

Article

Thermal-Preference Profiles Reveal Individual Differences in Residential Outdoor Thermal Comfort Under a Hot-Humid Climate: A Case Study for Age-Friendly Architectural Design Using Explainable Machine Learning

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Abstract

Individual differences in outdoor thermal comfort (OTC) are critical to the healthy use of urban public spaces, yet whether thermal preference can shape OTC independently of demographic characteristics remains largely unexamined. Using residential outdoor spaces in Fuzhou, a representative hot-humid city in China, as a case, this study combines field measurements and questionnaire data from 296 respondents (72.6% aged 60 or above) with explainable machine learning and K-Modes clustering to examine how thermal preference drives individual differences in OTC. Three stable preference profiles were identified—heat-sensitive (56.4%), wind-seeking (20.3%), and heat-tolerant (23.3%)—which exhibit markedly different thermal responses. The neutral globe temperature ranges from 29.90 °C for the heat-sensitive profile to 35.85 °C for the heat-tolerant profile, a difference of 5.95 °C, whereas the comfort bandwidth is widest for the heat-sensitive profile (9.03 °C) and narrowest for the heat-tolerant profile (4.13 °C), the former being 2.2 times the latter. The profiles are independent of sex and BMI and only weakly correlated with age, yet their explanatory power for the variance in thermal comfort vote (TCV) ($\eta^2 = 0.254$) is 4.9 to 23.1 times that of the demographic variables. The thermal environment contributes far more to TCV than the visual environment (74.4% versus 25.6%), with globe temperature (T_g) as the strongest single factor. Overall, differentiated design that adopts the most heat-sensitive profile as the constraint boundary covers the comfort needs of a broad population more effectively than demographic stratification. The novelty of this study lies in introducing psychologically grounded thermal-preference profiles as an operational stratification dimension for architectural design, offering age-friendly hot-humid residential environments a preference-oriented pathway toward refined, human-centered outdoor space design.



Academic Editor: Cinzia Buratti

Received: 1 June 2026

Revised: 4 July 2026

Accepted: 8 July 2026

Published: 10 July 2026

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Keywords: thermal preference; outdoor thermal comfort; explainable machine learning; visual–thermal environment; hot-humid climate; individual differences

1. Introduction

As global warming and the urban heat island effect continue to intensify, heatwaves are becoming increasingly frequent, and the influence of urban outdoor thermal environments on public health and the use of public space has attracted widespread attention [1,2]. Outdoor thermal comfort (OTC) refers to the subjective evaluation of comfort with respect

to outdoor hot and cold conditions, and has become an important indicator for assessing the quality of urban public spaces [3,4]. Studies have shown that a comfortable outdoor environment can promote residents' outdoor activities and improve their physical and mental health, whereas uncomfortable environmental experiences may induce thermal discomfort and negative emotions, thereby suppressing the willingness to engage in outdoor activities [5,6]. In the hot-humid climate zone of southern China, the combination of high temperature and high humidity is particularly pronounced, and summer outdoor heat stress has become a long-standing environmental challenge that severely constrains the usability of outdoor public spaces in residential areas [7,8]. Therefore, gaining an in-depth understanding of residents' OTC and its underlying mechanisms is of great significance for fully realizing the health benefits of urban public spaces.

The factors influencing OTC have been extensively studied in the existing literature. On one hand, physical variables such as air temperature [9], mean radiant temperature [10,11], wind speed [12], and relative humidity [13] have been confirmed to be closely related to OTC; on the other hand, a growing number of studies have pointed out that OTC is not determined by the thermal environment alone, and that the visual environment also exerts a substantial influence. For example, Jia et al. [14] found multi-channel interactions among visual, auditory, and thermal perception; Zhao [15] showed that perceived aesthetic quality can enhance residents' thermal tolerance; and Lau and Choi et al. [16], using explainable machine learning to analyze street-view images, found that the visual element with the strongest influence on thermal perception was not greenery. These studies indicate that the visual and thermal environments jointly shape OTC, and that an interaction may exist between the two.

However, a review of research in related fields reveals that most studies focus on environmental factors themselves, while relatively little attention has been paid to individual differences, particularly the psychological dimension of thermal preference. Here, thermal preference denotes an individual's desired direction of change for a given environmental factor (for example, a wish for lower air temperature, higher wind speed, or weaker solar radiation), and thus reflects a psychological disposition rather than a demographic attribute. Existing studies typically attribute individual differences in OTC to demographic characteristics such as sex, age, or body mass index [17,18], while overlooking the role that thermal preference, as a psychological disposition, plays in the perceptual process. This gap is consequential for the residential context, where age-friendly outdoor spaces must serve heterogeneous long-term residents, and where architectural design decisions on shading, greenery, and ventilation depend on how comfort needs vary across individuals. Theoretically, individuals with similar demographic characteristics may still produce markedly different comfort evaluations of the same thermal environment owing to differences in thermal preference. Identifying the structure of thermal preference among residents and clarifying its relationship with demographic characteristics and the visual–thermal environment would help to more comprehensively characterize individual differences in OTC, yet this issue still awaits systematic investigation.

In summary, this study adopts a case-study approach, using residential outdoor spaces in Fuzhou, a representative hot-humid city in China, to examine the role of thermal preference in residents' OTC and to decode individual differences in OTC within the perceptual context of the visual–thermal environment. Because previous studies have shown that thermal preference influences OTC [5,6,19], this study hypothesizes that, under a hot-humid climate, the response of OTC to the visual–thermal environment differs systematically among thermal-preference profiles. Clarifying this issue is directly relevant to architectural design, as it determines whether age-friendly residential outdoor spaces should be

designed around demographic groups or around thermal preference. Accordingly, this study addresses the following questions:

- (1) Can stable preference profiles be identified based on multidimensional thermal preference? Do the thermal response curves of each profile (neutral temperature, comfort bandwidth, and maladaptation slope) differ?
- (2) Are thermal-preference profiles independent of demographic variables such as sex, age, and BMI? How does their explanatory power for the variance in OTC compare with that of demographic variables?
- (3) What are the relative contributions of the visual and thermal environments to OTC, and is there a significant interaction between them? Does this relative contribution vary across thermal-preference profiles?

2. Materials and Methods

2.1. Study Site

This study adopts a case-study approach: rather than surveying many cities, it examines a single, well-characterized hot-humid residential context in depth, so as to resolve individual differences in OTC at a fine grain that broad cross-city comparisons cannot capture. The study area is located in Fuzhou (26.08° N, 119.30° E), on the southeastern coast of Fujian Province, China, a representative city of the hot-humid climate that belongs to the humid subtropical zone (Köppen–Geiger classification Cfa). Six survey sites were selected within a typical mid-rise residential community in the main urban area of Fuzhou as the research objects (see Figure 1 for details). In addition, to more comprehensively reflect the characteristics of outdoor spaces in residential areas under a hot-humid climate, the six sites differ in building enclosure, vegetation coverage, and openness, and can be classified into two categories: relatively open and relatively enclosed. All sites are public spaces where residents' summer outdoor activities are most concentrated. To minimize olfactory interference, none of the selected sites had noticeable odor characteristics, and respondents who were eating were excluded from the survey. Moreover, all sites were freely accessible to the public during the survey period. The six sites belong to the same community and are close to one another, with no obvious differences in economic or sociodemographic characteristics. To reduce the influence of sociocultural factors, the survey avoided periods with special group activities such as festivals, promotions, and banquets. During the questionnaire survey, a Kestrel 5500 handheld weather meter and a BES-01 globe-temperature data logger were used to simultaneously record the microclimatic parameters at each site, in order to characterize the summer climate of Fuzhou.

Site 1: A relatively open entrance space of a residential cluster, enclosed by mid-rise residential buildings, planted with a small number of trees, and predominantly hard-paved. Seating is provided, and there is slight pedestrian and vehicular traffic noise. Site 2: A relatively open cluster road space, flanked by mid-rise residential buildings, predominantly hard-paved, with limited tree coverage, ample direct sunlight, and slight traffic noise. Site 3: A relatively open boundary space of the residential area, with low building enclosure, sparse vegetation, predominantly hard-paved, and noticeably affected by traffic noise from the surrounding roads. Site 4: A relatively open street-facing space of the residential area, immediately adjacent to the community's main road, planted with a small number of trees, predominantly hard-paved, with some traffic noise. Site 5: A well-vegetated internal pedestrian space of the cluster, with rows of trees planted along the walkway providing some shade, predominantly hard-paved, with relatively low noise. Site 6: A relatively enclosed semi-outdoor pilotis (stilt) space, formed by the open ground floor of a building with structural shading overhead, very little vegetation, relatively dim lighting, and essentially no traffic noise.



Figure 1. Location of the survey sites.

2.2. Questionnaire Design

The questionnaire consisted of three parts (see Table 1). The first part was designed to obtain demographic information, including (1) sex, (2) age, (3) length of residence, and (4) height and weight (used to calculate BMI). The second part was designed to obtain respondents' outdoor thermal comfort vote (TCV), using the five-point ASHRAE scale (−2 to 2). The third part was designed to obtain four-dimensional thermal preference, including air-temperature preference (TPR), relative-humidity preference (RHPR), wind-speed preference (VPR), and solar-radiation preference (SPR); each dimension had three options: −1 (prefer lower/weaker), 0 (no change), and 1 (prefer higher/stronger), with the specific coding shown in Table 1. Respondents were required to acclimatize in the outdoor environment for at least 15 min before completing the questionnaire. A reliability test (Cronbach's alpha) showed that the four thermal-preference dimensions had a Cronbach's alpha of 0.83; according to the criterion established by Landis and Koch (1977), a Cronbach's alpha greater than 0.80 indicates adequate reliability. The internal consistency of the thermal-preference scale used in this study was therefore good.

Table 1. Subjective questionnaire on thermal comfort and thermal preference.

		−1	0	1
Thermal comfort	Thermal comfort vote (TCV)	Uncomfortable (−2/−1)	Neutral	Comfortable (1/2)
Thermal preference	Air-temperature preference (TPR)	Lower	No change	Higher
	Relative-humidity preference (RHPR)	Drier	No change	More humid
	Wind-speed preference (VPR)	Lower	No change	Higher
	Solar-radiation preference (SPR)	Weaker	No change	Stronger

2.3. Field Survey

The field survey was conducted from 7 to 12 August 2025, during the high-temperature period of summer in Fuzhou (mean air temperature 34.3 °C, mean relative humidity 60.9%), covering representative high-temperature days. Respondents were randomly selected by the survey staff; individuals with alcohol or drug dependence or mental illness were excluded. Every participant was informed of the content and purpose of the questionnaire, and the survey proceeded only after their consent was obtained. The survey at each site was conducted during the same time window, 8:00~18:00, under clear weather conditions (no precipitation, no strong wind). A total of 296 valid questionnaires were collected, with respondents aged 60 and above accounting for 72.6% of the sample. The minimum sample size was calculated using G*Power 3.1 [20]; considering the statistical power level and effect size ($f^2 = 0.15$, $\alpha = 0.05$, 8 predictors), the required minimum sample size was 108. The statistical power ($1-\beta$) of the valid sample in this study was 0.99, which effectively reduces the risk of Type I error.

The thermal environment parameters were measured in accordance with the ISO 7726 (1998) standard [21], with all sensors uniformly placed at a pedestrian height of 1.1 m. Air temperature, relative humidity, and wind speed were measured with a Kestrel 5500 handheld weather meter, and globe temperature was measured with a BES-01 globe-temperature data logger; the instrument models, measurement ranges, accuracy, and sampling frequencies are shown in Table 2. In addition, visual-environment data were collected with a 5.7 K high-resolution panoramic camera (Insta360 ONE X2, Shenzhen Arashi Vision Co., Ltd., Shenzhen, China) at a height of 1.5 m; the panoramic images were processed with a DeepLabV3+ semantic segmentation model to calculate the green view index (GVI), building view index (BVI), and sky view index (SVI), and a color richness index (CRI) was calculated based on statistics in the CIELab color space. Mean radiant temperature (MRT) was calculated using the forced-convection formula of ISO 7726 (1998), and the Universal Thermal Climate Index (UTCI) was derived from T_a , RH, wind speed, and MRT; UTCI was used only to describe the level of summer heat stress and was not included in the main predictive model.

Table 2. Parameters of the thermal-environment measurement instruments.

Instrument	Measured Parameter	Range	Accuracy	Sampling Frequency
Kestrel 5500 handheld weather meter	Air temperature	−29 to 70 °C	0.2 °C	1 min
	Relative humidity	0 to 100%	±2%	1 min
	Wind speed	0.4 to 40 m/s	±3%	1 min
BES-01 globe-temperature data logger	Globe temperature	−40 to 120 °C	0.2 °C	1 min

2.4. Statistical Analysis

This study jointly employed a random forest-SHAP framework, K-Modes clustering, response-curve fitting, and regression analysis. Here, SHAP (SHapley Additive exPlanations) is an explainable machine-learning technique that attributes a model's prediction to each input variable, thereby quantifying how much each environmental factor contributes

to the outcome. The analyses were organized around the three research questions. To address Question 1, random forest regression models were built with each preference dimension as the target, and SHAP values were used to quantify the driving contribution of each environmental variable; in parallel, K-Modes clustering was applied to the four-dimensional preferences to identify preference profiles, with the number of clusters K determined from bootstrap stability, the Gap statistic, and interpretability. To address Question 2, three complementary approaches—chi-square tests of independence, logistic regression, and comparison of η^2 effect sizes—were used to test the predictive power of demographic variables for profile membership and to verify the net effect of the profiles independent of age. To address Question 3, a random forest regression model was built with thermal comfort vote (TCV) as the target and eight environmental variables as predictors, and SHAP values were used to quantify feature importance and pairwise interactions; in addition, TCV response curves were fitted against T_g , RH, and T_a within each profile, and three indicators were extracted: the neutral temperature (the globe temperature at which thermal sensation is neutral), the comfort bandwidth (the temperature span over which conditions remain comfortable), and the maladaptation slope (the rate at which comfort deteriorates once conditions depart from neutral). All analyses were performed in Python 3.11, with robustness controlled via permutation tests, variance inflation factor (VIF) diagnostics, and FDR correction.

3. Results

3.1. Participant Demographics

The demographic characteristics of the respondents are presented in Table 3. A total of 296 valid samples were collected; males accounted for 54.4%, the mean age was 63.4 years ($SD = 18.8$), and older adults aged 60 and above formed the largest group (72.6%). A total of 97.3% of respondents had lived locally for more than 10 years; the mean BMI was 22.97 ($SD = 2.47$), with 65.9% in the normal range and 28.4% overweight.

Table 3. Demographic characteristics of the respondents.

Indicator	Category	N	Percentage (%)
Sex	Male	161	54.4
	Female	135	45.6
Age (years), mean = 63.4	<30	10	3.4
	30–44	54	18.2
	45–59	17	5.7
	≥60	215	72.6
Length of residence (years), mean = 19.6	3–10	8	2.7
	≥10	288	97.3
BMI (kg/m^2), mean = 22.97	Underweight (<18.5)	8	2.7
	Normal (18.5–24)	195	65.9
	Overweight (24–28)	84	28.4
	Obese (≥28)	9	3.0

The distribution of respondents' thermal comfort votes (TCV) is shown in Figure 2. The proportions of each category, from highest to lowest, were: slightly uncomfortable (−1, 43.2%) > neutral (0, 22.6%) > slightly comfortable (1, 21.3%) > uncomfortable (−2, 9.5%) > comfortable (2, 3.4%). Overall, responses were concentrated in the negative and neutral range, indicating that under the hot-humid summer conditions, respondents generally leaned toward feeling “slightly uncomfortable.”

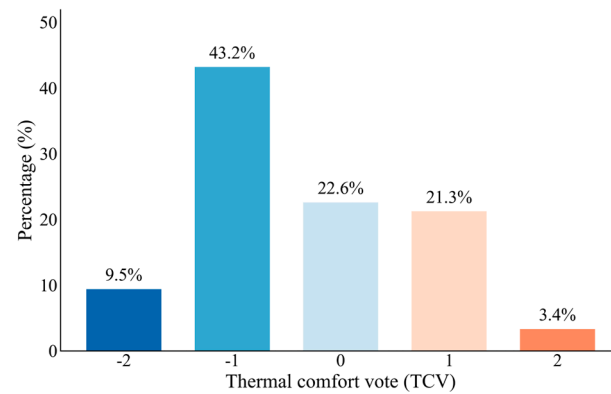


Figure 2. Distribution of thermal comfort votes (TCV).

3.2. Relative Contribution of the Visual and Thermal Environments to TCV

This subsection addresses Research Question 3. A random forest–SHAP framework was used to examine the relative contribution of the visual and thermal environments to TCV. Under repeated 5-fold cross-validation, the full-sample model achieved $CV-R^2 = 0.666$ (± 0.040) and $RMSE = 0.581$, indicating good explanatory power. The SHAP feature importance of each variable is shown in Table 4, ranked as follows: T_g (0.271) > RH (0.201) > T_a (0.192) > v (0.089) > SVI (0.077) > BVI (0.070) > GVI (0.063) > CRI (0.049). Aggregating and visualizing this importance by category (Figure 3) shows that the contribution of the thermal environment (74.4%) exceeds that of the visual environment (25.6%), indicating that TCV is dominated by the thermal environment, with the visual environment serving as a non-negligible secondary channel. Within the thermal environment, the ranking is $T_g > RH > T_a$, confirming that globe temperature, as a composite indicator of radiant heat load, is the strongest thermal stress factor; within the visual environment, the ranking is $SVI > BVI > GVI$, suggesting that the perception of openness (sky view index) contributes more than the green view index.

Table 4. SHAP feature importance for the full sample.

Variable	Category	Mean SHAP	Importance Rank
T_g	Thermal	0.271	1
RH	Thermal	0.201	2
T_a	Thermal	0.192	3
v	Thermal	0.089	4
SVI	Visual	0.077	5
BVI	Visual	0.070	6
GVI	Visual	0.063	7
CRI	Visual	0.049	8

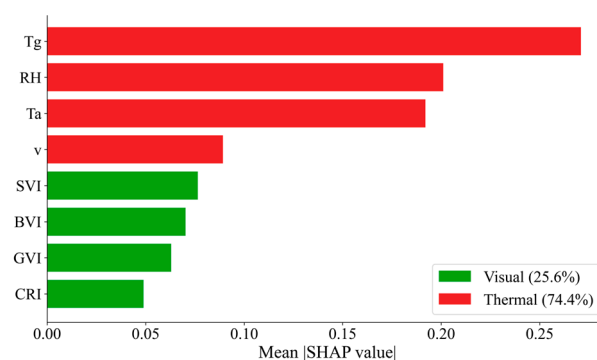


Figure 3. Feature importance for the full sample.

The pairwise interaction strengths among the variables are shown in Figure 4. The three strongest interactions all occur within the thermal environment: $T_g \times RH$ (0.226) > $T_a \times T_g$ (0.180) > $T_a \times RH$ (0.176), whereas no interaction of comparable magnitude exists between the visual and thermal environments. This indicates that TCV is shaped by the synergistic effects of multiple thermal variables—globe temperature, relative humidity, and air temperature do not contribute independently but rather modulate one another; for example, the effect of rising globe temperature on TCV may be further amplified under high-humidity conditions. This result is consistent with reports that temperature–humidity coupling enhances heat stress under hot-humid climates, suggesting that comfort assessment should focus on the combined effects of thermal variables rather than treating them in isolation.

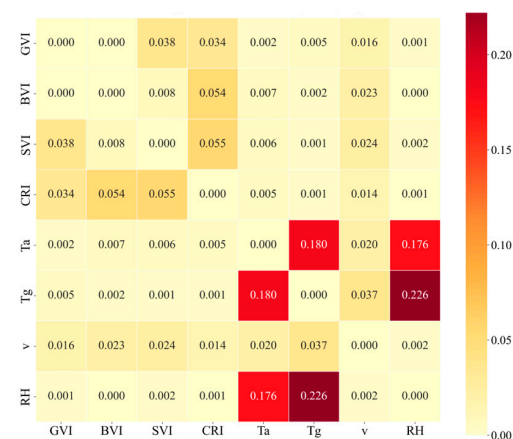


Figure 4. Pairwise interaction-strength matrix of the variables.

3.3. Identification and Response Curves of Thermal-Preference Profiles

3.3.1. Environmental Drivers of the Preference Dimensions

This subsection addresses Research Question 1. The environmental drivers of each preference dimension are shown in Figure 5. The strongest driver of all four dimensions is globe temperature (T_g), with driving strengths of: humidity preference (30.3%) > solar preference (29.7%) > wind-speed preference (28.9%) > temperature preference (27.8%), with very small differences among them (all around 30%). This indicates that T_g is the common primary driver underlying multidimensional subjective needs, that is, the radiant heat load of the hot-humid summer exerts a pervasive influence across the thermal, humidity, wind, and solar perceptual channels, rather than acting solely on temperature perception itself. The first two dimensions of multiple correspondence analysis (MCA) jointly explain 37.65% of the inertia, indicating that the four-dimensional preferences have a compressible latent structure, which provides a basis for the subsequent profile clustering.

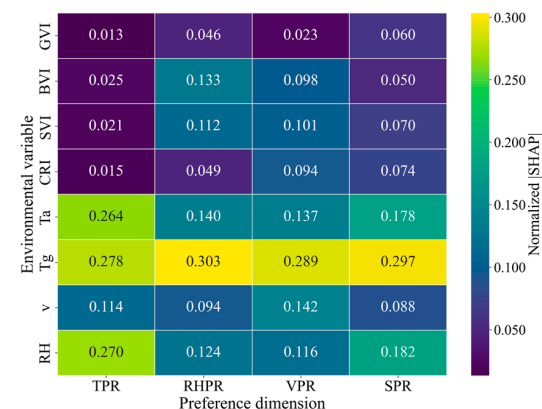


Figure 5. Normalized |SHAP| values for each preference dimension.

3.3.2. K-Modes Clustering and Profile Identification

A multi-criteria comparison of the candidate numbers of clusters is shown in Table 5, and the robustness diagnostics for the choice of K are shown in Figure 6. The silhouette coefficient and the elbow method (Figure 6) tend to favor a larger K for categorical data and are therefore of limited reference value; this study consequently relies primarily on clustering robustness. As shown in Table 5, the bootstrap ARI is highest (0.556) and most stable at K = 3; the Gap statistic, applying the Tibshirani criterion, also identifies K = 3 as optimal, with a minimum cluster size of 60 (20.3%), which satisfies the sample-size requirement for the subsequent response-curve fitting. Considering robustness, interpretability, and sample adequacy together, K = 3 was selected.

Table 5. Multi-criteria comparison of different numbers of clusters K.

K	Cost	Silhouette Coefficient	Smallest Cluster <i>n</i>	Smallest Cluster (%)	Bootstrap ARI	Gap
2	304.0	0.426	103	34.8	0.536	0.063
3	228.0	0.404	60	20.3	0.556	0.134
4	188.0	0.386	47	15.9	0.449	0.090
5	149.0	0.449	30	10.1	0.524	0.116
6	136.0	0.481	23	7.8	0.534	0.157

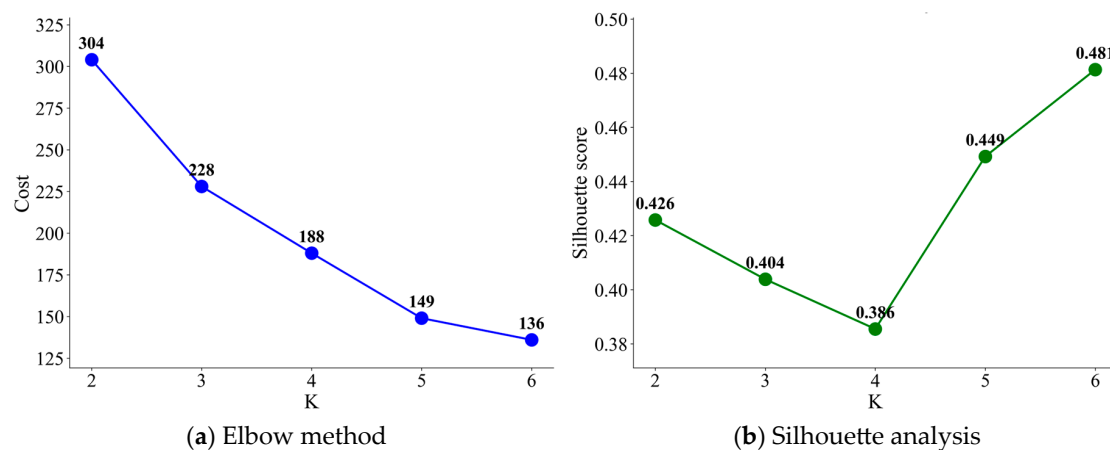


Figure 6. Robustness diagnostics for the choice of K.

The sample size, modal pattern, and internal consistency of the three profiles are shown in Table 6, with their cluster centers shown in Figure 7. First, the heat-sensitive profile (56.4%) has “lower temperature, higher wind speed, weaker solar radiation” as its modal pattern, representing an active heat-dissipation-seeking type, with the lowest mean TCV (−0.79). Second, the wind-seeking profile (20.3%) has “lower temperature, higher wind speed, drier” as its mode, reflecting a dual demand for wind and lower humidity. Finally, the heat-tolerant profile (23.3%) is neutral across all four dimensions, exhibiting stronger adaptability to hot-humid conditions, with the highest mean TCV (0.39). The observed frequencies of the three profiles are 24.7, 29.7, and 21.1 times the random expectation, respectively, indicating that the preferences within each profile are highly coherent rather than coincidental.

Table 6. Sample size, modal pattern, and internal consistency of the three preference profiles.

Profile	N (%)	TPR	RHPR	VPR	SPR	Observed/Expected Ratio
Heat-sensitive	167 (56.4%)	−1	0	1	−1	24.7
Wind-seeking	60 (20.3%)	−1	−1	1	0	29.7
Heat-tolerant	69 (23.3%)	0	0	0	0	21.1

Note: −1 = lower, 0 = no change, 1 = higher.

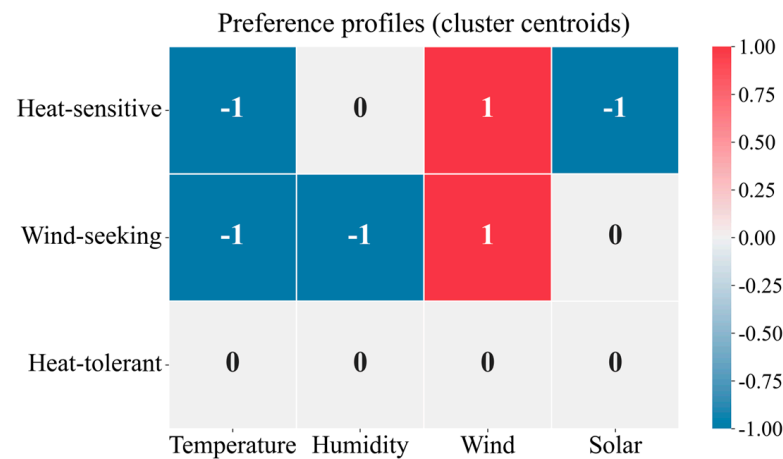


Figure 7. Cluster centers of the three profiles.

3.3.3. Profile Response Curves and the Triad of Indicators

Using Tg as the representative variable, TCV–Tg response curves were fitted within each profile (Figure 8), and three indicators—neutral temperature, comfort bandwidth, and maladaptation slope—were extracted (Table 7). The three profiles differ markedly across all three indicators. For neutral temperature, the heat-sensitive profile is the lowest (29.90 °C) and the heat-tolerant profile the highest (35.85 °C), with the wind-seeking profile intermediate (34.69 °C), a spread of 5.95 °C. For comfort bandwidth, the heat-sensitive profile is the widest (9.03 °C) and the heat-tolerant profile the narrowest (4.13 °C), the former being 2.2 times the latter. For the maladaptation slope (absolute value), the ordering reverses: the heat-tolerant profile is the steepest (0.242) and the heat-sensitive profile the gentlest (0.111), again a 2.2-fold difference.

Table 7. Tg-based response-curve indicators for the three profiles.

Group	N	Slope	Neutral Temperature (°C)	Comfort Bandwidth (°C)	R ²
Full sample	296	−0.183	33.97	5.46	0.403
Heat-sensitive	167	−0.111	29.90	9.03	0.225
Wind-seeking	60	−0.176	34.69	5.68	0.349
Heat-tolerant	69	−0.242	35.85	4.13	0.525

A cross-profile comparison of the three indicators is shown in Figure 9. The three profiles exhibit a consistent gradient along the order “heat-sensitive—wind-seeking—heat-tolerant”: the profile with the lowest neutral temperature corresponds to the widest comfort bandwidth and gentlest slope, while the profile with the highest neutral temperature corresponds to the narrowest bandwidth and steepest slope. This reveals that “more heat-tolerant” does not equate to “more forgiving”—although profiles with a higher neutral temperature can maintain a neutral thermal sensation in hotter environments, their tolerance range for deviations from the neutral temperature is narrower, and they rapidly enter a state of maladaptation once this range is exceeded. The nearly 6 °C difference in neutral temperature between the heat-sensitive and heat-tolerant profiles exceeds the cross-city differences across climate zones reported in the existing literature, indicating that the magnitude of individual differences within the same hot-humid environment can be comparable to differences across climates. Therefore, using only the full-sample neutral temperature (33.97 °C) as a design reference may deviate substantially from the needs of the heat-sensitive profile, which accounts for 56.4% of the sample; profile-oriented differentiated design can better cover a broad population.

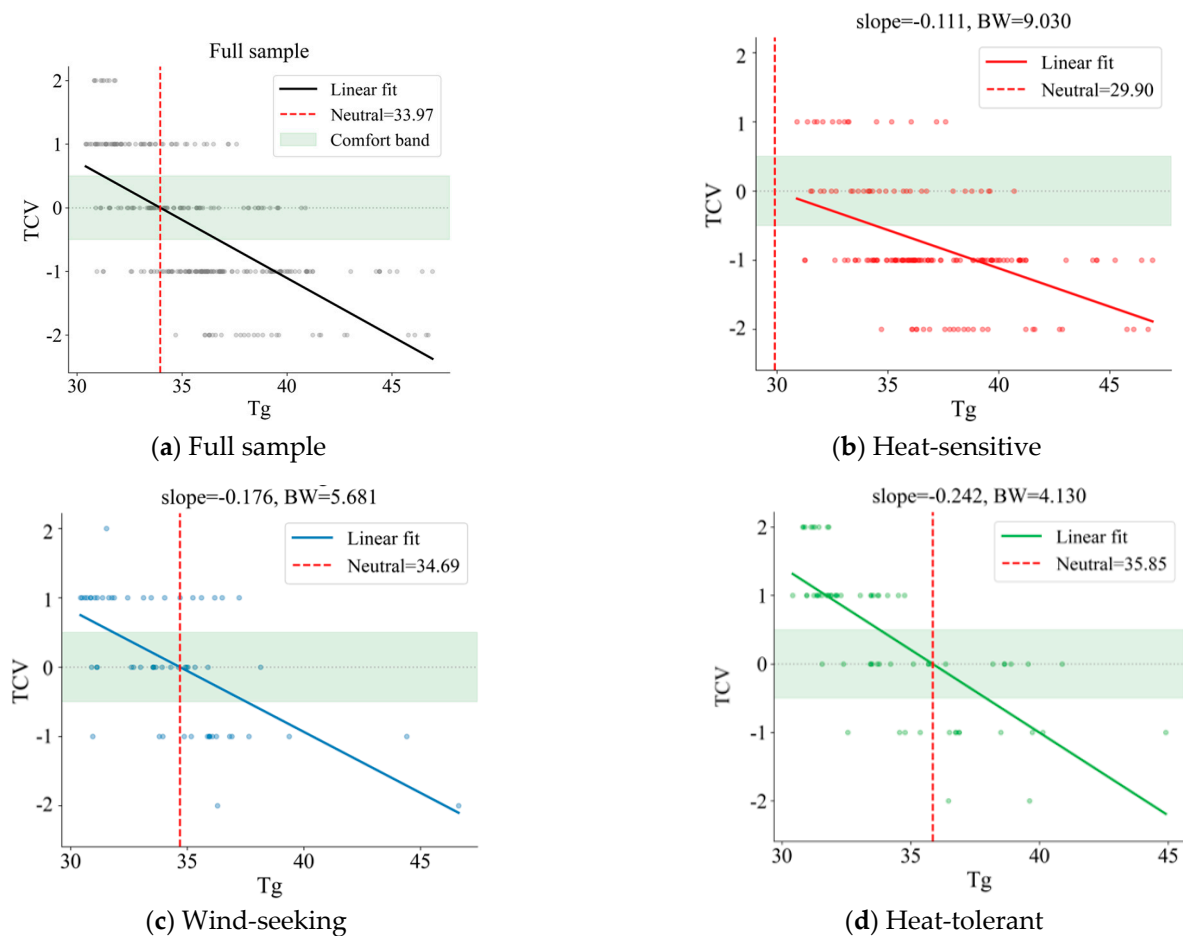


Figure 8. Tg-TCV response curves for each profile. Note: the green band indicates the comfort zone; the red dashed line indicates the neutral temperature.

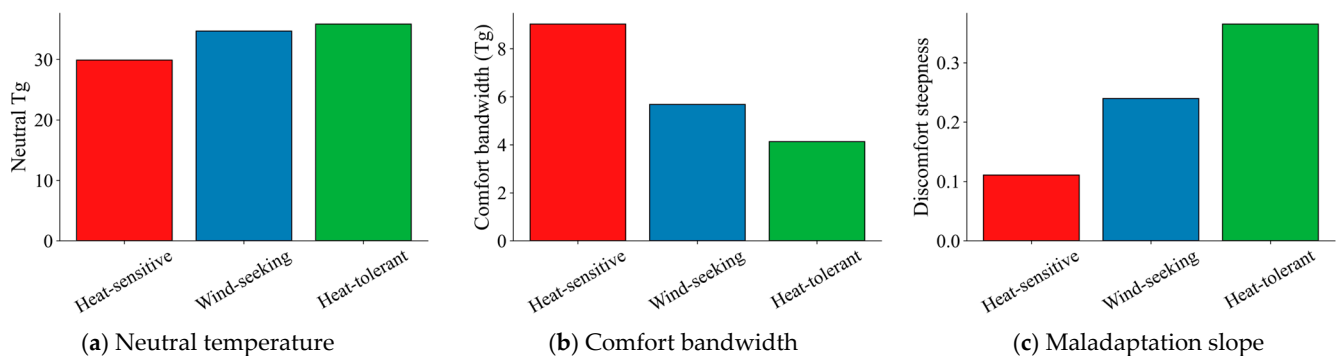


Figure 9. Comparison of the response-curve indicators across the three profiles.

3.3.4. Relative Contribution of the Visual and Thermal Environments Within Each Profile

To test whether the relative contributions of the visual and thermal environments differ across profiles, a separate random forest-SHAP model was built for each profile subsample; the visual/thermal contributions for each profile are shown in Table 8. The CV-R² values of the three profiles are 0.402, 0.228, and 0.607, respectively, all above zero, indicating credible fits. A visualized comparison of the within-profile contributions is shown in Figure 10, which reveals a striking disparity in visual contribution among the three profiles: the heat-sensitive profile is highest (29.6%), followed closely by the wind-seeking profile (28.4%)—both near 30%—while the heat-tolerant profile is lowest (7.2%), about one-quarter of the highest value, with its TCV almost entirely explained by the thermal environment (92.8%).

This indicates that the thermal-preference profile not only determines an individual's thermal response curve but also modulates the weight of the visual environment in thermal comfort: for heat-sensitive individuals, the visual environment is a non-negligible part of the thermal comfort evaluation, whereas for heat-tolerant individuals, thermal comfort is determined almost entirely by the physical thermal environment.

Table 8. Relative contributions of the visual and thermal environments within each profile.

Profile	N	Visual Contribution (%)	Thermal Contribution (%)	Strongest Single Variable	CV-R ²
Heat-sensitive	167	29.6	70.4	Ta	0.402
Wind-seeking	60	28.4	71.6	Tg	0.228
Heat-tolerant	69	7.2	92.8	RH	0.607

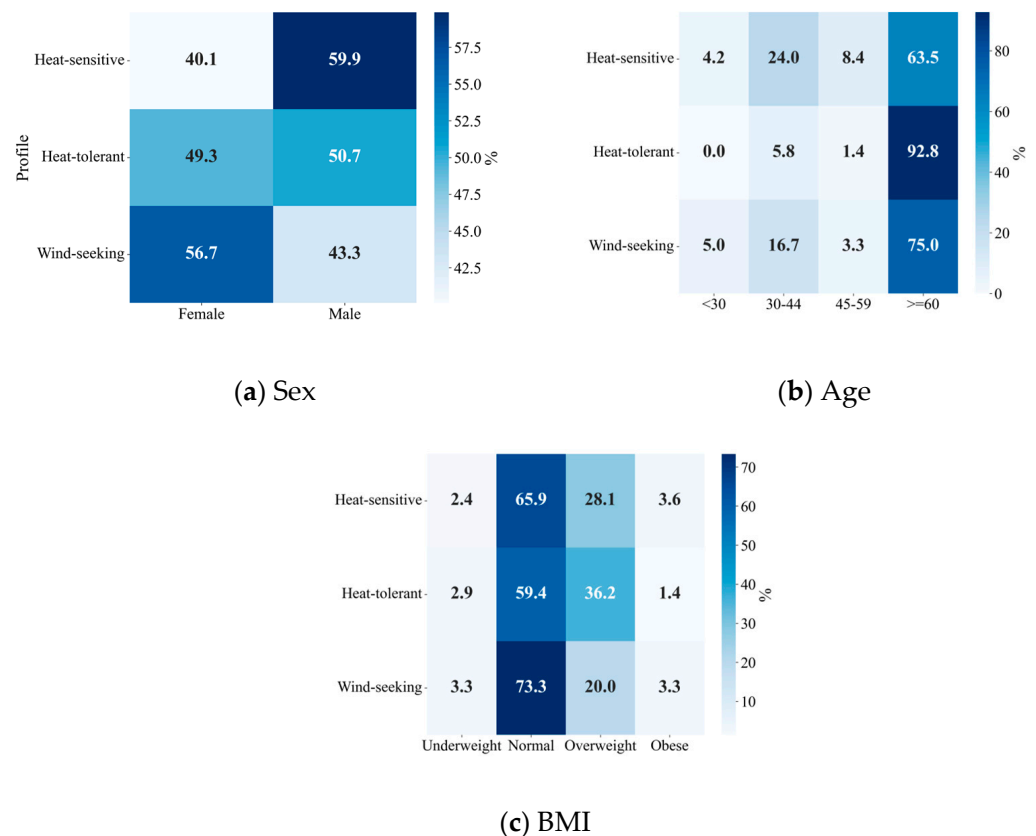


Figure 10. Contingency distributions between the profiles and demographic variables.

3.4. Evidence That the Profiles Are Independent of Demographics

This subsection addresses Research Question 2. To test whether the thermal-preference profile is independent of demographic characteristics, this study used three complementary lines of evidence. First, chi-square tests of independence showed no significant association between the profile and sex ($\chi^2 = 5.36$, $p = 0.069$, Cramér's $V = 0.135$) or BMI ($\chi^2 = 4.85$, $p = 0.564$, $V = 0.090$), and only a weak association with age ($V = 0.223$); the contingency distributions of the three are shown in Figure 10. The weak association with age is mainly attributable to the relatively higher concentration of middle-aged and older adults within the heat-tolerant profile, consistent with reports of reduced thermal sensitivity among older adults. Second, a logistic regression jointly predicting profile membership from sex, age, and BMI achieved an accuracy of only 0.581, just about 1.7 percentage points above the majority-class baseline (0.564), indicating that the predictive information carried by demographics is limited. Finally, in terms of explanatory power for the variance in TCV (Figure 11), the profile ($\eta^2 = 0.254$) is 4.9 times that of age (0.051), 18.1 times that of sex

(0.014), and 23.1 times that of BMI (0.011); all three demographic variables together account for less than one-quarter of the explanatory power of the profile.

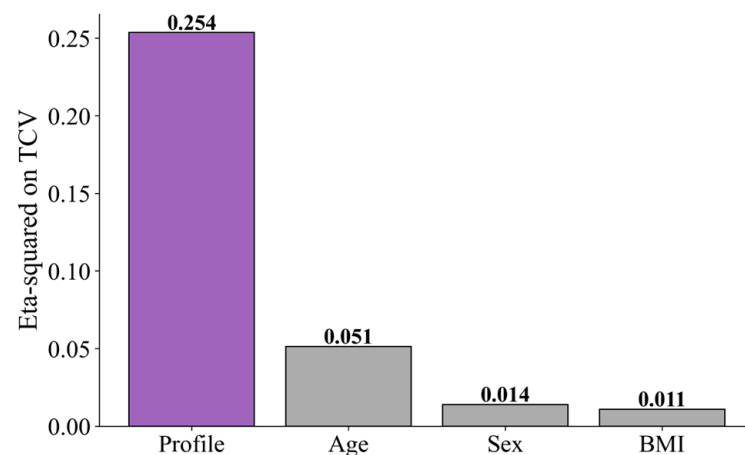


Figure 11. Comparison of the variance explained (η^2) in TCV by the profile and by demographic variables.

The net effect of the profile independent of age is shown in Table 9. Age-stratified η^2 shows that, within the ≥ 60 subsample, the η^2 of the profile for TCV is 0.246, essentially consistent with the full sample (0.254), while it is 0.155 in the < 60 subsample, indicating that the explanatory power is not confounded by age. The incremental analysis from sequential regression is even more direct: after controlling for age, the profile still explains an additional 20.9% of the TCV variance, whereas after controlling for the profile, age explains only an additional 0.9%.

Table 9. Variance in TCV explained by the profile and by age.

Model	R ²	Adjusted R ²	Incremental R ²
Age only	0.061	0.058	—
Profile only	0.262	0.257	—
Profile + Age	0.270	0.263	Profile (controlling for age) = 0.209; Age (controlling for profile) = 0.009

Taken together, these three lines of evidence indicate that the thermal-preference profile is independent of sex and BMI, only weakly associated with age, and its explanatory power cannot be substituted by age; it should therefore be regarded as a relatively independent individual-difference dimension related to psychological disposition.

3.5. Comprehensive Thermal Indices and Robustness

The field measurements were conducted during the high-temperature period of summer in Fuzhou (7–12 August 2025) under clear, precipitation-free weather. During the measurement period, the air temperature was approximately 33–35 °C, the globe temperature approximately 34–38 °C, and the relative humidity generally above 57%, reflecting overall high-temperature, high-humidity conditions.

A summary of the environmental conditions at each survey site is shown in Table 10. Within the sample, 51.0% fell in the UTCI “strong heat stress” range (32–38 °C), 48.0% in the “very strong heat stress” range (38–46 °C), and 1.0% reached “extreme heat stress,” with none falling in the no-heat-stress or cold-stress ranges, confirming the high heat load of the outdoor residential environment in Fuzhou summers. The Spearman correlation between UTCI and TCV ($r = -0.667$, $p < 0.001$) is nearly identical to that between Tg and TCV ($r = -0.673$), indicating that Tg alone is sufficient to characterize heat stress; the

main analysis therefore uses T_g as the representative variable, with UTCI serving as a robustness reference.

Table 10. Visual and thermal environmental indicators at each survey site.

Site	N	Ta (°C)	Tg (°C)	MRT (°C)	v (m/s)	RH (%)	UTCI (°C)	GVI	BVI	CRI	TCV
S1	39	33.58	34.14	35.24	0.56	61.50	36.49	0.25	0.43	28.11	−0.59
S2	62	33.31	34.18	36.06	0.68	64.97	36.87	0.23	0.39	26.09	−0.44
S3	42	34.83	36.28	39.10	0.59	60.83	38.82	0.00	0.67	21.52	−0.83
S4	63	35.14	38.45	44.17	0.55	57.37	39.84	0.06	0.53	26.50	−0.54
S5	55	34.22	35.77	38.22	0.43	60.63	37.90	0.22	0.35	25.58	0.11
S6	35	34.50	35.49	37.04	0.43	59.82	37.83	0.03	0.81	23.20	0.34

The survey sites might be thought to introduce a data-stratification structure. As Table 10 shows, the six sites do exhibit the expected heterogeneity in T_g , UTCI, GVI, and BVI—for example, Site S4 carries the highest radiant heat load and a correspondingly more negative TCV. However, the association between profile distribution and site is weak (Cramér’s $V = 0.210$), and the cross-site composition of the profiles (Figure 12) confirms that the identified profiles are not an artifact of specific sites but a structure of individual differences that is robust across sites. In terms of statistical robustness, the SHAP and permutation feature-importance rankings are highly consistent (Spearman $r = 0.976$), and 12 of the 14 tests remained significant after Benjamini–Hochberg FDR correction, supporting the reliability of the conclusions.

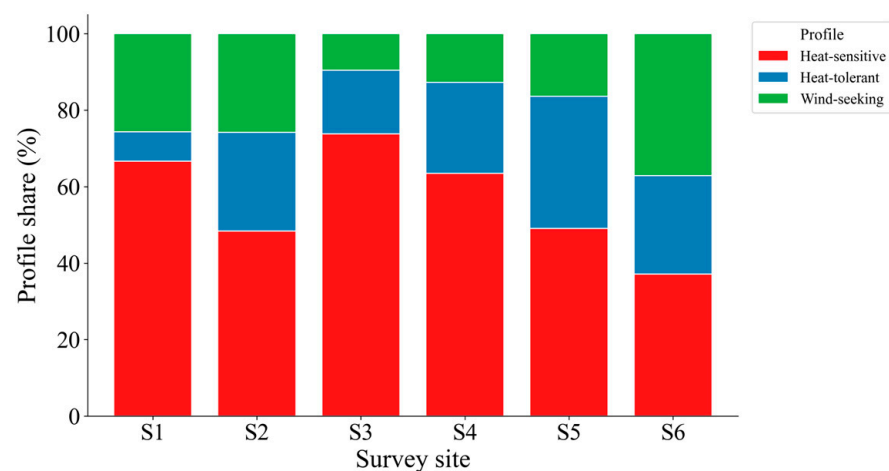


Figure 12. Profile composition at each survey site.

4. Discussion

4.1. Relative Contribution and Coupling Mechanism of the Visual and Thermal Environments

Previous research on outdoor thermal comfort has mostly adopted a physical-intervention perspective, emphasizing the cooling effects of greenery [22,23], urban form [3,24], shading [25], water bodies [26], and evaporative misting [27,28], while paying less attention to the relative contribution of the visual and thermal environments and their coupling mechanism [11]. This study quantifies that issue: the visual environment contributes 25.6% and the thermal environment 74.4%, and even after including color richness (CRI) the visual environment still accounts for about one-quarter of the explained variance. This finding is consistent with reports by Du et al. [9] and Zhu et al. [10] that the visual environment influences thermal comfort, but it advances beyond their qualitative accounts by assigning explicit quantitative weights. In recent years, explainable machine learning has been used to disentangle the complex nonlinear relationships and

individual–environment interactions underlying outdoor thermal comfort [29–31], and this study follows the same approach.

Within the thermal environment, the three strongest interactions ($T_g \times RH$, $T_a \times T_g$, $T_a \times RH$) all occur among thermal variables, indicating that the synergistic amplification of temperature and humidity is key to shaping TCV under a hot-humid climate; this echoes the radiant-temperature-dominated conclusions reported in cold-region [18] and heat-island [32] studies. More importantly, the visual contribution varies markedly across profiles: heat-sensitive (29.6%) > wind-seeking (28.4%) > heat-tolerant (7.2%), with the highest being about four times the lowest. This indicates that the thermal-preference profile also modulates the weight of the visual environment in thermal comfort—for heat-sensitive individuals, visual improvements (increased greenery, shading) are genuinely effective [23], whereas for heat-tolerant individuals, TCV is determined almost entirely by the thermal environment, and visual interventions yield limited benefit.

4.2. Relationship Between Thermal-Preference Profiles and Demographics

Previous studies have largely shown that demographic variables such as sex, age, and BMI are related to thermal comfort [33,34], and that different population groups (e.g., children [35], outdoor exercisers [36], and rural older adults [37]) exhibit different thermal responses. However, this study finds that the profile is far more efficient than demographics in explaining individual differences in TCV: its explanatory power ($\eta^2 = 0.254$) is 4.9, 18.1, and 23.1 times that of age (0.051), sex (0.014), and BMI (0.011), respectively. This does not negate the relevance of demographics, but indicates that a demographic association does not necessarily make it the primary source of individual differences.

The profile is only weakly associated with age (Cramér's $V = 0.223$), which arises from a somewhat higher proportion of middle-aged and older adults in the heat-tolerant profile—a direction consistent with reports by Wu et al. [38] and Wang et al. [8]. Even so, the profile cannot be substituted by age: after controlling for age, it still explains an additional 20.9% of the TCV variance, whereas after controlling for the profile, age explains only a further 0.9%. Accordingly, the thermal-preference profile should be regarded as an individual-difference dimension that is relatively independent of demographics and related to psychological disposition; incorporating it into modeling is likely to outperform demographic stratification alone [14,39].

4.3. Design Implications of Profile-Specific Response Curves

Existing studies have mostly focused on group differences across cities or climate zones [15,40], with field measurements already covering diverse climatic contexts such as India [41], cold-humid regions [42], semi-arid regions [43], the Mediterranean [44], and subtropical campuses [45]. The present study instead finds that the difference in neutral T_g among the three profiles within the same hot-humid environment reaches nearly 6 °C, a magnitude comparable to cross-climate differences, thereby refining this variability down to the profile level within the same site. The triad of indicators further reveals that “more heat-tolerant” does not equate to “more forgiving”—profiles with a higher neutral temperature have a narrower comfort bandwidth and a steeper maladaptation slope. This approach of characterizing individual differences through clustering is consistent with previous studies that have used clustering or mixture models to disentangle heterogeneity in the outdoor thermal environment [46].

This implies that using the full-sample mean (neutral $T_g = 33.97$ °C) as a uniform reference would deviate substantially from the heat-sensitive profile, which accounts for 56.4% of the sample; profile-oriented differentiated design can better cover a broad population [47]. Specifically, the heat-sensitive profile has a neutral T_g of only about 29.90 °C and

a visual contribution of 29.6%; in highly irradiated open sites (e.g., S3, S4), priority should therefore go to increasing greenery, providing shading, and incorporating landscape-based cooling [22,23,48–51]. The wind-seeking profile would benefit most from improved ventilation in enclosed, low-wind sites (e.g., S5, S6) [2,52]. The heat-tolerant profile, with its narrow tolerance range and thermal contribution as high as 92.8%, calls instead for suppressing sharp temperature–humidity fluctuations rather than visual interventions [17].

4.4. Research Limitations

This study has several limitations. First, as a single-case study it involved only one city, one season, and one space type, with a relatively high proportion of older adults in the sample, which limits generalizability. In terms of the Köppen–Geiger climate classification, Fuzhou belongs to the humid subtropical zone (Cfa); the findings are therefore expected to transfer most directly to other Cfa cities with hot, humid summers, whereas their applicability to other climate zones (for example, arid or cold-humid regions) requires further verification [53]. Future research should accordingly be conducted across multiple Köppen climate zones and seasons and cover different population groups, for example by incorporating adaptive comfort measurements under hot-humid climates [54], distinguishing permanent residents from transient populations [55], and carefully selecting representative measurement sites [56]. Second, subjective indicators such as thermal pleasure, visual pleasure, and spatial aesthetics could be added, along with finer-grained visual and perceptual analysis [57]. Third, physiological indicators are also an important basis for comfort assessment; when subjective perception shows no significant difference, physiological measures may still differ, and combining the two would be valuable. Finally, multi-city validation and longitudinal research on the dynamic stability of population preferences are also directions worth pursuing further.

5. Conclusions

This study uses Fuzhou, a representative city of the hot-humid climate, as a case to investigate how the summer visual–thermal environment and thermal-preference profiles influence residents' outdoor thermal comfort (TCV).

First, regarding the relative contribution of the visual and thermal environments to overall thermal comfort, a clear difference was observed, with the thermal environment (74.4%) far exceeding the visual environment (25.6%); globe temperature (T_g), relative humidity (RH), and air temperature (T_a) are the core thermal factors, and the three strongest pairwise interactions ($T_g \times RH$, $T_a \times T_g$, $T_a \times RH$) all occur within the thermal environment, dominating the formation of outdoor thermal comfort in hot-humid regions. Notably, the contribution of the visual environment is not fixed but varies substantially with profile type—decreasing from 29.6% in the heat-sensitive profile to 7.2% in the heat-tolerant profile, with the highest being about four times the lowest.

Second, cluster analysis identified three stable thermal-preference profiles—heat-sensitive (56.4%), wind-seeking (20.3%), and heat-tolerant (23.3%)—whose thermal responses differ markedly from one another: the neutral temperature is highest for the heat-tolerant profile (35.85 °C) and lowest for the heat-sensitive profile (29.90 °C), a difference of nearly 6 °C, comparable in magnitude to the inter-city differences reported in the existing literature; the comfort bandwidth is widest for the heat-sensitive profile (9.03 °C) and narrowest for the heat-tolerant profile (4.13 °C), the former being 2.2 times the latter. This indicates that the profiles can effectively explain individual heterogeneity in outdoor thermal comfort.

Third, the explanatory power of the thermal-preference profile and demographic characteristics was further compared. The results show that the profile has no significant

association with sex or BMI, only a weak association with age (Cramér's $V = 0.223$), and that it cannot be explained by age: its explanatory power for the variance in TCV ($\eta^2 = 0.254$) is 4.9, 18.1, and 23.1 times that of age (0.051), sex (0.014), and BMI (0.011), respectively; after controlling for age, the profile still explains an additional 20.9% of the TCV variance, whereas age, after controlling for the profile, explains only an additional 0.9%. This indicates that the profile is an individual-difference dimension that is relatively independent of demographics.

In summary, outdoor thermal comfort during the hot-humid summer is dominated by the thermal environment and significantly modulated by individual thermal-preference profiles; consequently, using the full-sample mean (neutral $T_g = 33.97^\circ\text{C}$) as a single design reference would deviate substantially from the needs of the heat-sensitive profile, which accounts for 56.4% of the sample. These findings translate into concrete design implications for age-friendly hot-humid residential environments. First, differentiated spatial design should adopt the needs of the heat-sensitive profile as the constraint boundary, prioritizing greenery, shading, and landscape-based cooling in highly irradiated open sites to lower the effective radiant load toward the profile's low neutral temperature [50]. Second, for the wind-seeking profile, layout and building enclosure should be organized to promote natural ventilation in enclosed, low-wind sites [52]. Third, for the heat-tolerant profile, whose comfort is governed almost entirely by the thermal environment and whose tolerance range is narrow, design should focus on suppressing sharp temperature–humidity fluctuations rather than on visual interventions. Finally, incorporating thermal-preference profiles as a stratification factor into research on the heterogeneity of outdoor thermal comfort offers an effective way to improve the fit between sites and thermal comfort and to refine the assessment system.

Author Contributions: Conceptualization, F.D. and Y.B.; methodology, F.D. and H.L.; software, F.D.; validation, F.D., H.L. and W.Z.; formal analysis, F.D.; investigation, F.D., H.L. and W.Z.; resources, Y.B.; data curation, F.D.; writing—original draft preparation, F.D.; writing—review and editing, Y.B. and H.L.; visualization, F.D.; supervision, Y.B.; project administration, Y.B.; funding acquisition, F.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Department of Finance of Fujian Province, grant number GY-Z24180 (Research and Development of Prefabricated Three-Dimensional Greening Carbon-Reduction Modules for Buildings).

Institutional Review Board Statement: This study is an anonymous questionnaire study involving human subjects, conducted in accordance with the Declaration of Helsinki, and approved by the Science and Technology Ethics Committee of Fujian University of Technology (approval No. FJUT-J2026081) on 25 June 2026.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Acknowledgments: The authors would like to thank all the respondents who participated in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Glossary of Key Concepts

Outdoor thermal comfort (OTC): the subjective evaluation of how comfortable people find the outdoor thermal environment.

Thermal preference: an individual's desired direction of change for a given environmental factor, for example a wish for lower air temperature, higher wind speed, or weaker solar radiation; it reflects a psychological disposition rather than a demographic attribute.

Thermal-preference profile: a subgroup of individuals who share a similar multidimensional pattern of thermal preferences, identified in this study by K-Modes clustering (heat-sensitive, wind-seeking, and heat-tolerant).

Neutral temperature: the globe temperature at which the average thermal sensation is neutral, that is, neither warm nor cool.

Comfort bandwidth: the span of globe temperature over which conditions are still judged comfortable; a wider bandwidth denotes greater tolerance.

Maladaptation slope: the rate at which thermal comfort deteriorates as conditions depart from the neutral temperature; a steeper slope denotes a faster loss of comfort.

Visual–thermal environment: the joint perceptual context formed by what people see (greenery, sky, buildings, and color) and the physical thermal conditions (air temperature, humidity, wind, and radiation).

Explainable machine learning (SHAP): a modeling approach that predicts an outcome and also attributes that prediction to each input variable, revealing how much each factor contributes.

Abbreviations

The following abbreviations are used in this manuscript:

OTC	Outdoor Thermal Comfort
TCV	Thermal Comfort Vote
TPR	Air-Temperature Preference
RHPR	Relative-Humidity Preference
VPR	Wind-Speed Preference
SPR	Solar-Radiation Preference
Ta	Air Temperature
Tg	Globe Temperature
RH	Relative Humidity
v	Wind Speed
MRT	Mean Radiant Temperature
UTCI	Universal Thermal Climate Index
GVI	Green View Index
BVI	Building View Index
SVI	Sky View Index
CRI	Color Richness Index
BMI	Body Mass Index
SHAP	SHapley Additive exPlanations
MCA	Multiple Correspondence Analysis
ARI	Adjusted Rand Index
VIF	Variance Inflation Factor
FDR	False Discovery Rate
SD	Standard Deviation

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