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Revisiting the dynamics of car cabin environment and driver comfort

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Revisiting the dynamics of the car cabin environment and its impact on driver comfort is essential, as these concepts have not been explored in recent years. Older methods of assessing driver comfort and cabin environments require elaborate experimental settings and prolonged engagement of study participants, making repeatability difficult. Therefore, this study develops a model for study models the car cabin environment based on temperature, humidity, and CO₂ levels using a thermal imager, an air quality device, and open-source temperature and humidity data. This study also determines whether the impact of the cabin thermal environment on driver comfort (skin dryness, eye fatigue, body fatigue, and body heat) can be quantified based on driver perceptions. The study results showed that body fatigue decreased from 4.2 to 2.7 when the average relative humidity is reduced from 37.2% to 24.2%, and the temperature dropped from 41.8°C to 40.0°C. Notably, the impact of air temperature on the cabin thermal environment was 1.8 times stronger than that of the car skin temperature. Cabin temperature was found to be a better predictor of driver (dis)comfort than cabin humidity and CO₂ levels. A 10 min exposure to summer heat in the UAE was found to have a significant effect on drivers' perceptions of body fatigue, body heat, and eye fatigue. Overall, these findings have implications for car cabin ergonomics and future thermal comfort research.

KEYWORDS

cabin environment, driver comfort, thermal camera, likert scale, linear regression

1 Introduction

Studies concerning rising heat in urban areas seldom discuss its impact on car cabins and drivers (Joubert et al., 2011; Nakano and Tanabe, 2020; Marcotullio et al., 2022). For example, Nakano and Tanabe (2020) investigated the thermal impacts of air-conditioned (AC) and non-AC spaces on occupants, focusing exclusively on the heat characteristics of the built environment. Similar studies on the heat impacts of AC and non-AC car cabins on drivers have not been discussed in the relevant literature. This selective focus has led to the literature that proposes heat management strategies disconnected from driver needs. For example, one study presented how to determine optimal tree placement to mitigate urban heat (MacLachlan et al., 2021). Another study

proposed enhancing basic services, infrastructure, awareness, and education among residents to enhance urban heat management practices (Adegun et al., 2022). A driver-centered approach to the impacts of urban heat is lacking in the literature.

Overheated vehicle cabins cause, on average, 37 child deaths per annum in the United States (Horak et al., 2017). High humidity in the car cabin can affect driver concentration, situation handling, eye comfort, and visual fatigue (Tsutsumi et al., 2007). Because CO₂ concentration in the car cabin is associated with driver fatigue (Mathur, 2016), the in-cabin environment has implications for driver health and comfort, but studies have neglected this underlying relationship. Crizzle et al. (2017) searched several renowned databases (Pubmed, CINAHL, Scopus, and PsycINFO) for articles on the health and wellness of truck and bus drivers in Canada and the United States; their analysis of 33 peer-reviewed articles published between 2000 and 2017 revealed that smoking, obesity, hypertension, poor diet, lack of exercise, stress, and sleep were evaluated as major problems for drivers (Crizzle et al., 2017). This exclusion of the cabin environment impact from the literature on driver health and comfort could undermine the significance of regulating cabin environment. Policymakers, fleet managers, and drivers might disregard the cabin thermal profile and air quality.

Summertime temperatures in the UAE can reach 51°C, uncomfortable to remain outdoors. The effects of this heat level on workers in the construction and oil and gas industries have been well documented in the literature (Siddique et al., 2019). Comprehensive programs to reduce heat-related illness for workers in the UAE and other Middle Eastern countries exist (Joubert et al., 2011). However, the effects of heat on car drivers are typically disregarded based on the assumption that car ACs are sufficient to offer the appropriate degree of comfort. Instead, the focus is almost exclusively on 'at risk' workers, such as farmers, construction laborers, firefighters, miners, soldiers, and proletarians (Xiang et al., 2014). This neglect has resulted in a lack of engineering and administrative control measures to reduce drivers' exposure to heat. The use of complex experimental settings in previous studies (Tsutsumi et al., 2007; Mathur, 2016) could have contributed to a lack of research on driver comfort and the cabin environment. For example, Tsutsumi et al. (2007) required study participants to sit in a climate chamber for 5 h to evaluate the impact of the cabin environment on their comfort levels. Finding volunteers to sit for that long in a controlled environment, even when it is pleasant, is difficult. Creating a climate chamber may also not be feasible in many cases. Thus, introducing simpler and more intuitive methods to profile the car cabin environment and its impact on driver health can encourage more scholars (or policymakers, for that matter) to participate in this research domain.

This exploratory study has two main goals: (i) to revisit the dynamics of the car cabin environment in the context of hot UAE summers, and (ii) to demonstrate the usefulness of a simpler,

psychometric approach to evaluate the impact of cabin environment on driver comfort. The study assumes that the cabin environment can be modeled using external factors such as car skin temperature, air temperature, and air humidity. Thermal conditions (temperature and relative humidity) and air exchange (CO₂ concentration) are considered the main attributes of the cabin environment (Croitoru et al., 2015; Szczurek and Maciejewska, 2016). The impact of these factors—temperature, relative humidity, and CO₂ concentration—on driver comfort is evaluated using four constructs: body fatigue, eye fatigue, body heat, and skin dryness. These constructs are widely regarded as measures of driver comfort (Tsutsumi et al., 2007; Danca et al., 2016). This study is expected to contribute to the literature on car cabin thermal dynamics and associated driver comfort levels. This study is novel because it explores the impact of cabin thermal environments on driver comfort, which has remained unexplored in the context of the UAE, despite the country's soaring levels of heat witnessed during the summers. The use of real field settings, as opposed to climate chambers to elicit more accurate driver responses is another innovative aspect of this study. The latter (climate chamber) methodology, used in most studies concerning cabin environment and driver comfort, does not mimic real-life situations wherein car users (while walking to the parking lot) face external environmental heat before experiencing the cabin thermal environment. This pre-exposure to heat might affect how drivers rate their cabin environment. Finally, this study simplifies existing research methods for assessing the drivers' comfort level by employing fewer instruments and relying more on psychometric approaches based on statistical analysis to explore the relationship between cabin environment and driver comfort.

2 Materials and methods

The overall objective of this study is to measure the impact of external thermal conditions, including car skin temperature, on the cabin thermal profile, and relate it to driver comfort. The air conditions outside the cars are expected to affect the air conditions inside the cars, thereby affecting driver experience (level of comfort). Because car ACs can alter cabin conditions (temperature and humidity), drivers' experiences before and after turning on the ACs are evaluated. Exposure to non-AC conditions would help simulate the external environment conditions that drivers face while walking to and from the car parking. While long-term (more than 15 min) exposure to high-temperature levels can induce heat stroke, little is known about the impact of short-term heat exposure.

This study included a car cabin and driver comfort monitoring experiment, conducted on 26 May 2022, at the UAE University visitors' parking area located in Al Ain city, UAE. The experimental settings included ten white cars parked under different shading conditions: eight under an

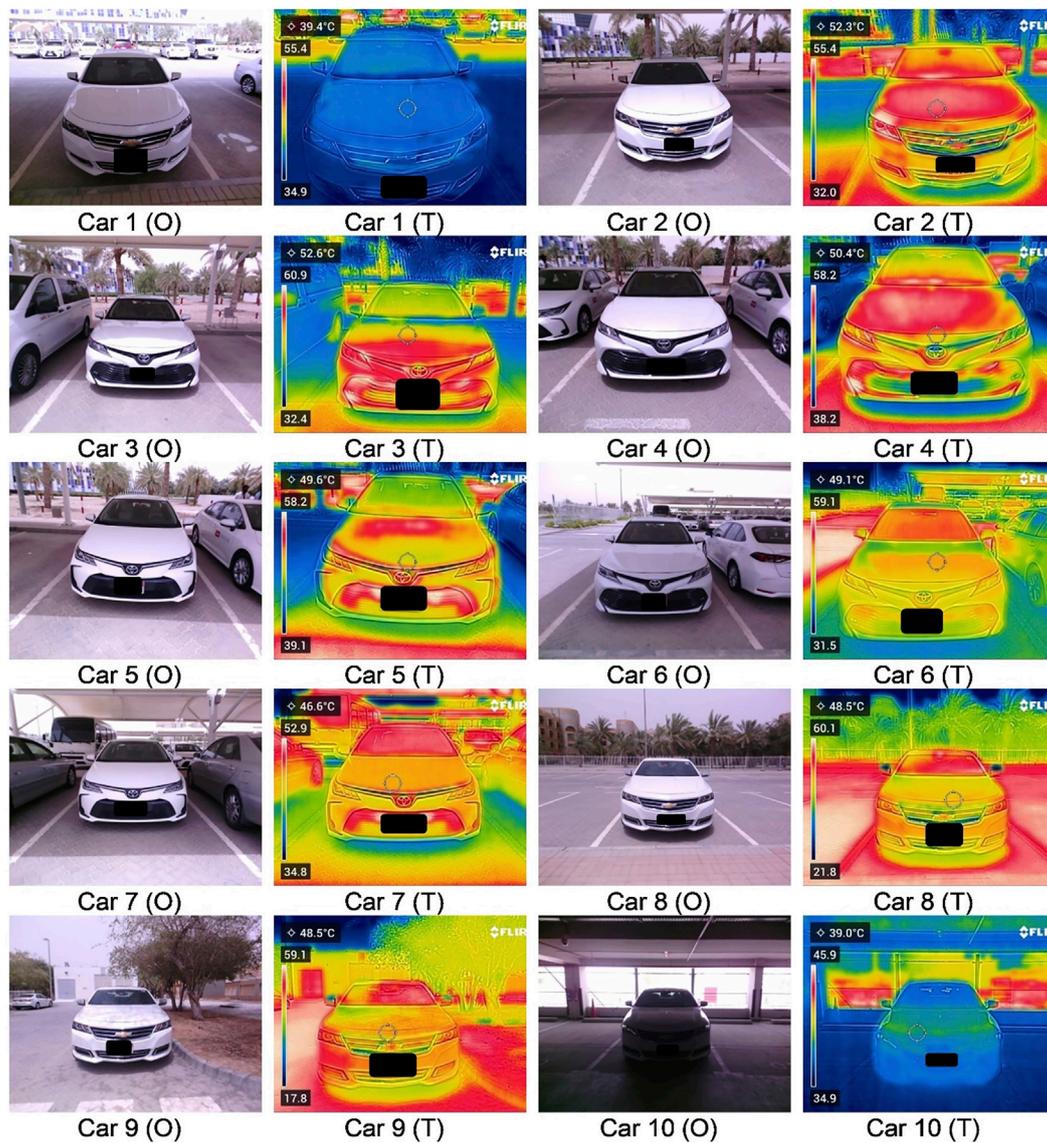


FIGURE 1
Optical and thermal images of cars parked under various shading conditions.

outdoor covered parking lot, one under a tree, and one in an indoor parking compound. Different shading conditions were meant to introduce random variation in the car cabin thermal environment. All cars had the same (white) color to rule out the reported impact of car color on the cabin thermal profile (Levinson et al., 2011). Because car materials can impact the cabin thermal environment (Marshall et al., 2019). Cars of similar make and model were used in this experiment to neutralize this effect. All cars were gulf variants of standard sedans of Japanese origin. At random periods during the day, the research team visited each car individually to monitor the car skin temperature and cabin air quality (temperature,

humidity, and CO₂ levels). A handheld thermal imager was used to photograph the cars (Figure 1). Because various components of the car body showed different temperatures, for the sake of consistency in recorded values, the temperature of the hottest part of the car skin was recorded.

Car cabin temperature and humidity levels were measured using an off-the-shelf air quality monitor. The device could log temperature and humidity levels at 10 s intervals. The surrounding air temperature and humidity levels were retrieved from an open-source metrological data repository that records weather data at hourly resolution (Weatherspark,

TABLE 1 Thermal profiling of car skin, car cabin, and the surrounding air.

Car no.	Car skin temperature (T_s)	Cabin humidity (H_c)	Cabin temperature (T_c)	Air humidity (H_a)	Air temperature (T_a)
1	38.0	40.0	35.0	41.0	32.0
2	48.5	35.2	40.0	37.0	33.0
3	51.0	46.2	38.6	32.0	34.0
4	51.6	39.8	39.5	28.0	35.0
5	53.7	45.2	41.5	22.0	38.0
6	47.8	39.5	43.0	17.0	39.0
7	47.7	37.7	41.9	15.0	40.0
8	50.6	29.6	50.0	12.0	40.5
9	47.3	28.0	49.7	11.0	41.0
10	37.7	30.3	38.7	11.0	41.0
Mean	47.4	37.2	41.8	22.6	37.4

2022). The temperature was assumed to remain constant throughout each hourly interval. Table 1 shows the thermal properties of the car skin, car cabin, and surrounding air. Note that the cabin humidity (H_c) and cabin temperature (T_c) values show the averages of 5 minutes of data logged for each car (Table 1).

To measure the impact of cabin air quality on driver experience, two study participants were assigned per car to sit in the front seats for 10 min. The car AC was kept off for the first 5 min and on for the last five. Moreover, the car windows were kept closed during the experiment. In total, 11 participants participated in the driver perception survey: ten respondents (one per car) and one surveyor (the same person for all ten cars). The reason for assigning a different participant each time was to ensure that the study participants did not face heat-related illnesses such as heat exhaustion, or worse heat stroke, which could set in after 10–15 min of exposure to the heat levels observed in the UAE. The surveyor, who had to successively sit in all ten cars, was protected from the heat by limiting his sitting time to that part of the experiment when car ACs were turned on. Notably, the participants were told that they could leave the car (or turn on the AC) at any point during the experiment, should the cabin environment start feeling too hot. The purpose was to record the impact of changing thermal conditions on driver comfort. Apart from H_c and T_c , the cabin- CO_2 (C_c) levels were also logged to understand the impact of CO_2 concentration on driver comfort. The comfort level was measured in terms of body fatigue, eye fatigue, body heat, and skin dryness, using a five-point Likert scale where one meant the least impact and five meant the greatest.

Table 2 shows the passenger experience data under varying car cabin conditions. Each case includes 5-min average cabin air quality data with a corresponding passenger comfort rating. Humidity was measured in relative %, the temperature in $^{\circ}C$, and CO_2 in parts per million. In total,

there were 20 cases, and data were collected at various times of the day.

3 Results

Data analysis (Table 1) shows that the mean car cabin temperature ($41.797^{\circ}C$) exceeds the mean air temperature ($37.350^{\circ}C$) but is lower than the mean car skin temperature (47.390). This occurred even though all cars were parked under shaded conditions. The car parked under a tree shade registered a cabin temperature of $50^{\circ}C$ (nine units higher than the average cabin temperature of the sample cars). Because all cars used in the experiment were white, the impact of car color on cabin temperature could be ignored. The highest variation in temperature was observed in the car skin temperature ($SD = 5.4206$).

3.1 Car cabin temperature

Linear regression modeling assumptions were tested to model car cabin temperature as a dependent variable and air temperature and car skin temperature as predictors. Table 3 shows the correlations among the variables of interest. The correlation between air temperature and car skin temperature was 0.02 and was not significant. To alleviate multicollinearity concerns, the correlations between independent variables (air temperature and car skin temperature in this case) should not exceed 0.7 (Gregorich et al., 2021). Thus, multicollinearity is not a concern here. Another desirable condition is the correlation value between predictor variables and outcome variables should exceed 0.3 (Ratner, 2009). Table 3 shows that the correlation values between cabin temperature and air temperature and car-skin temperature were 0.7 and 0.405, respectively. These correlation values are desirable.

TABLE 2 Passenger experience under varying cabin thermal conditions.

Case No	H _c	T _c	C _c	Body fatigue	Eye fatigue	Body heat	Skin dryness
1	40.0	35.0	1998.0	3	4	4	5
2	35.2	40.0	1,207.2	4	2	4	5
3	46.2	38.6	2828.1	4	2	4	1
4	39.8	39.4	2440.6	3	2	3	4
5	45.2	41.4	1,580.2	5	3	3	5
6	39.5	43.0	3,718.8	5	5	5	5
7	37.7	41.8	2347.1	5	5	5	5
8	29.6	49.9	2350.1	5	5	5	5
9	28.0	49.7	2117.1	5	5	5	3
10	30.3	38.7	1795.9	3	1	2	2
Averages	37.2	41.8	2238.3	4.2	3.4	4.0	4.0
11	24.0	32.0	2283.0	2	2	3	4
12	29.0	39.6	2725.0	3	1	3	4
13	34.3	36.6	3,908.0	3	1	3	1
14	23.3	37.4	2610.0	1	1	2	3
15	23.7	39.1	2950.7	3	1	2	3
16	24.9	42.5	3,334.5	3	3	4	4
17	25.7	40.5	2900.0	3	3	4	4
18	16.9	49.4	2624.4	4	4	4	4
19	19.9	45.7	2159.6	4	3	3	1
20	20.6	37.1	2455.0	1	1	1	1
Average	24.2	40.0	2795.0	2.7	2.0	2.9	2.9

TABLE 3 Correlations between car cabin temperature, air temperature, and car-skin temperature.

Correlations

		T _c	T _a	T _s
Pearson Correlation	T _c	1.000	0.700	0.405
	T _a	0.700	1.000	0.020
	T _s	0.405	0.020	1.000
Sig. (1-tailed)	T _c	.	0.012	0.123
	T _a	0.012	.	0.478
	T _s	0.123	0.478	.
N	T _c	10	10	10
	T _a	10	10	10
	T _s	10	10	10

The normal probability–probability (P-P) plot shows that the points follow a linear trend (Figure 2). Although the points deviate from the line slightly in the middle, overall, they follow a linear line, which is satisfactory. The scatterplot (Figure 2) shows point distribution as none exceeds +3 or −3 units (standard deviation) along either axis. This compactness may be attributed to the small sample size used in this study. For studies involving larger sample sizes, outliers are usually observed. Such points (outliers) may be removed from the analysis. Further discussion in this regard is beyond the scope of this article and interested readers might want to refer to the relevant literature (Terrin et al., 2005; Sarikaya and Gleicher, 2018).

Other parameters measured to test modeling assumptions included standard residual and Cook's distance (Table 4). The standard residual values ranged from −0.971 to 1.397 which is well within the threshold limit (± 3). Likewise, the average Cook's Distances was 0.226; well below the threshold of 1.0 which shows

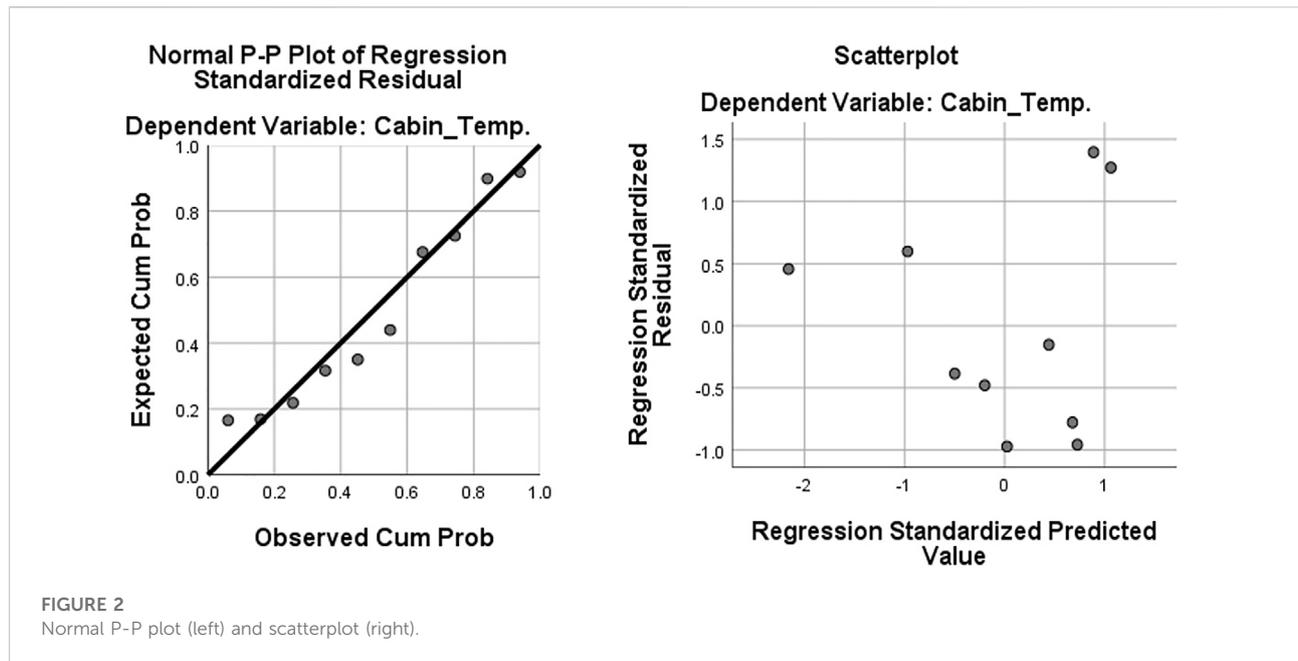


TABLE 4 Residual statistics.

Residuals statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	33.521	45.870	41.797	3.8314	10
Std. Predicted Value	-2.160	1.063	0.000	1.000	10
Standard Error of Predicted Value	1.146	2.672	1.715	0.484	10
Adjusted Predicted Value	30.383	46.304	41.850	4.8639	10
Residual	-3.1489	4.5271	0.0000	2.8587	10
Std. Residual	-0.971	1.397	0.000	0.882	10
Stud. Residual	-1.505	1.582	-0.008	1.079	10
Deleted Residual	-7.5610	5.8052	-0.0527	4.4862	10
Stud. Deleted Residual	-1.695	1.826	0.015	1.167	10
Mahal. Distance	0.225	5.217	1.800	1.635	10
Cook's Distance	0.001	1.058	0.226	0.324	10
Centered Leverage Value	0.025	0.580	0.200	0.182	10

a. Dependent Variable: T_C.

that overall, data points do not exhibit peculiarities. However, the maximum Cook's distance was 1.058 indicating the presence of at least one outlier (an influential term that can lead to a regression model presenting a distorted image). Identifying such influential terms requires finding the Cook's distance value of the individual data points. Removing the outliers from the data set requires finding the impact of such removal on the least square estimates. Such detailed analysis might not be warranted for exploratory studies such

as this one wherein the data points showed a reasonably low average value (of Cook's distance). Studies featuring large sample sizes and aiming to establish the relationships, however, need to analyze the possibility of removing of outliers from the data points. For more insights into this topic, interested readers should refer to [Cook \(1977\)](#).

The R-Square value for the model was 0.642, indicating that the predictor variables could predict 64% of the variation in the

TABLE 5 Model summary, ANOVA, and coefficients of cabin temperature.

Model summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	0.801a	0.642	0.540	3.2414	0.642	6.287	2	7	0.027

ANOVA^a

Model	Sum of Squares	Df	Mean Square	F	Sig.
1	132.119	2	66.059	6.287	0.027b
	73.549	7	10.507		
	205.668	9			

COEFFICIENTS AND COLLINEARITY^a

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error				Beta	Zero-order	Partial	Part	Tolerance
1	(Constant)	-9.715	14.766		-0.658	0.532					
	Ta	0.942	0.308	0.692	3.060	0.018	0.700	0.756	0.692	1.000	1.000
	Ts	0.345	0.199	0.391	1.730	0.127	0.405	0.547	0.391	1.000	1.000

a. Dependent Variable: Tc b. Predictors: Ta Ts

dependent variable (Table 5). However, given the small sample size in this study, adopting a conservative estimate of the R Square value (adjusted R-Square) seems reasonable. The adjusted R Square value of the model is 0.54. Usually, R-Square values of more than 0.3 indicate acceptable regression models. The analysis of variance (ANOVA) showed that the regression model was significant at a 95% confidence level i.e., the p -value was less than 0.05. More specific measures of multicollinearity include tolerance and variance inflation factors (VIF) (Miles, 2014). The tolerance describes how much variability of a predictor variable is not explained by other independent variables in the model. The desired value of *tolerance* should exceed 0.1. Likewise, the desired value of VIF should be below 3, though some scholars (O'Brien, 2007) permit higher VIF values. Table 5 shows that the tolerance and VIF value for both predictor variables is one, satisfying multicollinearity assumptions.

The air temperature variable has a standardized coefficient of 0.692 as compared to car skin temperature of 0.391, implying that more (nearly twice) variation in the outcome variable is explained by air temperature than car skin temperature. Notably, standardized coefficients offer a better comparison between the predicting power of independent variables compared to unstandardized coefficients. The unstandardized values of air temperature (0.942) and car skin

temperature (0.345) are important from a modeling perspective. Thus, the car cabin thermal environment prediction model takes the following form based on the results of this study. Note that the air temperature is a significant predictor of the car cabin temperature ($p < 0.05$), but the car skin temperature is not ($p > 0.05$).

$$\begin{aligned} \text{Car Cabin Temperature} = & 0.942 * (\text{Air Temperature}) \\ & + 0.345 * (\text{Car Skin Temperature}) \\ & - 9.715 \end{aligned} \quad (1)$$

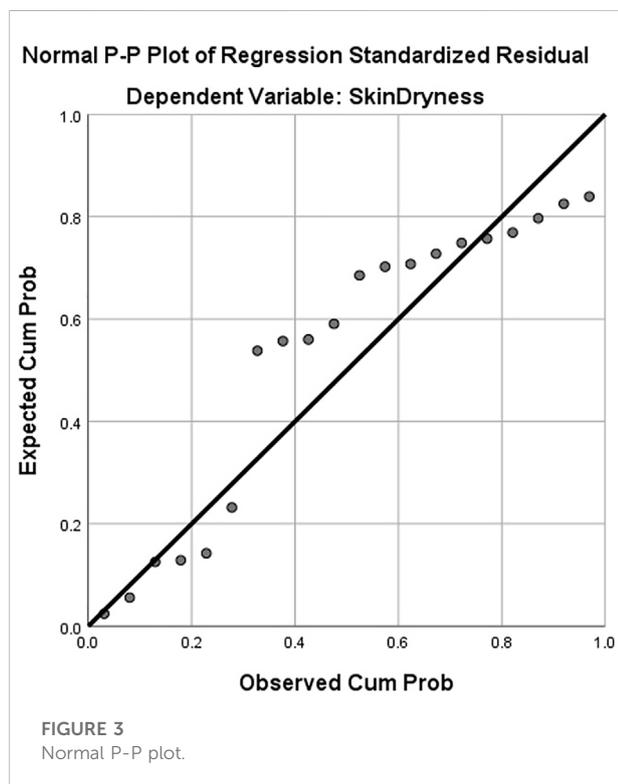
3.2 Passenger comfort evaluation

The impacts of cabin humidity, cabin temperature, and CO₂ concentration on the participants' perception of body heat, body fatigue, eye fatigue, and skin dryness were measured (Table 2). The participants rated their experience under 20 varying conditions. Since the driver engagement was brief (15 min) and there were distinct boundary conditions and respondents for every car, it was deemed necessary to validate that the recorded measurements would adequately

TABLE 6 Cronbach's alpha: Item-total statistics.

Item-total statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Body Fatigue	9.60	13.305	0.720	0.633	0.835
Eye Fatigue	10.35	10.661	0.836	0.769	0.783
Body Heat	9.60	12.884	0.865	0.797	0.789
Skin Dryness	9.60	13.200	0.536	0.327	0.913



describe driver comfort levels. To this end, the internal consistency of the driver comfort data was measured using Cronbach's α . A minimum α value of 0.7 is required to ensure internal consistency (Tavakol and Dennick, 2011). The α value for driver comfort data turned out to be 0.880 showing high internal consistency. To improve the validation, the analysis of the sensitivity of α value to the scale items was performed (Table 6). The analysis showed that the responses on skin dryness were not consistent, as α jumped to 0.913 upon removing *skin dryness* from driver comfort data. Therefore, skin dryness was excluded from subsequent regression modeling in this study. The

statistical significance of the relationships was also tested. Thus, the overall reliability of the research method was ensured.

To find if the skin dryness variable could be modeled using this data, a normal P-P plot of regression standardized residuals was plotted (Figure 3). The skin dryness rating data points did not satisfy the normality assumption. A non-linear regression or nonparametric statistical analysis was also unlikely to yield meaningful results because of the internal inconsistency of the measurement scale for skin dryness. Therefore, skin dryness was excluded from further analysis.

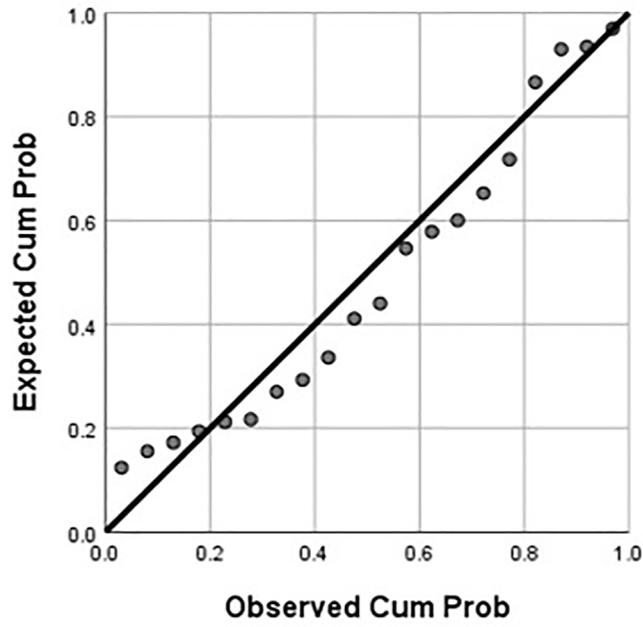
3.2.1 Perceived eye fatigue

Perceived eye fatigue was modeled as a function of H_c , T_c , and C_c levels. The correlations among predictor variables were less than 0.7, alleviating multicollinearity concerns. The correlation between cabin temperature and eye fatigue exceeded 0.3 indicating that temperature is a good predictor of eye fatigue. Humidity and CO_2 show insignificant weak correlations (<0.3) with eye fatigue. Diagnostic plots revealed that the assumptions of normality and homoscedasticity were satisfied (Figure 4). Other assumptions of linear regression including independence and linearity, were also satisfied but were not discussed here considering the exploratory nature of the study and for the sake of brevity. Interested readers are referred to the relevant literature (James et al., 2021) for further diagnostics of the data used in the study (Table 2).

The R-Square value for the model was 0.529, implying that the independent variables could predict a 52.9% variation in the dependent variable (Table 7). However, given the small sample size ($n = 20$), adopting a more conservative estimate of the R Square value (adjusted R Square) seems reasonable here. The adjusted R Square value for the model was 0.441 which is acceptable. The ANOVA results showed that the regression model was significant at a 95% confidence level i.e., the p -value is less than 0.05. The standardized coefficients of humidity,

Normal P-P Plot of Regression Standardized Residual

Dependent Variable: Eye Fatigue



Scatterplot

Dependent Variable: Eye Fatigue

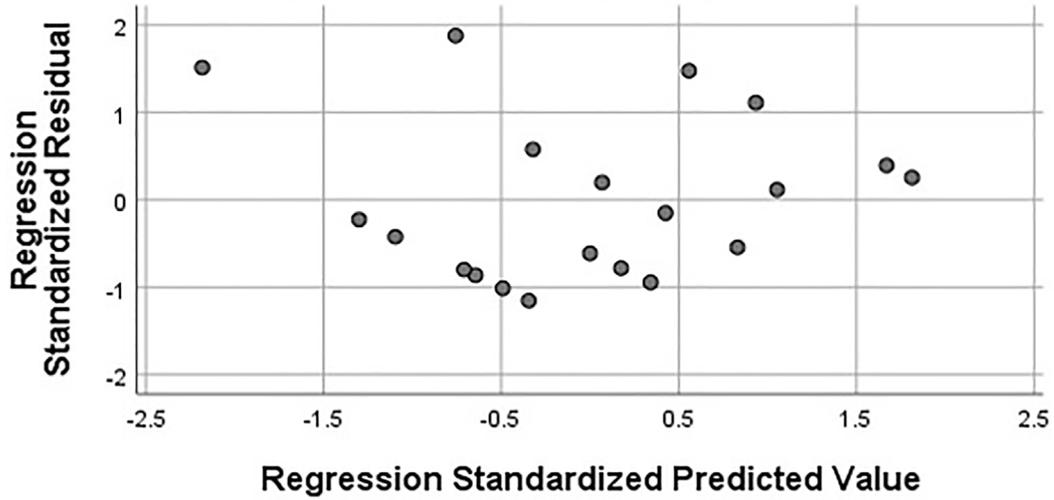


FIGURE 4
Diagnostic plots; eye fatigue.

TABLE 7 Model summary, ANOVA, and coefficients of eye fatigue.

Model summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	0.728a	0.529	0.441	1.140	0.529	6.000	3	16	0.006

ANOVA^a

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	23.401	3	7.800	6.000	0.006b
	Residual	20.799	16	1.300		
	Total	44.200	19			

COEFFICIENTS^A

Model		Unstandardized Coefficients		Standardized Coefficients			T	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta	Zero-order	Partial			Part	Tolerance	VIF		
1	(Constant)	-8.506	2.924				-2.909	0.010					
	HC	0.057	0.031	0.321			1.821	0.087	0.173	0.414	0.312	0.948	1.055
	TC	0.229	0.056	0.723			4.117	0.001	0.657	0.717	0.706	0.955	1.047
	CC	4.334E-5	0.000	0.019			0.109	0.915	-0.045	0.027	0.019	0.986	1.014

a. Dependent Variable: Eye_Fatigue b. Predictors: (Constant), CO₂, TC, HC

temperature, and CO₂ were 0.321, 0.723, and 0.019, respectively, showing that cabin temperature explains more than twice the variation in eye fatigue as compared to cabin humidity. CO₂ levels explained little to no variance in the outcome variable. Cabin temperature is a significant explanatory variable ($p < 0.05$), but humidity and CO₂ levels were not. The collinearity statistics were satisfactory (tolerance > 0.3 and VIF < 3). Overall, the eye fatigue prediction model takes the following form.

$$\text{Eye Fatigue} = 0.57*(H_c) + 0.229*(T_c) - 8.506 \quad (2)$$

Because the impact of CO₂ concentration was negligible (to the order of 10^{-5}), it was excluded from the final model.

3.2.2 Body fatigue

Like eye fatigue, body fatigue was modeled as a function of H_c, T_c, and C_c levels. The correlation between body fatigue with predictors was more than 0.3 in the case of H_c and T_c and less in

the case of C_c (Table 8). It implies that CO₂ level might not be a strong predictor of body fatigue. The correlation of body fatigue is highest for T_c (0.680), as shown in Table 8. Notably, the correlations among predictor variables were less than 0.7, reducing the multicollinearity concerns. Diagnostic plots showed that the assumptions of normality and homoscedasticity were not violated (Figure 5).

The adjusted-R Square value of the model was 0.787 which was significantly powerful, especially considering the small sample size (Table 8). Thus, the model could explain 78.7% of the variance of the body fatigue variable. The analysis of variance (ANOVA) showed that the regression model was significant at a 95% confidence level. The standardized coefficients of H_c and T_c were 0.606 and 0.801, respectively. It implied that the latter can explain 25% more variations in body fatigue than the former. On the other hand, the C_c level explained little to no variance in body fatigue (standardized coefficient = -0.035). T_c and H_c were statistically significant ($p < 0.05$), but C_c was not. The collinearity statistics are satisfactory (tolerance > 0.3 and

TABLE 8 Model summary, ANOVA, and coefficients of body fatigue.

Model summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	0.906a	0.821	0.787	0.570	0.821	24.394	3	16	0.000

ANOVA^a

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	23.756	3	7.919	24.394	0.000b
	Residual	5.194	16	0.325		
	Total	28.950	19			

COEFFICIENTS^A

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Correlations			Collinearity Statistics		
		B	Std. Error				Beta	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-7.439	1.461		-5.091	0.000						
	HC	0.087	0.016	0.606	5.570	0.000	0.447	0.812	0.590	0.948	1.055	
	TC	0.205	0.028	0.801	7.392	0.000	0.680	0.879	0.783	0.955	1.047	
	CC	-6.600E-5	0.000	-0.035	-0.332	0.744	-0.130	-0.083	-0.035	0.986	1.014	

a. Dependent Variable: Body_Fatigue

VIF<3). Overall, the body fatigue prediction model is written as follows:

$$\text{Body Fatigue} = 0.087*(H_C) + 0.205*(T_C) - 7.439 \quad (3)$$

Note that the impact of CO₂ concentration on body fatigue was negligible (to the order of 10⁻⁵) and was thus excluded from the final model.

3.2.3 Body heat

Like body fatigue and eye fatigue, body heat was also modeled using H_c, T_c, and C_c as predictor variables. Table 9 showed that the correlation between body heat and T_c was the highest (0.551) was statistically significant ($p < 0.05$). The intercorrelations among predictor variables were less than 0.7, thereby reducing the multicollinearity concerns. The correlations of T_c and H_c with body heat are more than 0.3 indicating that these predictors were good candidates for the intended regression modeling. C_c, on the other hand, showed insignificant ($p > 0.05$) and weak (<0.3) correlations with the body heat rendering its candidacy as a predictor

variable, questionable. Diagnostic plots showed that the assumptions of normality and homoscedasticity were valid (Figure 6).

Given the small sample size, adopting the adjusted R Square value seemed reasonable, which was 0.451 (Table 9). Thus, the model can explain 45.1% of the variance in Body Heat. The ANOVA results showed that the regression model was significant at a 95% confidence level i.e., the p -value was less than 0.05. The standardized coefficients of humidity, temperature, and CO₂ were 0.487, 0.656, and 0.149, showing that the cabin temperature explained the most variation in body heat. However, the CO₂ level explained little to no variance in the outcome variable. Both T_c and H_c were significant explanatory variables ($p < 0.05$), but the C_c Level was not. The collinearity statistics were also satisfactory (tolerance >0.3 and VIF < 3). Overall, the body heat prediction model takes the following form based on the results of this study.

$$\text{Body Heat} = 0.065*(H_C) + 0.156*(T_C) - 5.565 \quad (4)$$

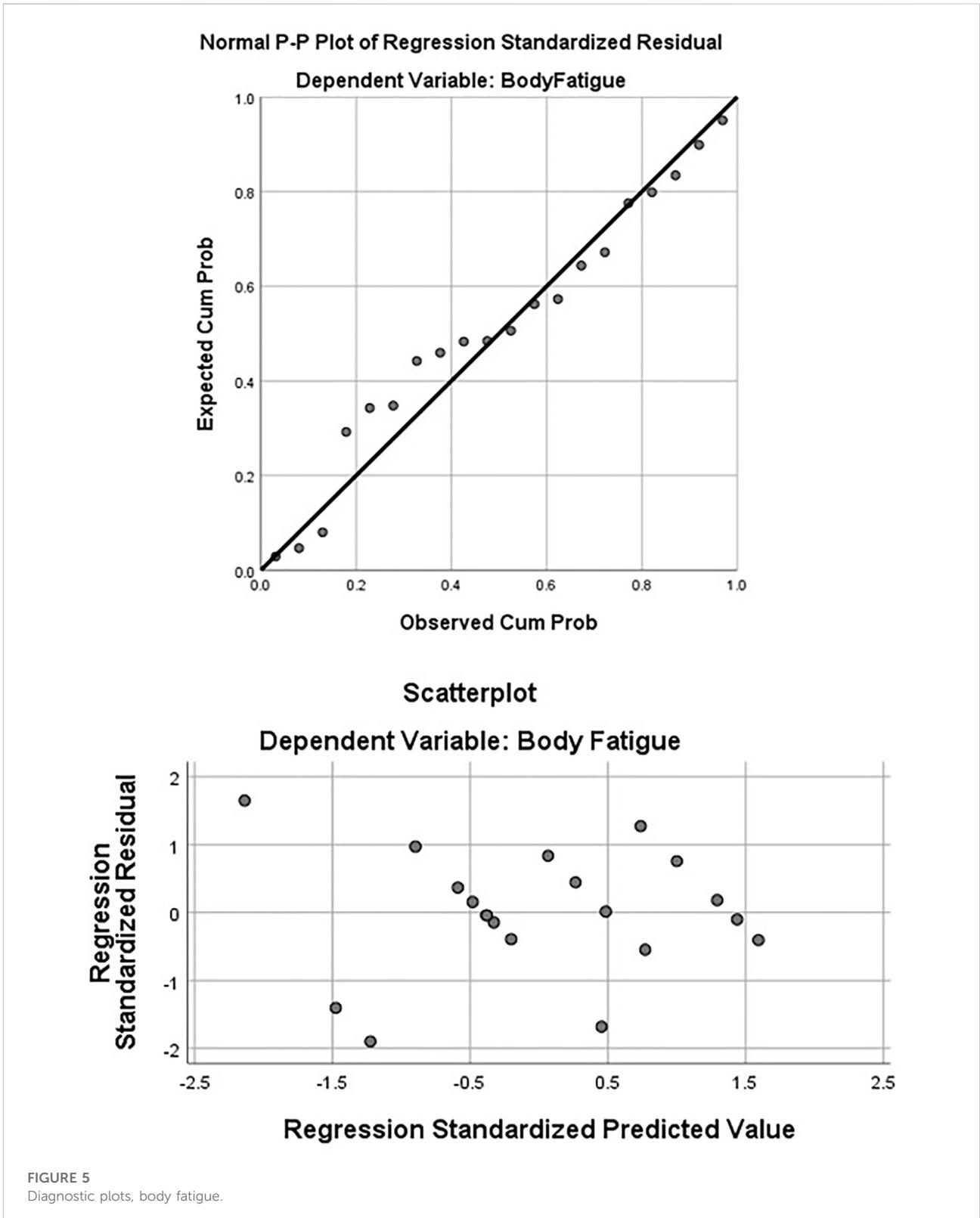


FIGURE 5
Diagnostic plots, body fatigue.

TABLE 9 Model summary, ANOVA, and coefficients of body heat.

Model summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	0.733a	0.538	0.451	0.849	0.538	6.206	3	16	0.005

ANOVA^a

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	13.418	3	4.473	6.206	0.005b
	Residual	11.532	16	0.721		
	Total	24.950	19			

COEFFICIENTS^A

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error				Beta	Zero-order	Partial	Part	Tolerance
1	(Constant)	-5.565	2.177		-2.556	0.021					
	HC	0.065	0.023	0.487	2.791	0.013	0.341	0.572	0.474	0.948	1.055
	TC	0.156	0.041	0.656	3.771	0.002	0.551	0.686	0.641	0.955	1.047
	CC	0.000	0.000	0.149	0.869	0.398	0.072	0.212	0.148	0.986	1.014

a. Dependent Variable: Body_Heat

Note that the impact of CO₂ concentration on body heat was not observed.

4 Discussions

The car cabin environment can be described in terms of thermal and air exchange parameters. The thermal factors used in this study were temperature and humidity and the air exchange factor was CO₂, which is consistent with the literature (Szczurek and Maciejewska, 2016). Intuitively, cabin temperature and humidity can be associated with the surrounding air temperature and humidity. However, simultaneously modeling air temperature and humidity as predictors can be misleading in that the two are strongly correlated, raising multicollinearity concerns. In this study, the correlation between air humidity and the air temperature was found to be perfect (0.995). This is why the cabin environment was studied only as a function of air temperature and not air humidity.

The driver perception of comfort data measured using a five-point Likert scale in this study is ordinal scale data (or at best interval scale data). Still, during the analysis, it is treated as ratio scale data which is a higher-level data type than the ordinal and interval scales. Future studies should treat such data carefully. Before using the data for parametrical statistical analysis, the assumptions of normality, linearity, homoscedasticity, and independence should be tested using diagnostic plots. If any of these assumptions do not hold, scholars should be careful in their choice of analysis methodology. Alternate analysis techniques are available for data that do not follow a normal distribution. For more discussion on this topic, interested readers are referred to the relevant literature on nonparametric statistical techniques (Kraska-Miller, 2013).

The correlation between cabin temperature and the surrounding air temperature was found to be strong (0.7) and significant ($p < 0.05$). However, the correlation between car skin temperature and car cabin temperature was weak (0.02). This may be attributed to several factors including shading conditions

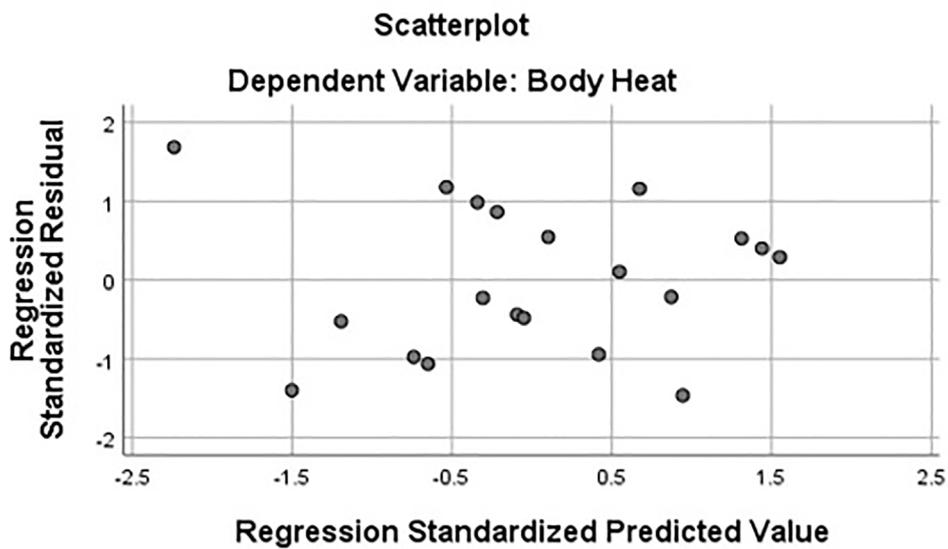
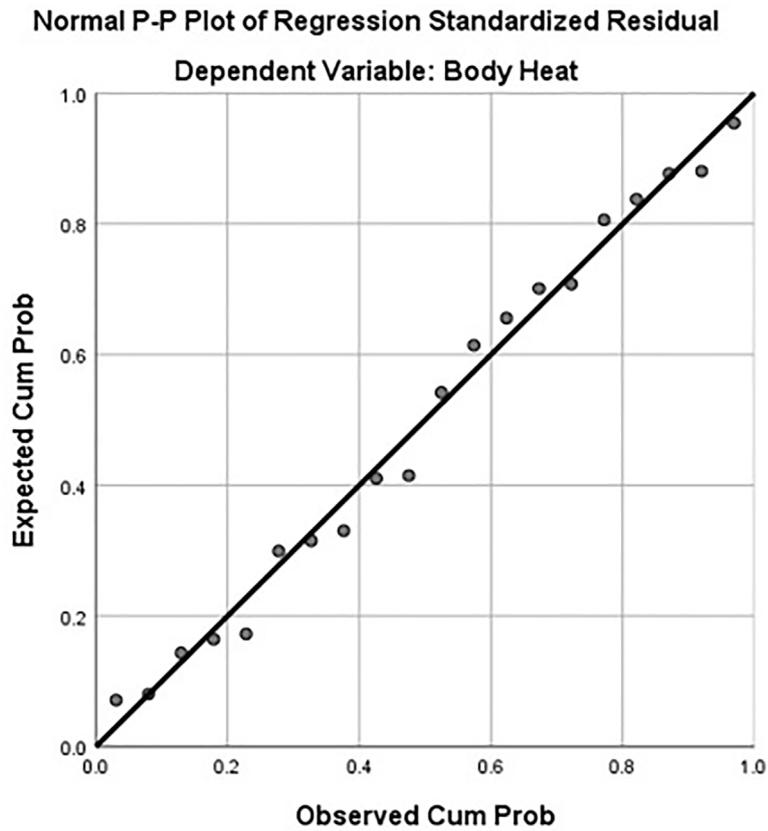


FIGURE 6 Diagnostic plots, body heat.

and the car skin temperature measurement technique used in this study which targeted maximum skin temperature instead of the average skin temperature. Still, this finding warrants further

investigation with a larger sample size. In the final regression model, the air temperature explained three times the variation in the car cabin temperature as compared to the car skin

temperature. Thus, air temperature is a better predictor of the car cabin thermal environment than car skin temperature.

Passenger comfort was measured using three constructs: body heat, body fatigue, and eye fatigue. The attempt to evaluate the fourth construct (skin dryness) was not successful as the internal consistency of data was low and diagnostic plots showed skin dryness data did not follow a normal distribution. The impact of cabin temperature on eye fatigue was estimated to be 2.25 times more than the impact of humidity (Table 7). An increase in temperature and humidity translated into an increase in eye fatigue. Eyeblink suppression and ocular surface irritation are known sources of eye fatigue for drivers (Sullivan, 2008). While more studies are needed to specify the repercussions of visual fatigue on driving tasks, an already-known characteristic of eye fatigue is that it has no permanent effect and can be resolved by taking rest (Megaw, 1995). The amount of rest needed to recover from visual fatigue is unknown (Sullivan, 2008).

The participants also reported an increase in body fatigue at high cabin temperatures and high humidity levels. The impact of cabin temperature on body fatigue was 132% more than that of cabin humidity. Likewise, for body heat, the temperature impact was 134% more than the humidity effect. However, the impact of CO₂ concentration on driver comfort (body fatigue, body heat, and eye fatigue) was negligible. This may be due to short-term exposure to the gas at low concentrations. The maximum level of CO₂ reached during the experiment was 3,908 ppm (Table 2). Future studies might consider assessing the impact of higher concentrations of CO₂ on driver fatigue.

One of the elements of novelty in this study is the use of real field settings to elicit drivers' perceptions of comfort levels concerning the changing cabin thermal profile. Previous studies used lab-based design to evaluate the dynamics of the car cabin environment and related driver experience (Tsutsumi et al., 2007; Mathur, 2016). Moreover, the literature does not offer any study on the impact of cabin heat on the driver comfort level in the UAE, given that the country features one of the hottest summers in the world. Driver experience in everyday situations is a product of both the external (air) and the internal (cabin) thermal profiles which differ from the lab-based experimental where the study participants usually sit in an AC environment before entering the climate chambers for the experiment. Hence, this study is expected to evoke a more lifelike thermal experience among drivers and to gather more realistic data on their comfort levels than the previous studies.

Another contribution of this study is the use of simple instruments only a thermal camera and an air quality measuring device is used for the cabin environment modeling. Another remarkable feature is the brief engagement time for the study participants (around 15 min including 10 min of sitting in the car and 5 min of filling out the questionnaire). Fewer equipment needs and shorter study duration mean that more stakeholders can use this method to study the cabin environment and driver comfort. Moreover, a psychometric approach was

employed to evaluate driver comfort, which was previously analyzed using elaborate experimental settings (Tsutsumi et al., 2007; Mathur, 2016). Besides health impacts, the cabin thermal environment affects fuel consumption (Mansour et al., 2018). Cabin heating issues are also linked with parking behavior (parking choice, duration, visiting hours, etc.). Therefore, this study is expected to attract a broad readership including transport and health policymakers, parking managers, and scholars.

This study's findings can be applied to the assessment of comfort conditions and the design of car cabins according to comfort requirements. Driver comfort improved significantly and quickly (within 5 minutes) as in cabin thermal parameters were enhanced. For example, the average body fatigue reduced from 4.2 to 2.7 when the average relative humidity was reduced from 37.2% to 24.2%, and the temperature from 41.8°C to 40.0°C (Table 2). This finding corroborates the literature that asserts a quicker response to thermal stress in car cabins (Danca et al., 2016). Likewise, eye fatigue and body heat were also reduced from 3.4 to 4.0 to 2.0 and 2.9, respectively. However, note that these improvements in thermal comfort parameters are relative, and not absolute i.e., the study does not quantify thermal comfort levels. Future studies might want to consider differentiating thermal comfort from discomfort to strengthen this study's findings toward improving the ergonomics of car cabin thermal environments.

The limited sample size is one of this study's limitations, which may have diminished the statistical analysis power. This also resulted in the lack of data required for model validation. Therefore, as the title suggests, this study should be treated as an exploratory study to guide future research in this domain. Another limitation is the direct measurement of constructs (body heat, body fatigue, and eye fatigue). Using Likert scale to measure complex constructs can be misleading. This limitation was addressed by ensuring an acceptable level of internal consistency in the employed scale (Table 6). Finally, the time of day when the reading is taken might affect body fatigue, eye fatigue, and body heat. For example, for the body fatigue readings taken in the afternoon, study participants might already be tired due to daylong activity which could affect their item rating on the Likert scale. Future research should consider accounting for the impact of such covariates.

5 Conclusion

This exploratory study demonstrated that modeling the car cabin thermal environment as a function of external air temperature and car skin temperature is feasible. Air temperature has a more pronounced impact on the cabin environment than car skin temperature. The cabin environment affects driver comfort level which can be measured using four constructs: body heat, body fatigue, eye fatigue, and skin dryness.

The first three constructs might be measured psychometrically, but skin dryness might not be measured in the same way. Respondents could not describe their feelings of skin dryness in an internally consistent manner, that is, they could not employ the same scale to rate skin dryness. This finding has implications for future studies that measure skin dryness or other similar constructs. The level of comfort was shown to be more sensitive to cabin temperature than it is to the cabin humidity and CO₂ levels. The CO₂ concentration studied in this experiment was 3,908 ppm, and its impact on driver comfort was negligible. This corroborates with the literature which suggests no serious health impacts for CO₂ levels below 5,000 ppm (Prill, 2000).

Car cabin environment modeling should be studied more often, focusing on passenger comfort. Simple research methods can facilitate various stakeholders in expanding the scope of this research domain. In this regard, methods requiring minimal instrumentation could facilitate relevant policymakers and practitioners in collecting empirical data for their specific needs. Thermal camera-based technologies are anticipated to become more widespread in near future; thanks in part to the advancement in drone-based thermal images. Aerial thermal photographs can help scan fleets of vehicles in parking lots and urban traffic revealing a wealth of information that was previously unavailable to parking managers and policymakers.

This study used only white cars to rule out the impact of car color on the cabin environment. Future studies might consider using different colored cars to gain more insight into the impact of car surfaces on the cabin environment. Moreover, the study used a small sample size that did not allow for evaluating the impact of shading conditions on the cabin environment. Future studies should consider increasing the sample size, that is, including more cars in the experiment, and allowing parking enough cars under different shading conditions to study and compare the impact of various parking types on the cabin environment and driver comfort. These findings would partly explain the choice, timing, and duration of parking, and would interest parking managers and urban transport planners whose businesses are sensitive to the dynamics of parking behavior. A large sample size will also allow for the validation of study findings.

Psychometric approaches to analyze constructs related to passenger comfort should be preferred over the other, more complex methods requiring instrumentation. This study demonstrated that reliable data on passenger comfort can be obtained and analyzed using effective parametric statistical techniques. Future studies should also consider using nonparametric statistical techniques, such as ordinal regression, should the assumptions of normality, homoscedasticity, independence, or linearity fail to hold. This, however, should be performed only on internally consistent data. In this regard, Cronbach's alpha is a useful parameter. Clear explanations of study constructs to study participants may aid in improving data internal consistency.

In this study, skin dryness could not be evaluated due to low internal consistency. Interested readers are referred to Tsutsumi et al. (2007) for alternative methods of measuring skin dryness.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

KA: designed the research study, purchase equipment, handle logistical arrangement for the car experiment, conducted car experiment and driver interview, contributed in the literature, data analysis, results, conclusion, review the overall manuscript. Eng. MR: contributed in the study design, literature, data analysis, results and discussion.

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Conflict of interest

Author MR was employed by The Urban Unit Private Limited.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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