASH		TSA		VENT
1	1	33	0	1992	161	1101	1	2	2	2	6
1	2	22	0	1992	161	1113	-1	2	2	2	5
1	3	43	0	1992	161	1120	-1	2	2	2	5
1	4	32	1	1992	161	1134	-1.2	2	2	3	5
1	5	21	1	1992	161	1145	-1	2	2	2	6
1	6	35	1	1992	161	1153	-1	2	2	2	5
1	7	36	0	1992	161	1202	-1	2	2	2	5
1	8	34	0	1992	161	1210	-1	2	2	2	3
1	9	40	0	1992	161	1217	-1	2	2	2	6
1	10	27	1	1992	161	1226	1	2	2	2	5

Figure 1: A screenshot from the dataset (partial image) of de Dear and Fountain's 1994 study. Day information is included and "Time" column shows minute-scale data (de Dear & Fountain, 1994).

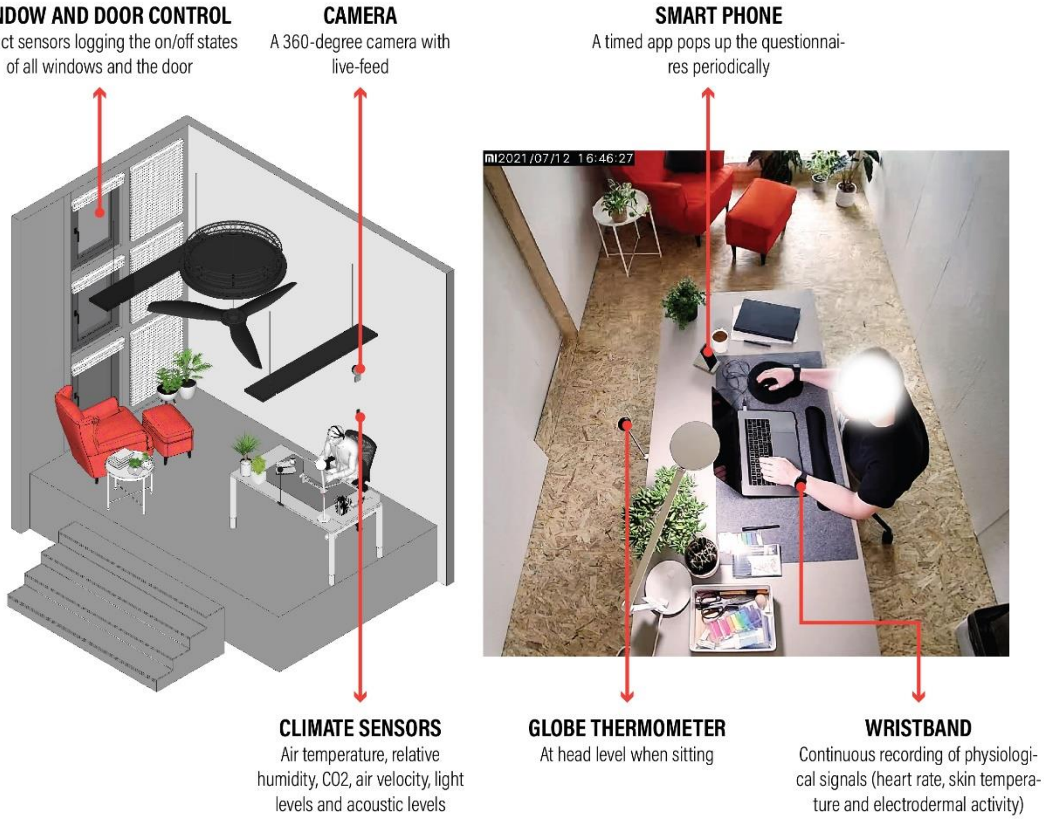

Figure 3. A more recent example for thermal comfort experiment setups. While the image is from a climate chamber (see SenseLab at (Kobas, Koth, & Auer, 2021)), both the climate and physiological sensors are mobile and can be applicable in real –world data collection projects.

Improving demographic data

As previously mentioned, the current database has 107,583 rows of data, of which corresponds to a thermal sensation, comfort and/or preference response by one person at a given moment. There is no way of knowing exactly how many test subjects comprise this data, however, considering there were 22,000 unique surveys may give an indication.

Had this been a longitudinal study, or a time-series database, this data would equal the following with a hypothetical calculation:

Considering there would be a repeated questionnaire and data collection every 30 minutes, 107,583 data points would cover 3,227,490 person*minutes, which makes 53,791 person*hours. Taking 1 day as 7 hours, 53,791 person*hours equal to 7684 person*workdays. Assuming that the data collection would be for one full week in each season, meaning each person would contribute 4 * 5 = 20 days, a total of 384 people would be involved in the making of this dataset.

By that account, assuming ideally proportional subject recruitment, 188 of these subjects would be male, 188 would be female and 8 would be intersex. Further distribution by age groups would even downsize the population size in each category.

At the moment the demographic data included in the dataset comprise age, sex, height and weight. However, only 60.86% of the dataset includes sex data, 38.62% includes age, and subjects' height and weight data are 17.34% and 21.33% respectively.

While the impact of age and sex on comfort perception has been known to researchers, further demographic components have been understudied so far. The physiological identifiers have been limited to binary sex options and BMI and BSA indicators.

Since the studies have extended to cover thermal physiology, a relevant subject background may include the following;

- Acute disorders, that alter thermoregulatory responses (a list can be found at (Cheshire, 2016)),
- Regular medication/Medication at the time of the experiment, that alters thermoregulatory responses (a list can be found at (Cheshire, 2016)),
- Disability/ies, since the majority of data is from able-bodied individuals,
- Regular wake time and sleep time, since the person's chronotype affects their thermal perception throughout the day (Kim et al., 2018; Kurz, 2008; Vieluf et al., 2021; Vldaček et al., 1988).

Bringing back unique identifiers would also be beneficial to allow the comparability.

Finally, with the increased amount of personal information including partial medical history, consent forms and ethical compliance documents become more important than ever. All necessary documents and forms should be acquired by the research team, and their existence could be noted in the database.

Including physiological data

The final improvement suggested is the inclusion of physiological data, matched with the survey data. This layer of data is maybe the most recent in current comfort research practices, however not equally unknown to other disciplines. Biomedical engineering and signal processing have focused on the use of biosignals, in our context used synonymously with physiological data since the 19th century. The transfer of the use of this data, however, had been transferred to the building physics domain especially in the last decade, mostly thanks to the availability of wearable sensors matching medical benchmarks.

A previous literature review by the authors looked into publications using this approach and listed the most relevant biosignals (Persiani et al., 2021). The findings suggested the following:

1. Brain function (EEG)
2. Heart
    1. Electrocardiogram (ECG)
    2. Heart rate (HR)
    3. Heart rate variability (HRV)
    4. Blood volume pressure (BVP)
3. Skin
    1. Skin temperature
    2. Infrared imaging
    3. Electrodermal activity (EDA)
4. Internal
    1. Core temperature
    2. Rectal temperature
    3. Cortisol concentration
5. Lungs
    1. Respiration and breath rate
    2. Respiration amplitude
6. Eyes
    1. Pupil activity
    2. Eye activity
    3. Electrooculogram (EOG)
7. Auxillary
    1. Voice/Speech analysis
    2. Facial cues
    3. Posture analysis

This extensive list however has a long way to be fully incorporated into comfort research, while it is still not fully clear how important some of these biosignals are for thermal physiology models.

Current research has seem to be focusing on the first four groups, since they are more critical in the central nervous system of the body and especially for heart and skin-related data, as well as core temperature, the sensing technology has become quite non-intrusive so that the subjects can be examined for prolonged amounts of times while not creating major bias.

The preferred sampling resolutions of each biosignal are different from one another; however, mostly they are on a millisecond scale. For example, a medical-grade Biopac data acquisition device can support EDA sampling up to 100,000 samples per second (Braithwaite et al., 2015). A wearable wristband device, Empatica E4, has a sampling rate of 4 Hz for EDA. While 4 data points per second seem to be an overshoot, for arousal analysis this is found to be not sufficient enough (Borrego et al., 2019). This makes finding the correct temporal resolution that would work for environmental, subjective feedback, adaptive behaviour and physiological data a task that needs further investigation. In a recent study from 2020, Tartarini & Schiavon look into a fitting sampling frequency for skin temperature, and suggest 300s to be accurate enough (Tartarini & Schiavon, 2020). Similar sensitivity analyses for other biosignals and in combination with each other would be highly beneficial.

In addition to the multiplied number of rows the physiological datasets would bring, they also come with extracted features, resulting in more columns as well. For example, cardiovascular data has different features, classified as time-domain, frequency-domain, and non-linear measures. It poses another further research topic as to whether the none time-domain indices can or should be integrated into the database. Either way, the below table shows the 9 widely used time-domain features of HRV data. Together with others, heart-related data features can create up to 30 additional columns.

Table 2. Time-domain HRV features (Shaffer & Ginsberg, 2017)

Parameter	Unit	Description
SDNN	ms	Standard dev. of NN intervals
SDRR	ms	Standard dev. of RR intervals
SDANN	ms	Standard deviation of the average NN intervals for each 5 min segment of a 24 h HRV recording
SDNN index (SDNNI)	ms	Mean of the standard deviations of all the NN intervals for each 5 min segment of a 24 h HRV recording
pNN50	%	Percentage of successive RR intervals that differ by <50 ms
HR Max − HR Min	bpm	Ave. difference between the highest and lowest heart rates during each respiratory cycle
RMSSD	ms	Root mean sq. of successive RR interval differences
HRV triangular index		Integral of the density of the RR interval histogram divided by its height
TINN	ms	Baseline width of the RR interval histogram

Similarly, EEG signal also has time-domain features that can be integrated into the time-series database, particularly the amplitude and power concentrated at the delta (0–4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz), and gamma (32–50 Hz) bands. However one must keep in mind that depending on the number of electrodes used, the number of columns would uniformly multiply. A medical-grade study might include 256 channels, while wearable EEG sets may go down to 4. This means for each electrode there will be another column showing the amplitude and/or power of relevant bands. Figure 4 shows an example diagram.

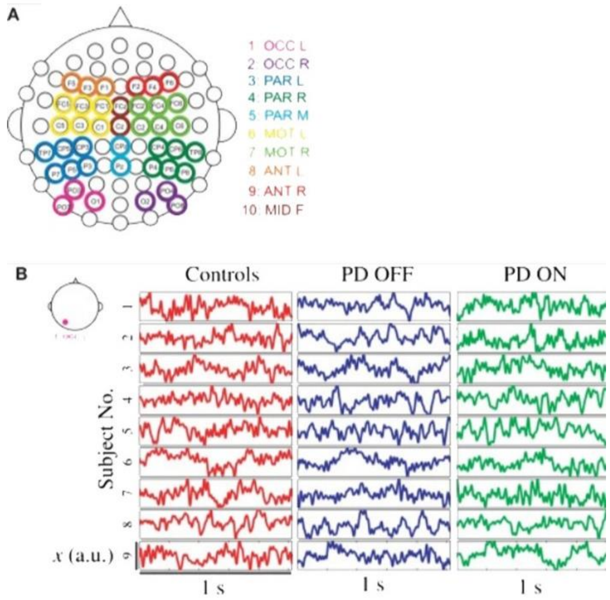

Figure 4. A. The placement of EEG electrodes; B. Timeseries from one electrode (Lainscsek et al., 2013)

A sensitivity study suggests for a reliable signal with a non-intrusive EEG cap, 35 electrodes is a good number (Lau et al., 2012), which still looks very high in the context of the larger dataset in mind.

Currently there are wearable headset-type EEG sets available at affordable prices for researchers, with acceptable accuracy (Williams et al., 2021). With that in mind, it would make sense to prepare for relevant infrastructure for either the next, or the following version of the database.

Including sensor and experiment design description

The inclusion of several sensors in the data collection processes also brings the necessity for a better description of the boundary conditions. This includes information about the sensors, including but not limited to their;

- Types: ie. for skin temperature, contact electrode, thermocouple, infrared, etc.
- Brand and models: to determine certain information automatically. Additionally, especially with biosignal data sensors comparative performance and accuracy studies are currently ongoing (Kutt et al., 2018; van Lier et al., 2020). Therefore it is relevant for future studies to state the brand and make of the sensors that were used.
- Ranges,
- Accuracy,
- Resolution,
- Sampling rate.

Finally, the placement of the sensors also should be stated. In the current database, this option exists for several environmental parameters with different height options, and it should be extended to the physiological data, in terms of body parts of the sensor placement.

Potential problems and setbacks

Database volume

Previously it was explained that 107,583 rows of data, if it were time-series, would be equal to 7642 person*workdays.

Another calculation from the reverse direction can hypothesize an acceptable lower resolution sampling period of 1 minute, for an entire 7-hour workday. This means one day*person now equals 420 rows, instead of one. Together with this, it is plausible to assume that data collection periods will easily be much longer, considering the ease of it.

An example from a recent work recorded climate and connected biosignal data from 5 participants, over 35 hours per subject (Kobas, Koth, Nkurikiyeyezu, et al., 2021). The resolution of environmental and behavioural data was matched to EDA data, sampled at 4 Hz. In the end, each participant's dataset grew to almost half a million rows of data for only 35 hours. The total dataset was 284MB – which may not seem much by itself, however, when compared to the size of the entire ASHRAE dataset, which is 54MB, it becomes clear how quickly data can grow. Furthermore, the example above has already been downsampled. When dealing with native resolutions, high-resolution devices such as EEGs would produce significantly more data. Existing open-access EEG datasets from neurological/psychological research show the data from a few sessions can go up to gigabytes easily (see various datasets available at Open Neuro (Stanford Center for Reproducible Neuroscience, 2022)). Potentially, prior to the integration of biosignals data into the main database, a downsampling and statistical averaging might be necessary to manage the database volume.

Keeping the higher resolution and longer data collection periods, it is inevitable that the database volume will grow large rapidly. To keep the database feasible to operate and maintain, in addition to finding the optimum time resolution, the database architecture should be carefully designed as well.

Lack of standardised data collection and sharing formats

While introducing why and how the physiological data should be integrated, some potential problems alongside the suggestions were already mentioned. The overall setback regarding this integration is mostly due to its novelty of it, which requires more experience in the field and further research. However, at this point, a standardisation effort for the data collection/experimental design methodology could be a useful stepping-stone, as the methodology then can evolve over time with the feedback from new applications.

Conclusions

Creating an open-source, global database covering the works of tens of researchers has been an incredible shift in the field of thermal comfort studies. The database contributed greatly to forming the adaptive comfort model, however, in recent years there has been a wide body of research pointing at developing the model towards a more dynamic setting. With this new approach, two new indices have become important in comfort experiments, the first one being time, and the second the physiological data. The paper aimed to look into the current structure of the dataset, and keeping it as a basis, suggested ways of improving it in order to encapsulate the new parameters.

References

Borrego, A., Latorre, J., Alcaniz, M., & Llorens, R. (2019). Reliability of the Empatica E4 wristband to measure electrodermal activity to emotional stimuli. *International Conference on Virtual Rehabilitation, ICVR*, *2019-July*(July). https://doi.org/10.1109/ICVR46560.2019.8994546

Braithwaite, J. J., Derrick, W. G., Jones, R., & Rowe, M. (2015). *A Guide for Analysing Electrodermal Activity (EDA) & Skin Conductance Responses (SCRs) for Psychological Experiments*. http://www.bhamlive.bham.ac.uk/Documents/college-les/psych/saal/guide-electrodermal-activity.pdf%5Cnhttp://www.birmingham.ac.uk/documents/college-les/psych/saal/guide-electrodermal-activity.pdf%0Ahttps://www.birmingham.ac.uk/Documents/college-les/psych/sa

Center for the Built Environment (UC Berkeley). (2022). *Global Comfort Data Visualization Tools*. https://cbe.berkeley.edu/research/global-comfort-data-visualization-tools/

Cheshire, W. P. (2016). Thermoregulatory disorders and illness related to heat and cold stress. *Autonomic Neuroscience: Basic and Clinical*, *196*, 91–104. https://doi.org/10.1016/j.autneu.2016.01.001

de Dear, R. J. (1998). Global database of thermal comfort field experiments. *ASHRAE Transactions*, *104*(Pt 1B), 1141–1152.

de Dear, R. J., & Brager, G. S. (1998). Towards an adaptive model of thermal comfort and preference. *ASHRAE Transactions*, *104*(Pt 1A), 145–167.

de Dear, R. J., & Fountain, M. E. (1994). Field experiments on occupant comfort and office thermal environments in a hot-humid climate. *ASHRAE Transactions*, *100*(2), 457–474.

Fanger, P. O. (1970). *Thermal Comfort*. Technical University of Denmark, Laboratory of Heating and Air Conditioning. Danish Technical Press.

Földváry Ličina, V., Cheung, T., Zhang, H., de Dear, R., Parkinson, T., Arens, E., Chun, C., Schiavon, S., Luo, M., Brager, G., Li, P., Kaam, S., Adebamowo, M. A., Andamon, M. M., Babich, F., Bouden, C., Bukovianska, H., Candido, C., Cao, B., … Zhou, X. (2018). Development of the ASHRAE Global Thermal Comfort Database II. *Building and Environment*, *142*, 502–512. https://doi.org/10.1016/j.buildenv.2018.06.022

Halawa, E., & Van Hoof, J. (2012). The adaptive approach to thermal comfort: A critical overview. *Energy and Buildings*, *51*, 101–110. https://doi.org/10.1016/j.enbuild.2012.04.011

Humphreys, M. A., & Nicol, J. F. (1998). Understanding the adaptive approach to thermal comfort. *ASHRAE Transactions*, *104*(Pt 1B), 991–1004.

Kim, J., Ku, B., Bae, J. H., Han, G. C., & Kim, J. U. (2018). Contrast in the circadian behaviors of an electrodermal activity and bioimpedance spectroscopy. In *Chronobiology International* (Vol. 35, Issue 10, pp. 1413–1422). https://doi.org/10.1080/07420528.2018.1486852

Kobas, B., Koth, S. C., & Auer, T. (2021). *SenseLab*. https://www.arc.ed.tum.de/klima/forschung/senselab/

Kobas, B., Koth, S. C., Nkurikiyeyezu, K., Giannakakis, G., & Auer, T. (2021). Effect of Exposure Time on Thermal Behaviour: A Psychophysiological Approach. *Signals*, *2*(4), 863–885. https://doi.org/10.3390/signals2040050

Kurz, A. (2008). Physiology of Thermoregulation. *Best Practice and Research: Clinical Anaesthesiology*, *22*(4), 627–644. https://doi.org/10.1016/j.bpa.2008.06.004

Kutt, K., Binek, W., Misiak, P., Nalepa, G. J., & Bobek, S. (2018). Towards the development of sensor platform for processing physiological data from wearable sensors. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 10842 LNAI*. Springer International Publishing. https://doi.org/10.1007/978-3-319-91262-2_16

Lainscsek, C., Hernandez, M. E., Weyhenmeyer, J., Sejnowski, T. J., & Poizner, H. (2013). Non-Linear Dynamical Analysis of EEG Time Series Distinguishes Patients with Parkinson's Disease from Healthy Individuals. *Frontiers in Neurology*, *4*(December), 1–8. https://doi.org/10.3389/fneur.2013.00200

Lau, T. M., Gwin, J. T., & Ferris, D. P. (2012). How Many Electrodes Are Really Needed for EEG-Based Mobile Brain How Many Electrodes Are Really Needed for EEG-Based Mobile Brain Imaging ? *Journal of Behavioral and Brain Science*, *2*, 387–393. https://doi.org/10.4236/jbbs.2012.23044

Li, P., Parkinson, T., Schiavon, S., Froese, T. M., de Dear, R., Rysanek, A., & Staub-French, S. (2020). Improved long-term thermal comfort indices for continuous monitoring. *Energy and Buildings*, *224*. https://doi.org/10.1016/j.enbuild.2020.110270

Lu, S., Wang, W., Wang, S., & Hameen, E. C. (2019). Thermal comfort-based personalized models with non-intrusive sensing technique in office buildings. *Applied Sciences (Switzerland)*, *9*(9). https://doi.org/10.3390/app9091768

Nkurikiyeyezu, K. N., Suzuki, Y., & Lopez, G. F. (2018). Heart rate variability as a predictive biomarker of thermal comfort. In *Journal of Ambient Intelligence and Humanized Computing* (Vol. 9, Issue 5). https://doi.org/10.1007/s12652-017-0567-4

Parkinson, Thomas, De Dear, R., & Candido, C. (2016). Thermal pleasure in built environments: Alliesthesia in different thermoregulatory zones. *Building Research and Information*, *44*(1), 20–33. https://doi.org/10.1080/09613218.2015.1059653

Parkinson, Tom, Dear, R. de, Foldvary, V., & Zhang, H. (2022). *ASHRAE Global Thermal Comfort Database II Query Tool*. http://www.comfortdatabase.com/

Persiani, S. G. L., Kobas, B., Koth, S. C., & Auer, T. (2021). Biometric data as real-time measure of physiological reactions to environmental stimuli in the built environment. *Energies*, *14*(1). https://doi.org/10.3390/en14010232

Ryu, J., Kim, J., Hong, W., & de Dear, R. (2019). On the temporal dimension of adaptive thermal comfort mechanisms in residential buildings. *IOP Conference Series: Materials Science and Engineering*, *609*(4), 042071. https://doi.org/10.1088/1757-899X/609/4/042071

Shaffer, F., & Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. *Frontiers in Public Health*, *5*(September), 1–17. https://doi.org/10.3389/fpubh.2017.00258

Stanford Center for Reproducible Neuroscience. (2022). *OpenNeuro*. https://openneuro.org/search/modality/eeg

Sydney School of Architecture Design and Planning. (2022). *ASHRAE RP-884 Adaptive Model Project - Data Downloader*. https://www.sydney.edu.au/architecture/staff/homepage/richard_de_dear/ashrae_rp-884.shtml

Tartarini, F., & Schiavon, S. (2020). pythermalcomfort: A Python package for thermal comfort research. *SoftwareX*, *12*, 100578. https://doi.org/10.1016/j.softx.2020.100578

van Lier, H. G., Pieterse, M. E., Garde, A., Postel, M. G., de Haan, H. A., Vollenbroek-Hutten, M. M. R., Schraagen, J. M., & Noordzij, M. L. (2020). A standardized validity assessment protocol for physiological signals from wearable technology: Methodological underpinnings and an application to the E4 biosensor. *Behavior Research Methods*, *52*(2), 607–629. https://doi.org/10.3758/s13428-019-01263-9

van Marken Lichtenbelt, W., Hanssen, M., Pallubinsky, H., Kingma, B., & Schellen, L. (2017). Healthy excursions outside the thermal comfort zone. *Building Research and Information*, *45*(7), 819–827. https://doi.org/10.1080/09613218.2017.1307647

Vellei, M., de Dear, R., Inard, C., & Jay, O. (2021). Dynamic thermal perception: A review and agenda for future experimental research. *Building and Environment*, *205*(August), 108269. https://doi.org/10.1016/j.buildenv.2021.108269

Vieluf, S., Amengual-Gual, M., Zhang, B., El Atrache, R., Ufongene, C., Jackson, M. C., Branch, S., Reinsberger, C., & Loddenkemper, T. (2021). Twenty-four-hour patterns in electrodermal activity recordings of patients with and without epileptic seizures. *Epilepsia*, *62*(4), 960–972. https://doi.org/10.1111/epi.16843

Vldaček, S., Kaliterna, L., Radossvić-Vidaček, B., & Folkard, S. (1988). Personality differences in the phase of circadian rhythms: A comparison of morningness and extraversion. *Ergonomics*, *31*(6), 873–884. https://doi.org/10.1080/00140138808966728

Wang, X., Li, D., Menassa, C. C., & Kamat, V. R. (2019). Investigating the Neurophysiological Effect of Thermal Environment on Individuals' Performance Using Electroencephalogram. *Computing in Civil Engineering 2019: Data, Sensing, and Analytics - Selected Papers from the ASCE International Conference on Computing in Civil Engineering 2019*, *158*(May), 598–605. https://doi.org/10.1061/9780784482438.075

Williams, N. S., McArthur, G. M., & Badcock, N. A. (2021). It s all about time: Precision and accuracy of Emotiv event-marking for ERP research. *PeerJ*, *9*, 1–17. https://doi.org/10.7717/peerj.10700

Yetton, B. D., Revord, J., Margolis, S., Lyubomirsky, S., & Seitz, A. R. (2019). Cognitive and physiological measures in well-being science: Limitations and lessons. *Frontiers in Psychology*, *10*(JULY). https://doi.org/10.3389/fpsyg.2019.01630

Zhang, F., De Dear, R., & Candido, C. (2016). Thermal comfort during temperature cycles induced by direct load control events. *Proceedings - 9th International Windsor Conference 2016: Making Comfort Relevant*, 747–762.