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Private vs. public emergency visits for mental health due to heat: An indirect socioeconomic assessment of heat vulnerability and healthcare access, in Curitiba, Brazil

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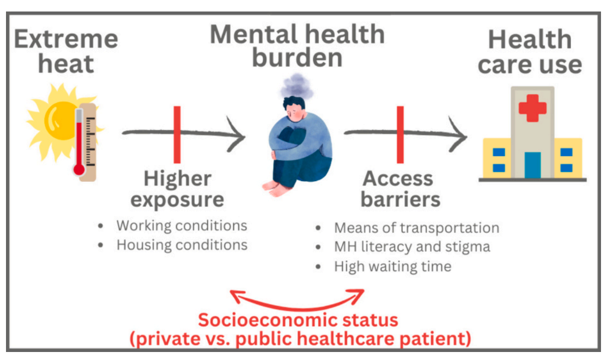
HIGHLIGHTS

- Indirect socioeconomic assessment of heat vulnerability and healthcare access.
- Patients from the public healthcare system have lower socioeconomic status than the private.
- Public patients likely face higher heat vulnerability, while private have greater heat adaptability.
- Need to increase equity between healthcare systems as climate change progresses.

GRAPHICAL ABSTRACT



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ABSTRACT

Few studies have explored the influence of socioeconomic status (SES) on the heat vulnerability of mental health (MH) patients. As individual socioeconomic data was unavailable, we aimed to fill this gap by using the healthcare system type as a proxy for SES. Brazilian national statistics indicate that public patients have lower SES than private. Therefore, we compared the risk of emergency department visits (EDVs) for MH between patients from both healthcare types. EDVs for MH disorders from all nine public (101,452 visits) and one large private facility (154,954) in Curitiba were assessed (2017–2021). Daily mean temperature was gathered and weighed from 3 stations. Distributed-lag non-linear model with quasi-Poisson (maximum 10-lags) was used to assess the risk. We stratified by private and public, age, and gender under moderate and extreme heat. Additionally, we calculated the attributable fraction (AF), which translates individual risks into population-

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representative burdens – especially useful for public policies. Random-effects meta-regression pooled the risk estimates between healthcare systems. Public patients showed significant risks immediately as temperatures started to increase. Their cumulative relative risk (RR) of MH-EDV was 7.5 % higher than the private patients (Q-Test 26.2 %) under moderate heat, suggesting their particular heat vulnerability. Differently, private patients showed significant risks only under extreme heat, when their RR became 4.3 % higher than public (Q-Test 6.2 %). These findings suggest that private patients have a relatively greater adaptation capacity to heat. However, when faced with extreme heat, their current adaptation means were potentially insufficient, so they needed and could access healthcare freely, unlike their public counterparts. MH patients would benefit from measures to reduce heat vulnerability and access barriers, increasing equity between the healthcare systems in Brazil. AF of EDVs due to extreme heat was 0.33 % (95%CI 0.16;0.50) for the total sample (859 EDVs). This corroborates that such broad population-level policies are urgently needed as climate change progresses.

1. Introduction

Climate change (CC) is assumed to impose a significant impact on mental health (MH) (IPCC, 2023a; Cianconi et al., 2020; Corvetto et al., 2023). The increased frequency, intensity, and geographical distribution of extreme heat (Emissions Gap Report 2022: The Closing Window, 2022) have already been linked to a higher MH emergency care demand (Corvetto et al., 2023). In MH patients, excessive heat can lead to exacerbations of MH disorders and heat-related illnesses, e.g., dehydration or heatstroke, either given the disease itself or psychotropic medications (Koop, 2022; Cusack et al., 2011). Adaptation strategies were supposed to remedy this emergency but are still underperforming and target mainly higher-income populations (IPCC, 2023b).

With increased MH consultations, healthcare demand and costs tend to rise proportionately (Tong et al., n.d.). In Brazil, this health assistance is characterized by a clear distinction between public and private healthcare sectors. The Public Brazilian Health System (SUS) is entirely free, which applies for fees and drugs, and is used by approximately 60 % of the population (IBGE, 2019). On the contrary, the private sector requires fees for services and medications from users, which enables quicker consultations due to the higher number of available professionals. A private MH consultation fee represents 20–50 % of the minimum wage, and health insurances have similar monthly prices. Consequently, a national survey from 2019 identified that public patients have lower income and education and are mostly black or brown compared to private healthcare patients (IBGE, 2019). In Curitiba, this income inequality is extremely high (IBGE, 2018), as illustrated by Fig. 1, where the highest quartile income is four times the wage of the lowest one.

A previous study by Corvetto and colleagues (Corvetto et al., 2023) with MH patients from the public system in Brazil already indicated a higher risk of emergency department visits (EDV_{MH}) under different heat exposures. However, few studies have investigated the overarching effect of socioeconomic status on the MH risk under a warming climate. Low-income populations have higher rates of mental disorders (Carod-Artal, 2017) and are likely to have a particular heat vulnerability due to housing and working conditions (Xu et al., 2020). Notably, one previous study in Brazil found that the risk of being hospitalized for MH increased more in lower-income cities than in higher-income ones under the same increase in temperature (Xu et al., 2020). Likewise, income- and MH-related healthcare-seeking barriers, such as stigma and limited MH literacy – the ability to comprehend the disorder and seek help – have been previously reported (Nutbeam and Lloyd, 2021). Without existing population-based studies directly addressing these questions, we intend to observe and compare the risk profile within the two healthcare systems for the first time in the country to indirectly assess the socioeconomic determinants of heat vulnerability and healthcare-seeking behavior.

Additionally, we aim to calculate the attributable fraction (AF) and number (AN). They are burden measurements in opposition to relative risk (RR), consequently resulting in different policy ramifications (Pan et al., 2019). The AF and AN are essential for clarifying the implications of our findings and their relevance to public health practice. While RR can suggest the individual risk that one patient has to be affected in the aftermath of an exposure, AF and AN can take this further by estimating the actual impact of the exposure on the population's health, providing more actionable insight for public health interventions. AF and AN can capture the burden related to the rising frequency of extreme heat events associated with CC (Emissions Gap Report 2022: The Closing Window, 2022) and the remarkably high prevalence of MH disorders (GBD 2019 Diseases and Injuries Collaborators, 2020). To our knowledge, no study in the country had ever compared public and private risk profiles or quantified the AF or AN of EDV_{MH}.

This broader perspective might help healthcare planners increase equity among MH patients and optimize resource allocation, ultimately increasing resilience during heat. Specifically, our research aimed to:

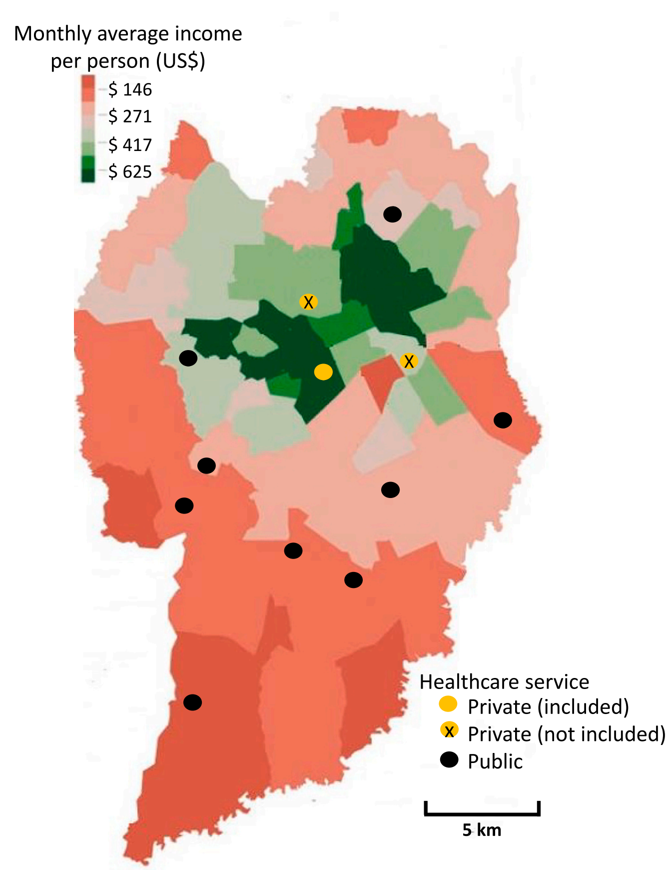

Fig. 1. Territory of Curitiba, subdivided into neighborhoods. The colors represent the average income per person (above ten years old). The health facilities are also displayed: yellow dots illustrate the private healthcare services, while the black dots represent the public ones. Yellow dots with crossing lines represent the private units that were not included in the study. Source: Brazilian Institute of Geography and Statistics (IBGE), 2010—last available census on the topic. Image adapted from gazetadopovo.com.br.

1. Quantify the risk of EDV (RR_{EDV}) for MH disorders due to moderate and extreme heat.
2. Compare the RR_{EDV} between public and private patients.
3. Calculate the AF and AN of MH EDV due to moderate and extreme heat exposure.

2. Methods

2.1. Brazilian healthcare system

The healthcare facilities in the Curitiba territory are displayed in Fig. 1. Firstly, the 'Urgency and Emergency Units' (UPAs) are public facilities designed to admit all public emergency cases. Curitiba has nine UPAs in the territory (black dots, Fig. 1), of which eight are in lower-income areas (Fig. 1). Secondly, the private sector includes hospitals, emergency centers, and numerous private clinics. The three private emergency centers are in central areas with higher average income, as demonstrated by the three yellow dots in Fig. 1.

2.2. Health dataset

Daily EDVs were assessed from all nine public UPAs and one private emergency center in Curitiba due to all MH disorders and suicide attempts from January 1st, 2017, until December 31st, 2021. Patient information was supplied to this research as a secondary data source. The Curitiba Health Secretary provided the public data—the same as the authors used in the recent study (Corvetto et al., 2023) and the Psychiatric Hospital and Emergency Center Porto Seguro supplied the private EDVs. Data consisted of gender, age, city of residency, visit date, and the International Classification of Diseases – 10th edition (ICD-10) code recorded on admission (Centers for Disease Control and Prevention, n.d.). All MH disorders (ICD-10 F00-F99) and suicide attempts (X60-X84) were included. Patients living outside of Curitiba were excluded. The Ethics Committee of the Municipal Health Secretary in Curitiba approved the research in October 2023. The data of the other two private facilities was not freely accessible, which prevented us from including them in this study.

2.3. Temperature dataset

Daily mean temperature (T_{mean}) was assessed from three meteorological stations located inside Curitiba territory or in the neighboring city, – directly on the border (Table S1 and Fig. S2, appendix). Given the irregular distribution of meteorological stations, we could not perform a subregional analysis in the city based on the nearest station; therefore, we averaged the dataset from all three stations. Pearson's correlation was performed to (i) validate data from the outer station using data from the two inner stations and (ii) confirm that data among all three sources were correlated and could be averaged. A Pearson's correlation of $\geq$0.7 was considered a cutoff. The monitoring sites had a maximum of 7 % missing values; however, when the T_{mean} was averaged, the data was 100 % complete.

2.4. Controlling for confounders

Daily relative humidity (%) and air pollutants (PM_{10} and O_3) were included in our models as confounding variables. Given the high rates of missing values, we could not control for other air pollutants, such as NO_2 and SO_2. Here, some of the meteorological sites were also located outside of the official Curitiba territory. Therefore, we also performed Pearson's correlation between the data from these stations and the data from the inner ones, as previously delineated. A correlation of $\geq$0.7 validated the use of meteorological data from outer sites. Detailed information on the geographical location of monitoring stations, Pearson's correlation values, and the rate of missing data are available in the appendix (Tables S1, S3, and Fig. S2).

2.5. Modelling

We first performed a time-series analysis of the sample for a maximum delayed period of 10 lags (0–10 lag), including a stratified analysis by private and public patients. Based on previous studies in Curitiba, we opted for a 10-lag period, showing that heat effects concentrate primarily on this short-term period (Corvetto et al., 2023; da Silva et al., 2020).

The time-series analysis was performed during a five-year period (2017–2021) using a distributed lag non-linear model (Gasparrini, 2014) and a quasi-Poisson distribution, assumed to account for the overdispersion of the data. The variables for the model were mean temperature (T_{mean}) – as the exposure –, and daily counts of EDV – as the outcome. We opted to use T_{mean} as exposure instead of minimum or maximum temperature, as we understand that heat stress in the human body can be better predicted by the average temperature patients undergo during the entire day rather than peaks of maximum or minimum temperature during the period.

Seasonality and long-term trends were controlled in the model through a natural cubic spline with 7 degrees of freedom (df). We included relative humidity (%), ozone (O_3), and particulate matter (PM10) in the model to control for potential confounding based on previous studies linking these variables to EDV due to MH disorders (EDV_{MH}) (da Silva et al., 2020; Vida et al., 2012). Finally, the day of the week (DOW) was included, as the daily numbers of EDV_{MH} vary significantly throughout the week.

Several sensitivity analyses were performed to best fit the model to our data. The choices were based on the quasi-Akaike Information Criterion (qAIC), which implies that a lower qAIC value indicates a better fit. The final parameters for the model, based on the qAIC, were (i) 7 df for time trend, (ii) 2 df for lag, (iii) 3 df for O_3 and PM_{10}, (iv) 3 df for humidity, (v) temperature centered at 0.50 (%), (vi) knots on the temperature curve placed on 1, 50, 99th percentiles, and (vii) the use of natural cubic spline (ns). The residual analyses are displayed in Fig. S4, the detailed qAIC values are in Table S5, and the individual influence of each confounder was quantified and presented in Table S6 (appendix).

The final model is represented by the equation below:

$$\begin{aligned} E\,(Yt) = \beta o + s\,(T, \text{timedf}) + f\,(T_{mean}, \text{lagdf}, \text{vardf}) + f\,(\text{Hum}, \text{df}) \\ + f\,(O_3, \text{df}) + f\,(PM_{10}, \text{df}) + \text{DOW} \sim \text{quasi–Poisson} \end{aligned}$$

where:

E (Yt): EDVs.

βo: y interception.

s (T, timedf): function of time, with 7df.

f (T_{mean}, lagdf, vardf): cross-basis function, with 10 and 2 df.

f (Hum, df) + f (O_3, df) + f(PM_{10}, df): cross basis functions for confounders, with 3 df.

DOW: day of the week, as a factor.

Subgroup analyses were performed primarily by private or public patients, followed by a further stratified analysis by age and gender. Age groups were divided into 18–64 and $\geq$ 65 years old. Given the deficient number of patients aged 0–17 (0.03 % of the total sample), we could not perform the corresponding analysis. Results are presented in cumulative RR_{EDV} (CRR_{EDV}) for different cumulative lags (0, 0–3, 0–6, and 0–10), which represents the risk resultant or cumulated from the entire period (e.g., 0 until 10 delayed days = 0–10).

Second, we pooled results and performed a meta-regression for statistical comparison between public and private CRR_{EDV}. We aimed to quantify the size of interaction between the two subgroups and see if the difference was statistically significant. Therefore, we performed a random-effects meta-regression analysis by taking the difference between the log CRR_{EDV} from public and CRR_{EDV} from private, using results from all cumulative lags, from lag 0 to cumulative lag 0–10 (*log CRR public*^{lag0} *– log CRR private*^{lag0}*, …, log CRR public*$^{lag0–10}$ *– log CRR private*$^{lag0–10}$). The level of heterogeneity will be represented here by the classic heterogeneity indicators I^2 and Q Test, which reflect how much the two effect sizes differ. $I^2 \leq 25$ % indicates low, 26–74 % moderate, and ≥ 75 % substantial heterogeneity.

The study was performed using *R* Software version 4.2.1 (R Core Team, 2021) through the packages 'dlnm' version 2.4.7. (Gasparrini, 2011) and 'metafor' version 4.4–0 (Viechtbauer, 2010). EDVs were analyzed under moderate (90th percentile of T_{mean} - 22.2 °C) and extreme heat (99th percentile of T_{mean} - 24.5 °C), compared to the median (50th percentile of T_{mean} - 18.02 °C). We considered a statistical significance of 95 % (confidence interval - CI) for the analysis.

2.6. Calculation of attributable fractions

AF represents the fraction of EDV_{MH} attributed to a specific exposure. We followed the methodology Gasparrini and Leone (2014) (Gasparrini and Leone, 2014) developed to calculate the EDV_{MH} due to moderate and extreme heat. This methodology allows and accounts for possible delayed effects from the exposure based on the DLNM functions. All EDV_{MH} attributed directly to moderate (range from 90th to 99th percentile of T_{mean}) and extreme heat (from the 99th percentile to the highest T_{mean} observed) was accounted for, considering the same counterfactual of 18.02 °C. AF was estimated at the lag of 0–6 days, based on our results (see Results section below), which indicated the most robust effects of heat at this delayed period after exposure. Subgroup analysis was performed for AF, and empirical CIs (95 %) were calculated through 1000 Monte Carlo simulations (Gasparrini and Leone, 2014). AF was then multiplied by the total number of cases in the given subgroup to obtain the attributable number (AN) of preventable cases due to extreme heat.

3. Results

3.1. Descriptive results

The total sample consisted of 256,406 EDVs (Table 1), of which 60 % were private (154,954) and 40 % were public sector patients (101,452). In both subgroups, most of the patients were women and patients aged 18–64. The subgroup aged 0–17 accounted for only 7894 EDVs (0.03 %). During the study period, the T_{mean} average was 17.8 °C. There were 167 days with moderate heat and 19 days with extreme heat.

3.2. Risk of MH EDV among public and private sector patients

Under moderate heat, only public CRR_{EDV} was significantly increased, peaking at lag 0–6, with 1.06 (CI 1.00; 1.13) (Table 2, Fig. 2). No significant results regarding moderate heat exposure were found for private patients. According to the meta-regression analysis (Table 3), the overall risk for EDV_{MH} among public sector patients was 7.5 % higher compared to the private sector (I^2 35.58; Q Test 26.23 %).

However, a divergent pattern was observed for extreme heat, where the private sector patients had a 4.3 % higher risk for EDV_{MH} than the public sector (I^2 0%; Q Test 6.16 %). The corresponding $CRRs_{EDV}$ were significant since lag 0 and peaked respectively at 1.24 (CI 1.05–1.46; lag 0–6) – the highest for this study – and 1.15 (CI 1.04–1.27; lag 0–6).

The exposure-response curves in Fig. 3, calculated at lag 0, highlight the difference between the two patterns. Risk for EDV_{MH} among public sector patients (left, in blue) increased immediately as temperatures began to rise, while private-related (right, in red) RR_{EDV} was only significant at extremely high temperatures, with a relatively high effect size. Plots from other lags and more association details are presented in the contour and 3D plots in the appendix (Figs. S7 and S8).

3.3. Analysis by gender and age

The following results from subgroup analysis are presented in Tables 2 and 3. Females from the public service had a 13.7 % higher risk of EDV_{MH} (I^2 57%; Q Test 45 %) than the private, under moderate heat, peaking at 1.10 (CI 1.03; 1.18). The risk of EDV_{MH} among private patients was not significant under this exposure. This pattern reversed as the heat became extreme - private subgroups now presented a relatively higher risk for EDV_{MH} by 2.9 % (I^2 0%; Q Test 5 %). CRR_{EDV} at lag 0–6 were 1.23 (CI 1.02; 1.49) vs. 1.20 (CI 1.08; 1.34), respectively.

Table 1
Descriptive health data from the general population, stratified by public and private healthcare sectors, age, and gender. Descriptive meteorological data from temperature and air pollutants are also presented.

	n (%)	Mean ± SD	Minimum	Percentiles			Maximum
				25th	50th	75th	
Total							
Total sample	256,406 (100 %)	/	26	88	139	192	287
Male	89,801 (35 %)	/	9	34	50	64	109
Female	166,604 (65 %)	/	13	54	88	127	211
0–17 years old	7894 (0.03 %)	/	0	2	4	6	20
18–64 years old	214,238 (83.50 %)	/	23	76	118	158	239
≥65 years old	34,278 (13.37 %)	/	0	8	17	29	63
Public							
Total	101,452 (40 %)	/	8	39	53	69	135
Male	41,361 (16.10 %)	/	4	16	22	28	58
Female	60,091 (26.40 %)	/	4	22	31	42	81
0–17 years old	6751 (0.03 %)	/	0	2	3	5	20
18–64 years old	87,747 (34 %)	/	8	33.25	46	60	119
≥65 years old	6955 (0.03 %)	/	0	2	3	5	15
Private							
Total	154,954 (60 %)	/	0	31	82	131	235
Male	48,440 (18.90 %)	/	0	9.25	26	40	80
Female	106,513 (41.50 %)	/	0	20.25	54	91.75	171
0–17 years old	1143 (0.01 %)	/	0	0	0	1	6
18–64 years old	126,491 (49 %)	/	0	27	67	105	189
≥65 years old	27,323 (10.70 %)	/	0	3	13	24	61
Meteorological variables							
T_{mean} (°C)	/	17.83 ± 3.61	4.20	15.30	18.02	20.52	27.30
Relative humidity (%)	/	81.91 ± 8.24	42.57	77.27	82.72	87.48	99.43
O3 (ppb)	/	12.92 ± 5.48	1.19	8.97	11.95	15.76	36.55
PM10 (μg/m^3)	/	17.69 ± 11.95	2.66	9.51	14.45	21.94	89.33

SD – standard deviation.

Table 2
Moderate and extreme heat effects on EDV_{MH} stratified for public and private health care systems and subgroup analysis. Cumulative RR_{EDV} (CRR_{EDV}) under moderate and extreme heat for sex and age subgroups, divided by private or public systems. Calculations for lag 0, 0–3, 0–6, and 0–10 are displayed.

CRR_{EDV}	a) Moderate heat.				b) Extreme heat.			
(CI 95 %)	Lag 0	Lag 0–3	Lag 0–6	Lag 0–10	Lag 0	Lag 0–3	Lag 0–6	Lag 0–10
Total sample	1.00 (0.99;1.02)	1.00 (0.95;1.06)	0.99 (0.92;1.07)	0.95 (0.86;1.05)	**1.05** (1.03;1.08)	**1.16** (1.07;1.26)	**1.18** (1.05;1.32)	1.06 (0.91;1.24)
Private	0.99 (0.97;1.02)	0.97 (0.89;1.06)	0.94 (0.83;1.05)	0.88 (0.76;1.03)	**1.07** (1.03;1.12)	**1.22** (1.07;1.38)	**1.24** (1.05;1.46)	1.02 (0.80;1.30)
Public	**1.01** (1.00;1.03)	**1.05** (1.01;1.10)	**1.06** (1.00;1.13)	1.03 (0.95;1.11)	**1.04** (1.02;1.06)	**1.12** (1.05;1.19)	**1.15** (1.04;1.27)	1.11 (0.99;1.26)
Subgroup analysis								
Female								
Private	0.99 (0.96;1.02)	0.95 (0.87;1.04)	0.91 (0.80;1.03)	0.85 (0.73;1.00)	**1.08** (1.03;1.12)	**1.23** (1.07;1.40)	**1.23** (1.02;1.49)	1.02 (0.79;1.31)
Public	**1.03** (1.01;1.04)	**1.08** (1.02;1.14)	**1.10** (1.03;1.18)	1.07 (0.97;1.17)	**1.05** (1.02;1.07)	**1.16** (1.07;1.25)	**1.20** (1.08;1.34)	**1.16** (1.00;1.34)
Male								
Private	1.00 (0.98;1.03)	1.01 (0.92;1.11)	0.99 (0.88;1.13)	0.95 (0.81;1.13)	**1.06** (1.02;1.11)	**1.19** (1.04;1.37)	1.21 (0.99;1.47)	1.04 (0.80;1.36)
Public	1.01 (0.99;1.02)	1.02 (0.97;1.06)	1.01 (0.93;1.09)	0.97 (0.89;1.08)	1.02 (0.99;1.05)	1.06 (0.97;1.15)	1.07 (0.95;1.21)	1.05 (0.89;1.24)
18–64 years								
Private	0.99 (0.97;1.02)	0.97 (0.89;1.06)	0.94 (0.83;1.05)	0.88 (0.76;1.03)	**1.07** (1.03;1.11)	**1.22** (1.07;1.38)	**1.24** (1.03;1.48)	1.05 (0.83;1.34)
Public	**1.02** (1.01;1.04)	**1.07** (1.03;1.12)	**1.09** (1.02;1.16)	1.06 (0.97;1.14)	**1.04** (1.02;1.06)	**1.13** (1.06;1.21)	**1.18** (1.08;1.30)	**1.18** (1.04;1.34)
≥65 years								
Private	0.99 (0.96;1.03)	0.97 (0.86;1.09)	0.94 (0.79;1.10)	0.88 (0.71;1.09)	**1.08** (1.02;1.14)	**1.21** (1.02;1.44)	1.18 (0.92;1.50)	0.90 (0.64;1.25)
Public	0.97 (0.93;1.00)	0.89 (0.78;1.02)	0.85 (0.71;1.04)	0.86 (0.67;1.11)	0.95 (0.89;1.01)	0.82 (0.67;1.01)	0.75 (0.57;1.00)	0.72 (0.49;1.07)

CI – confidence interval. Bold values represent the significant results ($p < 0.05$).

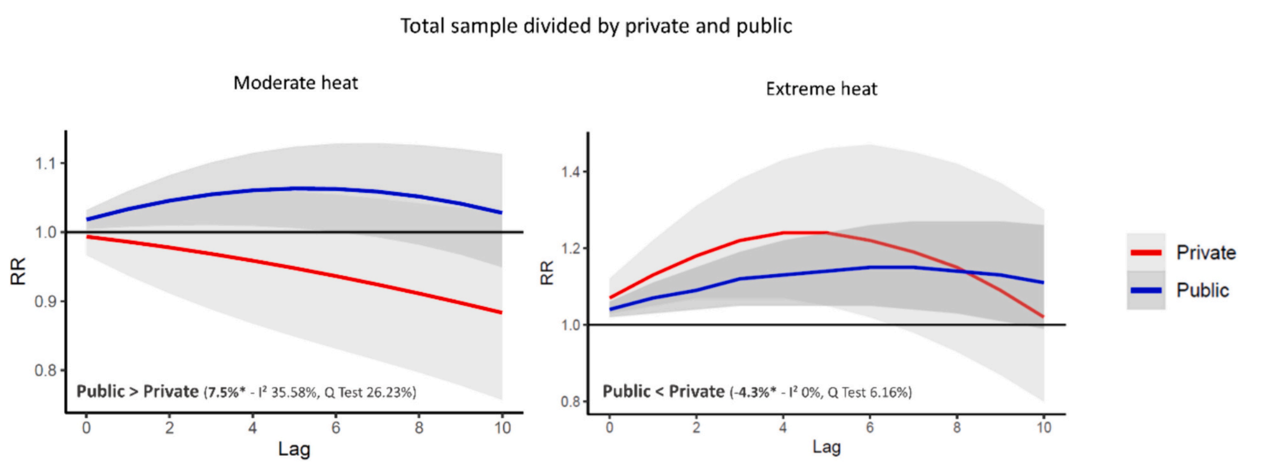

Fig. 2. Moderate (left) and extreme heat effects (right) estimated for private and public patients during all lags. The blue line represents public CRR_{EDV}, whereas the red line represents private CRR_{EDV}. *denotes statistically significant results.

Table 3
Results from the meta-regression analysis: the difference between public and private CRR_{EDV} calculated under moderate and extreme heat. The total sample, as well as gender and age subgroups, are displayed.

	a) Moderate heat				b) Extreme heat			
	△Public-private CRR_{EDV}	Prediction (CI 95 %)	I^2	Q Test	△Public-private CRR_{EDV}	Prediction (CI 95 %)	I^2	Q Test
Total sample	**+ 7.5 %**	**1.07** (1.05;1.10)	35.6 %	26.2 %	**- 4.3 %**	**0.96** (0.93;0.98)	0 %	6.2 %
Gender								
Female	**+ 13.7 %**	**1.14** (1.10;1.17)	56.6 %	45.1 %	**- 2.9 %**	**0.97** (0.95;0.99)	0 %	5.1 %
Male	+ 1.00 %	1.01 (0.99;1.02)	0 %	0.3 %	**- 6.7 %**	**0.94** (0.91;0.96)	0 %	6.5 %
Age group								
18–64	**+ 10 %**	**1.10** (1.07;1.13)	48.7 %	35.9 %	**- 3.6 %**	**0.96** (0.94;0.99)	0 %	6.1 %
≥65	**- 3.9 %**	**0.96** (0.94;0.99)	0 %	3.4 %	**- 33.4 %**	**0.75** (0.70;0.80)	37.7 %	26.7 %

Bold values represent the statistically significant results, $p < 0.05$.

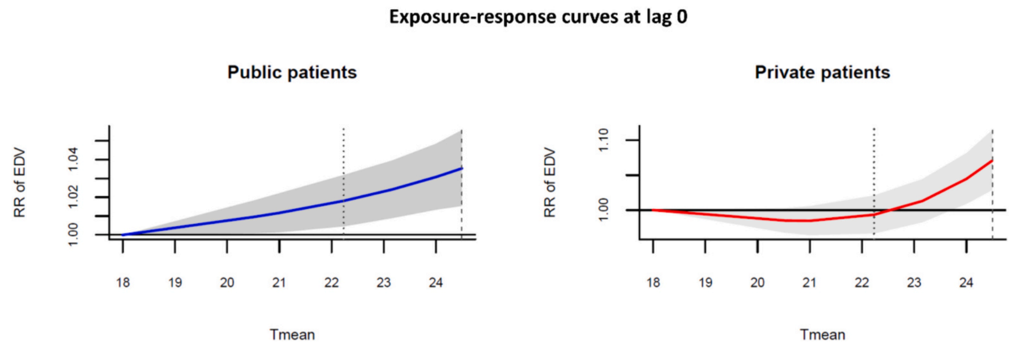

Fig. 3. Exposure-response curves at lag 0. Different temperature effects (above the 50th percentile) at lag 0 are estimated for public (left—blue line) and private (right—red line). The grey area represents the confidence interval of 95 %. Dotted lines denote moderate heat, and dashed lines denote extreme heat.

Male patients from the public system did not show any increase in CRR_{EDV} across the study, and there was no difference between public and private participants under moderate heat. However, the male patients in the private had a 6.7 % higher risk of EDV_{MH} than those in public (I^2 0%; Q test 6.47 %). The CRR_{EDV} peaked at 1.19 (CI 1.04; 1.37).

Patients aged 18–64 showed similar curve shapes and patterns of response as females (Table 2, Fig. S9). Patients from the public system had a 10 % higher risk of EDV_{MH} under moderate heat than the private (I^2 49%; Q Test 36 %). However, under extreme heat, the risk for private patients was 3.6 % higher than that for public (I^2 0%; Q Test 6.1 %). At lag 0–6, the CRR_{EDV} were 1.24 (CI 1.03; 1.48) vs. 1.18 (CI 1.08; 1.30).

Public patients aged ≥65 seemed not to be affected by heat exposure. Besides, their effects were consistently lower than those of their private counterparts, regardless of temperature exposure. For private patients aged ≥65, we observed a CRR_{EDV} of up to 1.21 (1.02; 1.44—lag 0–3) under extreme heat, which represented 33.4 % higher CRR_{EDV} than the public—the highest difference found in this study (I^2 37.70 %; Q test 26.66 %).

3.4. Attributable fraction and number

The burden of moderate heat on public patients was increased, except for males. The AF of EDV_{MH} among all public patients was 0.87 % (CI 0.19; 1.64), meaning that 883 public patients sought the emergency center because of moderate heat. Patients aged 18–64 and females had the highest stratified AFs: 1.17 % (CI 0.40; 1.89) and 1.28 % (CI 0.44; 2.13). No significant burden was observed for private patients under moderate heat.

Regarding extreme heat, the burden was significant on the total sample and most subgroups, and the private AFs were consistently higher than the public. We found that 0.33 % (CI 0.16; 0.50) of our total sample occurred due to extreme heat, representing 859 EDVs. Total private and public AFs were 0.40 % (CI 0.18; 0.63) vs. 0.23 % (CI 0.07; 0.39). The private share of patients aged ≥65 had a high AF of 0.41 % (CI 0.04; 0.70), while the public one had −0.53 % (CI -1.15; −0.06) and sought less care due to extreme heat (Table 4).

4. Discussion

This is the first study in Brazil to compare the risk of EDV_{MH} between public and private patients in relation to moderate and extreme heat and quantify the number of EDVs attributable to heat exposure. Considering the discrepant socioeconomic profiles of both patient groups, this analysis enabled the indirect assessment of heat vulnerability and healthcare-seeking behavior.

Our findings confirm the primary hypothesis and suggest that lower-income populations – represented by the public patients – have higher heat vulnerability and face more healthcare-seeking barriers,

Table 4
Attributable fraction (AF) and attributable number (AN) due to moderate and extreme heat. The maximum lag considered was 0–6.

AF (%) (CI 95 %)						
a) Moderate heat				b) Extreme heat		
	Total sample	Private	Public	Total sample	Private	Public
Total	0.36 (−0.43;1.13)	0.03 (−1.11;1.10)	**0.87** (0.19;1.64)	**0.33** (0.16; 0.50)	**0.40** (0.18; 0.63)	**0.23** (0.07; 0.39)
Age group						
18–64	0.49 (−0.30;1.25)	0.03 (−1.19;1.05)	**1.17** (0.40;1.89)	**0.35** (0.19; 0.51)	**0.40** (0.17; 0.62)	**0.27** (0.11; 0.43)
≥65	−0.41 (−1.99;0.96)	0.08 (−1.53;1.61)	**−2.45** (−5.18; −0.08)	0.21 (−0.08; 0.48)	**0.41** (0.04; 0.70)	**−0.53** (−1.15; −0.06)
Gender						
Female	0.39 (−0.46;1.19)	−0.10 (−1.38;1.02)	**1.28** (0.44;2.13)	**0.39** (0.19; 0.57)	**0.44** (0.18; 0.67)	**0.29** (0.11; 0.47)
Male	0.31 (−0.57;1.09)	0.31 (−1.03;1.57)	0.27 (−0.75;1.23)	**0.23** (0.06; 0.40)	**0.31** (0.03; 0.57)	0.14 (−0.08; 0.32)
AN						
Total	931	48	**883**	**859**	**625**	**234**
Age group						
18–64	1070	40	**1030**	**752**	**511**	**241**
≥65	−150	21	**−171**	73	**112**	**−37**
Gender						
Female	649	−106	**768**	**649**	**474**	**175**
Male	277	151	112	**211**	**152**	59

Bold values represent the statistically significant results at $p < 0.05$.

corroborating previous literature (Xu et al., 2020; Naicker et al., 2017; Basu et al., 2012; Sera et al., 2020; Osberghaus and Abeling, 2022). These similar patterns were found for the total sample, patients aged 18–64 and females. In these groups, significant CRR_{EDV} for public patients emerged immediately after a slight increase in temperature, and under moderate heat, their risk was higher than for the private (with moderate heterogeneity). This suggested a particular heat vulnerability among public system patients. Meanwhile, wealthier patients – represented by the private patients – could likely rely on adaptation means, such as air conditioning. These are robust protective factors and directly dependable on income (Sera et al., 2020; Osberghaus and Abeling, 2022). When temperatures became extremely high, we hypothesize that these adaptation means were insufficient. Thus, private patients sought healthcare freely, as evidenced by the high risk of EDV_{MH} observed in this study. Contrarily, under extreme heat, public patients had relatively lower CRR_{EDV}, possibly explained by healthcare-seeking barriers, preventing accessible and equitable healthcare use. In this context, a possible indicator is that public patients from 9 different centers constituted only 40 % of the observed admissions, in contrast to the 60 % observed in a single private facility.

The heat vulnerability from lower-income populations is mainly explained by the intense exposure through work and housing conditions. In economically disadvantaged communities, indoor temperatures can exceed outdoors' by up to 5 °C, as found by previous research in South Africa (Naicker et al., 2017). Likewise, people from poorer regions or backgrounds are likelier to have strenuous workloads and work outdoors – agriculture, fishery, construction – or in non-cooled environments (Thi et al., 2013).

Public MH patients may face healthcare access barriers, particularly during periods of extreme heat. These barriers commonly include lack or high costs of means of transportation, the impossibility of leaving work, higher service waiting times, limited financial resources, and the two variables directly related to MH: stigma and restricted MH literacy (Nutbeam and Lloyd, 2021; Basu et al., 2012; Fernando, 2010). Notably, 20 % of the variance in help-seeking delay was attributed to the stigma experienced by MH caregivers in a study investigating determinants of healthcare-seeking in Sri Lanka (Fernando, 2010). Furthermore, other studies revealed that being female and having a higher level of education were associated with decreased stigma and enhanced mental health literacy, influencing the choice to seek healthcare (Gasparrini, 2011). Our results confirmed this, as females in general – and especially the private-insured – had one of the highest $CRRs_{EDV}$ in the study. Likewise, in this context, stigma might be one of the reasons why males utilizing public services presented no significant effect across the study, in opposition to the private. Further access barriers might be related to the waiting time: private services offered a relatively shorter waiting time, according to a review on the topic, which plays a role in the decision towards health seeking (Basu et al., 2012). Besides, lower-income populations have less access to private transportation means. According to the last Brazilian national report, in 2010, the percentage of households owning a car in the peripherical area of Curitiba was substantially lower, where the public facilities are located (IBGE, n.d.).

Public patients aged ≥65 had relatively lower CRR_{EDV} both under moderate (low heterogeneity) and under extreme heat (moderate heterogeneity) despite the established heat vulnerability among older people (Fouillet et al., 2006). Similar to what happened during the 2003 heatwave in France (Fouillet et al., 2006), when thousands of older adults died of being unable to seek help, we hypothesize that this lower socioeconomic share of patients also remained unassisted. Further research is needed to confirm our results for patients aged ≥65, as the observed EDVs were relatively low and might have played a role in the outcomes. We could not perform an accurate analysis for patients aged 0–17, given the extremely low EDVs and the consequent weak statistical power. Thus, further studies with a focus on this population are highly recommended.

The RR metric is essential and denotes the individual risk in the presence of the exposure, regardless of how frequent this exposure is. That is when the AF and AN become crucial – they translate this individual risk into a population level by showing the total number of people affected and, therefore, the burden in terms of public policies. Notably, a disease may have a very high RR but either be caused by a rare phenomenon or the high RR be present in a small subgroup. In this case, public policies will probably act by focusing efforts specifically on the small, endangered subgroups. Contrarily, in this study context, we face a remarkably high rise in mental disorder prevalence (GBD 2019 Diseases and Injuries Collaborators, 2020) and a 232 % increase in extreme temperatures over the past 20 years (CRED and UNDRR, 2020), indicating that the observed AFs directly attributed to heat will rapidly increase. Moderate heat was responsible for a significant burden of about 900 EDV_{MH} on public patients, and females and patients aged 18–64 were particularly affected. Extreme heat days were less often, with nineteen days in the sample, but still, the burden was high – three times higher for private patients than for the public. Few previous studies analyzed MH-related AF and found similar results: 0.41 % related to alcohol misuse (Liu et al., 2020) and 0.28 % of schizophrenia hospitalization (Crank et al., 2023), both due to extreme heat. These AF analyses show that the burden heat imposes on MH is extensive and requires broader and population-level policies. Besides, the two healthcare systems, including insurance companies, should prepare for the overloading of EDV_{MH} as CC progresses. These sectors would benefit economically from CC mitigation actions.

Previous research by the authors in Curitiba, Brazil, was recently published (Corvetto et al., 2023). The focus was on the exposure-response relationship of heat and cold on MH in general and on MH-subgroups, such as neurotic disorders and suicide attempts. This present study intends to fill out socioeconomic knowledge gaps and potential bias by including data from private sources and then assessing indirect socioeconomic status through the utilized healthcare systems. Additional statistical analyses were implemented to delineate better the determinants of heat-related risk and health-seeking behavior under CC.

Some limitations of our study should be considered when interpreting the results. Firstly, this is an ecological study, and the individual variations within each compared subgroup could not be accounted for, such as income, ethnic information, employment, or occupation. Secondly, we had limited access to private EDVs since we could not access data from all three private emergency facilities in Curitiba. However, Fig. 1 shows that the two private buildings not included in the study are located in the same central, wealthy, and green area as the included facility. Thus, there is no reason to believe that their socioeconomic profile is different and that their inclusion would significantly influence the results. Thirdly, the intrinsic limitations of facility-based studies such as ours are that we may oversee a significant percentage of patients who did not seek care and were not, therefore, part of the analysis. For MH, this bias is relatively higher, as not only socioeconomic-related but also psychiatric-related barriers play a role. Fourthly, the exposure measurement was weighed from local meteorological stations, which does not reflect precisely the individual exposure. Fifthly, regarding the results, the heterogeneity in specific subgroups found by I^2 and Q tests was low, showing no strong difference in these groups. Likewise, the possible harvesting effect should be considered, especially for private patients, who showed extremely high RR_{EDV} at initial single lags and reduced at following lags under extreme heat (Fig. S7). Finally, this study is based in a specific area of Brazil, which limits our generalizability power. It would be beneficial to conduct similar analyses in the future to confirm our results and improve the generalizability of our findings.

Hence, while using a facility-based dataset offers crucial insights, we highly recommend future population-based studies in Brazil. These study designs can assess individual characteristics and the potential moderators of heat vulnerability. Besides, instead of measuring healthcare use, population-based research would directly assess the effects of heat on the MH symptoms and the health state of patients. We acknowledge, though, that population-based studies have higher costs and are extremely time-consuming.

Our findings indicate that policymakers and healthcare planners should increase equity between healthcare systems in Brazil by tackling MH heat vulnerability and healthcare access barriers. The results of AF and AN confirm that such measures are urgent and should be broad, as the burden is significant on a population level. We recommend (i) allowing free access to public transportation upon proof of consultation in the public system, which could remove the transportation barriers for patients who lack money for tickets; (ii) utilizing primary and local healthcare networks to proactively search public patients during extreme heat periods, especially aged ≥65, given the observed lower healthcare-seeking behavior compared to their private counterparts; (iii) implementing an early warning system to increase the rapid response of all MH patients and caregivers under an upcoming extreme heat event, with practical advises on dealing with heat (Laaidi et al., 2004); (iv) finally, intensifying public awareness campaigns and MH education, with focus on the public healthcare system (SUS), addressing the prevalent stigma and enhancing MH literacy. This measure would particularly benefit males.

5. Conclusion

Our findings suggest that public healthcare patients, who have lower SES, have a higher heat vulnerability and show a higher propensity to seek care already at slight increases in temperature. This indicates that they are very exposed and vulnerable to heat, lacking adaptive strategies. However, under extreme heat, private patients sought healthcare more than their public counterparts, indicating freer healthcare access. While our results still need to be corroborated by population-based studies, we hypothesize that the socioeconomic profile, indirectly represented by the healthcare systems, plays a role in shaping MH vulnerability and healthcare-seeking behaviors. MH patients would benefit from policies to increase heat resilience, especially of vulnerable subgroups, and from more equitable mental healthcare for private and public systems. Our results and potential policy implications can be extended to other similar countries in the world, notably some in Latin America and the Caribbean, which also present high socioeconomic inequality and similar healthcare system settings. Besides, our AF analysis indicates that broad population-level policies for MH patients are required as CC progresses and the heat-related burden increases proportionately.

CRediT authorship contribution statement

Julia F. Corvetto: Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Ammir Y. Helou:** Validation, Methodology, Data curation. **Hedi K. Kriit:** Validation, Methodology. **Andrea Federspiel:** Validation, Methodology, Data curation. **Aditi Bunker:** Validation, Methodology. **Prasad Liyanage:** Validation, Methodology. **Luis Felipe Costa:** Data curation. **Thomas Müller:** Validation, Supervision, Conceptualization. **Rainer Sauerborn:** Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

De-identified data reported in this research from the public service will be provided to researchers upon request for scientific purposes. These authors cannot share data from the private hospital, and further requests should be directed to the hospital directory. Data requestors will need to sign a data access agreement.

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Appendix A. Supplementary data

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