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Sensitivity of UTCI thermal comfort prediction to personal and situational factors – Residual analysis of pedestrian survey data

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Abstract

The Universal Thermal Climate Index (UTCI) assesses the interaction of ambient temperature, wind, humidity and radiant fluxes on human physiology in outdoor environments on an equivalent temperature scale. Based upon the dynamic thermal sensation (DTS) from the UTCI-Fiala model of human thermoregulation, the UTCI allows for thermal comfort prediction. Here we compare those predictions to thermal sensation votes as recorded on the 7-unit ASHRAE scale for two Brazilian cities, Curitiba and Pelotas. Outdoor comfort surveys from 1551 respondents in Curitiba and 1148 in Pelotas, respectively, yielded negligible bias and less than one unit root-mean square error (rmse), which was similar in magnitude for both study areas. Residual analysis revealed that factors such as age, sex, body composition, site morphology (open space, street canyon), climatic state (comfort/discomfort) and clothing choice only explained a small portion of the prediction error variance, which in the total sample was dominated for over 94% by residual inter-individual variability. Adding historical weather information from the previous three days gave superior information compared to longer time lags and helped to reduce the residual variance to 88%. Those findings underpin current limitations in individual thermal comfort prediction, whereas personal and situational factors hardly affected

UTCI predictive performance, which showed reasonable accuracy at the population level.

1   Introduction

The Universal Thermal Climate Index (UTCI) has become an established tool for assessing the outdoor thermal environment in the major fields of human biometeorology (Jendritzky et al. 2012; Jendritzky and Höppe 2017). The UTCI summarises the interaction of ambient temperature, wind, humidity and radiant fluxes on human physiology. The dynamic physiological responses are simulated by an advanced multi-node model of human thermoregulation (Fiala et al. 2012) coupled with a model of adaptive clothing choice in urban populations (Havenith et al. 2012). The model considers the distribution of clothing over different body parts, and the reduction of thermal and evaporative clothing resistances caused by wind and the movement of the wearer, who is assumed walking at 4 km/h (1.1 m/s) on the level. UTCI values are expressed using an equivalent temperature scale. This involved the definition of a reference environment with 50% relative humidity (but vapour pressure not exceeding 20 hPa), with still air and mean radiant temperature equalling air temperature, to which all other climatic conditions are compared.

The operational procedure (Bröde et al. 2012a) provides simplified algorithms to compute UTCI values from air temperature, wind speed, mean radiant temperature and water vapour pressure. It was supplemented by an assessment scale establishing UTCI threshold values that define different categories of thermal stress from extreme cold to extreme heat, with UTCI values from 18 to 26 °C complying with the thermal comfort zone (Bröde et al. 2012a, 2013).

Based upon the dynamic thermal sensation (DTS) from the UTCI-Fiala model of human thermoregulation (Fiala et al. 2012, 2003), the UTCI allows for thermal comfort prediction, which can be compared to observed thermal sensation votes on the ASHRAE thermal sensation scale (ASHRAE 2004). We have already presented the UTCI operational procedure and its application to outdoor thermal comfort surveys from Curitiba, Brazil (Bröde et al. 2012b, 2013). For interviews carried out in Curitiba, the observed clothing insulation was in good agreement with the UTCI-clothing model. In addition, the actual votes were well predicted by the DTS from the UTCI-Fiala model simulations carried out for UTCI reference conditions (Fiala et al. 2003, 2012). Specifically, the averaged error (bias) was found negligible and the

root-mean square errors (rmse) less than one unit on the 7-unit scale (ISO 10551 1995). Detailed simulations considering the individual climatic conditions and observed clothing insulation did not further improve the predictions indicating that the assumptions underlying the UTCI model are appropriate for the surveys carried out in Curitiba (Bröde et al. 2012b).

However, we had observed larger negative bias (i.e. underestimation) and rmse for the thermal sensation votes from a survey conducted in Glasgow, UK, where the pedestrians were wearing less insulating clothing than assumed by the UTCI model (Krüger et al. 2012; Bröde et al. 2014).

Regional differences in thermal comfort, as they have been reported in field studies within Europe (Nikolopoulou and Lykoudis 2006) and in tropical regions (cf. Chap. 6: Regional adaptation of the UTCI: comparisons between different datasets in Brazil, in this book), can be partly attributed to climatic and sociocultural aspects and to some extent to personal and situational influences. These comprise psychological and phys- iological factors related to thermal physiology (Havenith 2001; Havenith et al. 1998; Cabanac 1971), thermal aspects of occupant behaviour (Hellwig 2015; Schweiker et al. 2013, 2016, 2020b), and non-thermal factors affecting outdoor thermal comfort (Nikolopoulou 2011; Nikolopoulou et al. 2001; Nikolopoulou and Steemers 2003; Knez et al. 2009).

It is unknown, however, whether those personal and situational factors have an impact on the accuracy of the UTCI outdoor thermal comfort predictions. To address this we have expanded our data to include a recent survey carried out in Pelotas, another Brazilian city (Krüger et al. 2020), and have:

– analysed how the residues of UTCI predictions on thermal sensation depend on personal characteristics (sex, age, body composition) and urban site morphology (open spaces vs. street canyons); as well as

– considered effects related to recent experience (Nikolopoulou et al. 2001; Nikolopoulou and Steemers 2003) by including UTCI values available from a meteorological data archive, which were calculated days, weeks and months before each survey took place.

2 Material and Methods

Here, we briefly review the field surveys' methodology, as detailed descriptions are available in recent publications (Bröde et al. 2012b; Krüger et al. 2020), and in the Regional Adaptation chapter of this book (Chap. 6).

2.1 Outdoor Surveys

Field measurements with concurrent administration of comfort questionnaires were carried out in Curitiba, Brazil (25°26ʳS, 49°16ʳW, 917 m amsl, subtropical climate in elevation) and in Pelotas, Brazil (31°46ʳ18ʳʳS, 52°20ʳ33ʳʳW, 14 m amsl, humid subtropical climate). Both field studies used similar protocols, thus ensuring compatibility of the employed procedures. In both locations, surveys were carried out in pedestrian areas during daytime (typically from 10 a.m. to 4 p.m. local time) with portable weather stations recording air temperature, relative humidity, air velocity and globe temperature, from which mean radiant temperature was calculated (ISO 7726 1998).

We =applied a standard comfort questionnaire to collect personal information like age, sex, height and weight. Participants rated their thermal sensations using a symmetrical 7-unit two-pole scale ranging from 3 'cold' over 0 'neutral' to 'hot' (ISO 10551 1995). Intrinsic clothing thermal insulation was determined from the worn items observed on site according to standardised tables (ISO 9920 2007).

2.2 Data Analysis and Statistics

Only data of permanent residents (i.e. living for more than 6 months in the city) of adult age (older than 17 years) who had spent at least 15 min moving outdoors before the interview were considered eligible for the analysis. This yielded to 1148 responses from Pelotas and 1551 from Curitiba.

UTCI values were computed using the table look-up approach of the UTCI operational procedure (Bröde et al. 2012a) from measured air temperature, humidity, air velocity and mean radiant temperature. Predictions of dynamic thermal sensations (DTS) averaged over 2 h exposure time (Bröde 2019) were obtained from the output of the UTCI-Fiala model (Bröde et al. 2012a; Fiala et al. 2012) for reference clothing. In previous analyses, a more complex model incorporating actual clothing insulation did not reduce the prediction error (Bröde et al. 2012b, 2014). Therefore, we restricted our subsequent analyses on the DTS predictions for UTCI reference conditions, which are available as online dataset (Bröde 2019).

DTS prediction error was defined as the difference of DTS to the actual thermal sensation vote, with negative values indicating underestimation and positive values representing overestimation. We calculated the averaged error (bias), root-mean square error (rmse) and Pearson's correlation coefficient (r) to assess the deviations between predicted and measured thermal sensation votes.

General additive models (Wood 2017) with locally estimated smoothing splines (LOESS) and 95%-confidence intervals (CI) were computed to describe the average course of clothing insulation, of thermal sensation and of the prediction error considering the potentially non-linear relationships with air temperature and the UTCI, respectively. For comparing models with different predictors, Akaike's Information Criterion (AIC) was used to assess the goodness-of-fit (Zuur et al. 2009).

The influence of potential modifiers on the prediction error was assessed by computing bias, rmse and correlation coefficients for subgroups defined by city (Curitiba or Pelotas), sex and other classifying factors as described below. We calculated body mass index (BMI) from weight and height and classified the persons' body composition as 'underweight', 'normal', 'overweight' or 'obese' according to WHO guidelines (Bröde et al. 2012b; WHO 1995), which were also applied to build age subgroups as below 25 years (young), between 25 and 64 (adult) and above 64 (elderly). Two urban site morphology groups were defined: 'street canyons' and 'open spaces or crossroads'. We used the thermal state classification according to the UTCI assessment scale with the thermal comfort zone corresponding to UTCI values from 18 to 26 °C, cold discomfort below 18 °C and warm discomfort above 26 °C (Bröde et al. 2012a, 2013). The deviation of worn clothing insulation (Icl_{obs}) from the UTCI-clothing model (Icl_{mod}) was determined as percentage deviation, i.e. (Icl_{obs} − Icl_{mod})/Icl_{mod}*100. Percentage deviation was classified in three levels as more than 20% below (<80% Icl_{mod}) or above (>120% Icl_{mod}) or within 20% of Icl_{mod}, the clothing insulation from the UTCI model.

Variance components of prediction error attributable to the factors described above were obtained separately for both cities and for the total sample, respectively, by fitting linear mixed models (Schützenmeister and Piepho 2012) considering the factors as random and using the package 'VCA' of R 4.0.2 (R Core Team 2020).

The data were supplemented by historical weather records for time periods preceding the survey campaigns, which comprised records in hourly intervals of UTCI values derived from ERA5-HEAT (Di Napoli et al. 2020). From this data, we calculated daily averages of UTCI from the recordings obtained between 10 a.m. and 4 p.m. (corresponding to the usual time frame of the surveys). For each study area, we obtained averaged historical UTCI values at 1, 3, 7, 14, 28 and 56 days prior to the actual campaign. This allows the study to cover in a logarithmic manner periods from days, weeks to almost two months. The differences between actual and historical UTCI values corresponding to the mean for the time frame of the surveys were

used as predictors of the DTS prediction error by fitting cubic regression splines by generalized additive models GAM (Wood 2017). For the variance component analysis, these differences were classified in intervals 3 °C (actually as cool/warm as in previous period), < 3 °C (actually cooler than in previous period), > 3° (actually warmer), with the thresholds corresponding to the inter-quartile range for the lagged values (Fig. 3a).

3 Results

3.1 Prediction of Clothing Insulation and Thermal Sensation

Clothing thermal insulation showed considerable inter-individual variation, but on average dropping with increasing air temperature in both study areas (Fig. 1a). It was in good agreement with the UTCI-clothing model, especially at low temperatures in Curitiba and at higher temperatures in both cities. Although the observed insulation oscillated around the UTCI model between 12 and 25 °C, overall mean deviations (bias) from the UTCI-clothing model were negligible with a typical error (rmse) of 0.25 clo and correlation coefficients ranging between 0.7–0.8 (Table 1).

Thermal sensations also varied largely and increased with the UTCI (Fig. 1b). Generally, bias was negligible and rmse was less than one unit on the 7-unit thermal sensation scale (Table 1). These figures, including the correlation coefficients slightly above 0.6, were very similar in both study areas.
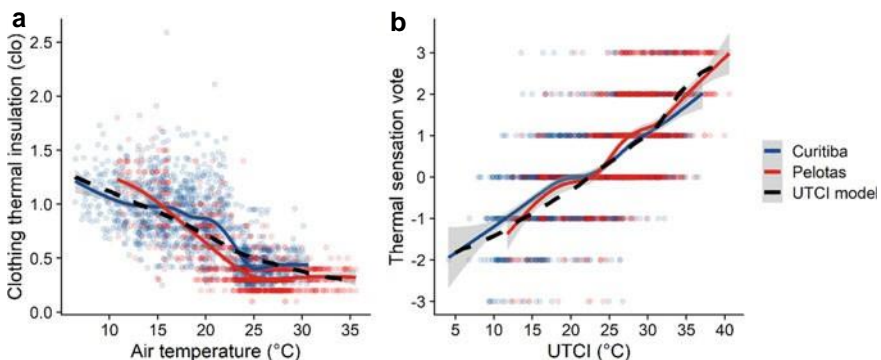

Fig. 1 Individual recordings in Curitiba and Pelotas superimposed by smoothing splines with 95% confidence intervals for clothing thermal insulation related to air temperature (**a**) and thermal sensation votes (3: 'cold',…,0: 'neutral',…, 3: 'hot') related to UTCI (**b**). Black dashed lines indicate predictions by the UTCI model

Table 1 Number of respondents (n), averaged errors (bias), root-mean-square errors (rmse) and Pearson correlation coefficient (r) by study area between observed and predicted clothing insulation (clo), and for the observed thermal sensation votes (7-unit scale) compared to the dynamic thermal sensation predicted by the UTCI-Fiala model for the UTCI reference environment

	n	Clothing insulation (clo)			Thermal sensation (7-unit scale)		
		bias	rmse	r	bias	rmse	r
Curitiba	1551	0.02	0.25	0.69	-0.12	0.95	0.61
Pelotas	1148	-0.09	0.21	0.78	-0.12	0.97	0.63
Total	2699	-0.02	0.23	0.77	-0.12	0.96	0.65

3.2 Factors Influencing Thermal Sensation Prediction Error

There were only small changes in the bias, rmse and correlation presented for the different subgroups in Table 2 compared to the overall results (Table 1). The BMI categories showed a tendency of increased underestimation error with increasing obesity. There was a small underestimation bias due to warmer sensations reported in canyons compared to open spaces (Table 2), as well as slightly increased under- estimation bias with young respondents and under cold discomfort conditions more relevant in Curitiba (Fig. 2b). However, the variance component analysis (Fig. 2) revealed that all factors only accounted for a very small portion of total variance, which was dominated by residual inter-individual variability (Fig. 2a), amounting to more than 90% in relative terms (Fig. 2b).

Table 2 Averaged thermal sensation prediction errors (bias) and root-mean-square errors (rmse) by study area comparing observed thermal sensation votes to DTS predicted by the UTCI model in relation to the modifying factors age, body composition (BMI), sex, site morphology, thermal comfort/discomfort zone according to the UTCI and deviation of worn clothing insulation from Iclmod of the UTCI clothing model

Factor	Curitiba		Pelotas		Total	
	bias	*rmse*	*bias*	*rmse*	*bias*	*rmse*
Age						
young	-0.23	0.97	-0.19	0.99	-0.21	0.98
adult	-0.09	0.94	-0.10	0.97	-0.09	0.96
elderly	-0.10	0.96	0.08	0.84	-0.04	0.92
BMI category						
underweight	0.02	0.95	0.10	0.96	0.05	0.95
normal	-0.09	0.94	-0.10	1.02	-0.09	0.97
overweight	-0.15	0.97	-0.07	0.90	-0.12	0.94
obese	-0.21	0.97	-0.25	0.97	-0.23	0.97
Sex						
female	-0.11	1.01	-0.15	0.99	-0.13	1.00
male	-0.13	0.91	-0.06	0.93	-0.11	0.92
Site morphology						
Open Space	0.05	0.98	-0.08	0.99	-0.03	0.99
Street Canyon	-0.21	0.93	-0.25	0.90	-0.22	0.93
UTCI zone						
cold discomfort	-0.30	0.99	-0.24	0.95	-0.29	0.98
comfort	-0.14	0.89	0.02	0.98	-0.09	0.92
warm discomfort	0.06	0.98	-0.15	0.97	-0.07	0.97
Clothing insulation worn (clo)						
Under-dressing (<80% Icl$_{mod}$)	-0.14	0.97	-0.06	0.93	-0.09	0.95
Conformity (100±20% Icl$_{mod}$)	-0.08	0.94	-0.22	1.00	-0.13	0.96
Over-dressing (>120% Icl$_{mod}$)	-0.16	0.96	-0.12	1.02	-0.15	0.98

3.3 Prediction Error and Historical Weather Data

While Fig. 3a indicates only slight variation in the distribution of changes in UTCI compared to prior values with different time lags, Fig. 3b illustrates the influence of those lagged values on thermal sensation prediction error for the survey data from both study areas and the total sample,

respectively, against the background of the large individual variation. The AIC values (Fig. 3c) indicate that 3 days lag information fitted better than longer lag periods, and were superior to using 1-day lag values.

The fitted spline functions in Fig. 3b for lags greater than one week exhibited monotonically decreasing prediction errors with increasing lagged values. On the other hand, the information from shorter previous periods (lag 1–3 days) displayed a U-shaped variation with a reduced underestimation of thermal sensation turning to slight overestimation at both negative and positive ends of the differences between actual and lagged UTCI values.
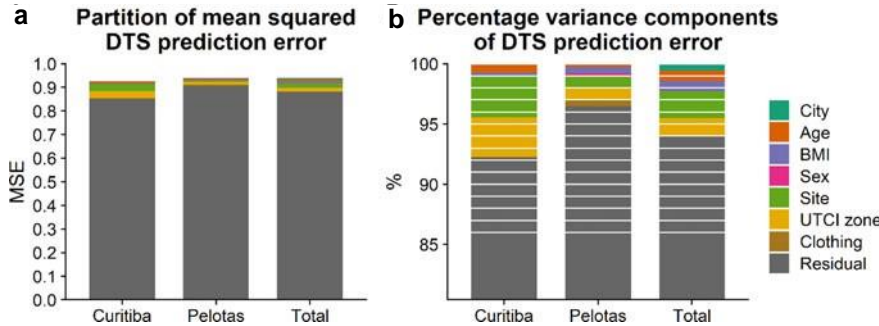

Fig. 2 Partitioning of the variance for the DTS prediction error into factors corresponding to Table 2 shown separately for the study areas and the total sample as absolute mean square error (MSE) (**a**) and in relative terms (**b**), respectively. Note that factor "city" only applies to the total sample and that panel (**b**) does only show the range above 80%
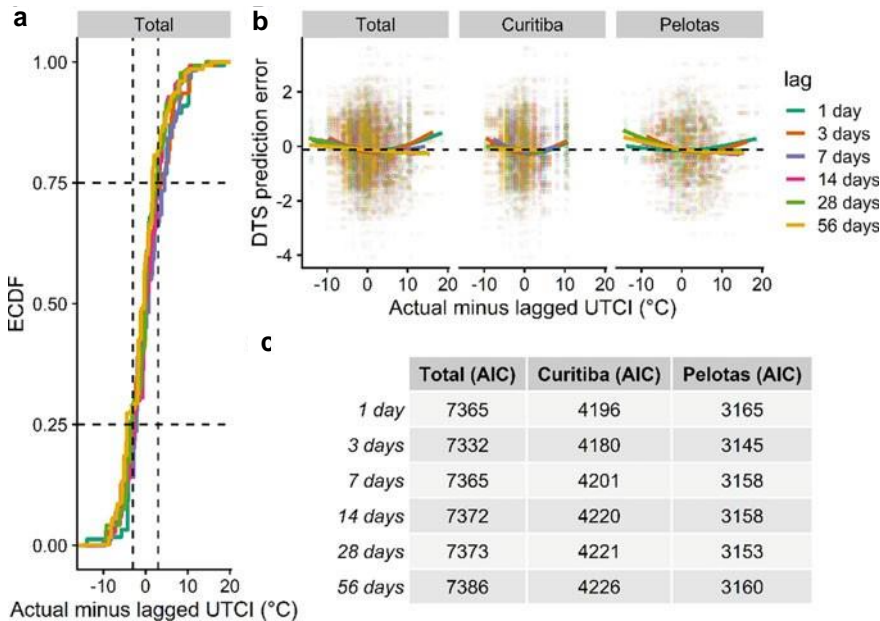

Fig. 3 a Empirical cumulative distribution function (ECDF) of the difference of actual UTCI to lagged values averaged over different lag periods from 1 day to 8 weeks for the total sample. Vertical reference lines at 3 and 3 °C approximately intersect with the 1st and 3rd quartiles, respectively. **b** Individual DTS prediction errors in the study areas and the total sample, respectively, in relation to the difference of actual to lagged UTCI values with cubic regression spline functions fitted separately for different lag periods. Dashed horizontal reference lines indicate mean bias from Table 1. **c** Values

of Akaike's Information Criterion (AIC) assessing the goodness-of-fit for the separate functions in (**b**) with lower values indicating superior fit

a Percentage variance components of DTS prediction error

Legend:
- City
- Age
- BMI
- Sex
- Site
- UTCI zone
- Clothing
- ΔUTCI-to-3-days-lag
- Residual

b

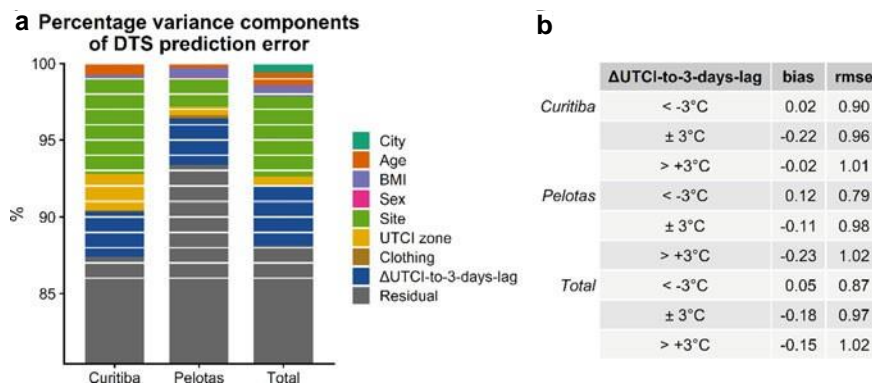|	ΔUTCI-to-3-days-lag	bias	rmse
Curitiba	< -3°C	0.02	0.90
	± 3°C	-0.22	0.96
	> +3°C	-0.02	1.01
Pelotas	< -3°C	0.12	0.79
	± 3°C	-0.11	0.98
	> +3°C	-0.23	1.02
Total	< -3°C	0.05	0.87
	± 3°C	-0.18	0.97
	> +3°C	-0.15	1.02

Fig. 4 a Relative partitioning of the variance for the error in thermal sensation votes (TSV) predicted by the UTCI model into factors considered in Fig. 2 plus the difference of actual UTCI to lagged values averaged over 3 days (ΔUTCI-to-3-days-lag) shown separately for the study areas and the total sample. Note that factor "city" only applies to the total sample and that the left panel does only show the range above 80%. **b** Bias and rmse for the categories of ΔUTCI-to-3-days-lag in the study areas and the total sample, respectively

The categorized analysis for the best fitting 3 days lag period (Fig. 4b) corroborated this U-shape only in Curitiba, but not in Pelotas and the total sample, where the decreased negative bias only occurred in connection with a preceding warmer (negative difference) period. This suggests that a largely warmer period preceding the actual day resulted in diminished warm sensations of the respondents and thus a reduced negative bias. Only in Curitiba, we found this also for cooler past days (Fig. 4b).

Figure 4, which presents the variance components of DTS prediction error in relative terms, depicts that the consideration of UTCI values from the 3 previous days reduced the residual inter-individual variability by 3–4%. This was even slightly increased in combination with the other factors, e.g. for the total sample reducing residual variance from over 94% (Fig. 2) to 88% (Fig. 4).

4   Discussion

The dynamic thermal sensations (DTS) calculated by the UTCI-Fiala model for UTCI reference climatic conditions provided essentially unbiased predictions of actual thermal sensation votes recorded in outdoor field surveys with rmse typically less than 1 unit on the 7-unit thermal sensation scale. Given that thermal sensation votes in the range of 1 are applied to define thermal comfort in survey studies (Rossi et al. 2012), this level of accuracy appears reasonable. Sex, age, body composition, site morphology, thermal status, and clothing choice hardly affected the prediction error with only marginal differences between Pelotas and Curitiba.

However, the large portion of 90% and more of unexplained inter-individual residual variance indicates current limitations in individual thermal comfort modelling. We had previously noted that explicitly considering individual clothing insulation in the heat exchange model did not improve the predictions (Bröde et al. 2012a, 2014). This might be explainable by inter-individual differences in human thermoregulation, probably interconnected with the clothing choice.

Recently, attempts to adapt a thermo-physiological model to Asian populations have been made by modifying the passive part of the system, i.e. anthropometry (Zhou et al. 2013). Nevertheless, given

the limited influence of personal characteristics found in our study, it remains questionable, whether such alterations will sufficiently account for psychological influences (Nikolopoulou and Steemers 2003; Nasrollahi et al. 2020) or even semantic differences in perceiving thermal comfort in different cultures or regions (Tochihara et al. 2012; Schweiker et al. 2020a; Pantavou et al. 2020). Achieving a better understanding on the psychological part of thermal comfort (Lenzholzer and Nikolopoulou 2020) remains crucial for adequately considering regional (Nikolopoulou and Lykoudis 2006) and inter-cultural differences (Havenith et al. 2020).

Additional information on prior weather as a surrogate of short-term experience (Nikolopoulou and Steemers 2003) could only help reducing the large inter- individual residual variance if it refers to a short previous period, with an optimum fit for 3 days lag in our study. This concurs with earlier results for a survey carried out in Glasgow (Bröde et al. 2014), though in that study 1 day lagged values fitted best to the data. It also confirms regression analyses from earlier studies (Nikolopoulou et al. 2001) showing lower capacity of temperatures recorded at longer time lags for neutral temperature prediction. The reduced bias due to diminished warm sensations following a preceding short warmer period (Figs. 3 and 4) may be attributable to habituation or short-term acclimation (Krüger et al. 2017; Lam et al. 2021), which are considered in another chapter of this book (Chap. 5: Long and short-term acclimatization effects on outdoor thermal perception versus UTCI). Corresponding effects due to a previous cooler period only occurred in Curitiba, but had also been observed for Glasgow, UK (Bröde et al. 2014). The mechanisms underlying such regional differences still have to be elucidated, which could be facilitated by databases summarizing outdoor thermal comfort studies as described in another chapter of this book (cf. Chap. 11: Proposed framework for establishing a global database for outdoor thermal comfort research, in this book).

5 Conclusions

The accuracy of UTCI predictions of outdoor thermal comfort as experienced by pedestrians in two Brazilian urban areas was acceptable at the population level, thus confirming recent studies in Brazil and other regions (Xue et al. 2020; Krüger and Drach 2017). The personal and situational factors considered in this study hardly affected UTCI predictive capability.

As an outlook, recently developed personal monitoring systems have shown the potential to move forward towards an individualized assessment of thermal stress related to comfort and health in outdoor environments (Hondula et al. 2021; Sugg et al. 2020; Runkle et al. 2019; Buller et al. 2018). This may be supplemented by integrating human thermal modelling with emerging technologies (Anderson et al. 2021), with climate modelling (Brecht et al. 2020; Di Napoli et al. 2020) or weather fore- casts (Petersson et al. 2019), as exemplified in the Operational Forecasting chapter of this book (Chap. 10, in this book).

6 Acknowledgement

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