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Characterizing the performance of emergency medical transport time metrics in a residentially segregated community

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ABSTRACT

Objective: To derive and characterize the performance of various metrics of emergency transport time in assessing for sociodemographic disparities in the setting of residential segregation. Secondarily to characterize racial disparities in emergency transport time of suspected stroke patients in Austin, Texas.
Data sources: We used a novel dataset of 2518 unique entries with detailed spatial and temporal information on all suspected stroke transports conducted by a public emergency medical service in Central Texas between 2010 and 2018.
Study design: We conducted one-way ANOVA tests with post-hoc pairwise *t*-tests to assess how mean hospital transport times varied by patient race. We also developed a spatially-independent metric of emergency transport urgency, the ratio of expected duration of self-transport to a hospital and the measured transport time by an ambulance.
Data collection/extraction: We calculated ambulance arrival and destination times using sequential temporospatial coordinates. We excluded any entries in which patient race was not recorded. We also excluded entries in which ambulances' routes did not pass within 100 m of either the patient's location or the documented hospital destination.
Principal findings: We found that mean transport time to a hospital was 2.5 min shorter for black patients compared to white patients. However, white patients' transport times to a hospital were found to be, on average, 4.1 min shorter than expected compared to 3.4 min shorter than expected for black patients. One-way ANOVA testing for the spatially-independent index of emergency transport urgency was not statistically significant, indicating that average transport time did not vary significantly across racial groups when accounting for variations in transport distance.
Conclusions: Using a novel transport urgency index, we demonstrate that these findings represent race-based variation in spatial distributions rather than racial bias in emergency medical transport. These results highlight the importance of closely examining spatial distributions when utilizing temporospatial data to investigate geographically-dependent research questions.

1. Introduction

Abundant research demonstrates clear disparities in acute ischemic stroke (AIS) treatment and outcomes by race, gender, and age [1-7]. Geographic factors can also influence access to healthcare and health outcomes [8,9]. For example, the regional incidence of stroke is highest in the eleven contiguous states constituting the Stroke Belt [10-12]. Numerous additional studies demonstrated geographic variability in stroke incidence, healthcare access, adherence to performance metrics, and prevalence of patient risk factors [13-22]. Availability of emergency medical services (EMS), a crucial component of stroke care, also varies by location [23].

EMS decisions impact patient outcomes in stroke via differentiation of AIS from stroke mimics, large vessel occlusion detection, and transport efficacy. A systematic review found that pre-hospital delays are a larger contributor to overall delays in care than were in-hospital delays and are associated with race, age, and socioeconomic status (SES) [24,25]. While the past few decades have seen substantial reductions in in-hospital delays, there has been comparably little improvement in pre-hospital delays [26]. Moreover, despite the importance of EMS transport, few studies have reported durations of the various stages of EMS transport [27].

Disparate emergency medical care is particularly significant given the abundant literature showing decreased benefit of interventions as time from stroke onset increases [28-30]. Permanent brain tissue

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damage from ischemia grows exponentially thus rendering most valuable the immediate time after stroke onset [31]. Additionally, stroke treatments are time-sensitive, and the 2019 AHA/ASA Guidelines do not recommend the use of intravascular thrombolysis outside of a three- to 4.5-h window or endovascular thrombectomy outside of a 24-h window [32]. Lastly, models using data from large, multi-center trials have suggested that EMS decisions in the field can influence outcomes in AIS patients [33,34].

Investigating disparities in emergency medical transport can prove challenging because geography is intimately associated with race and SES [35]. Segregation refers to systematic variations in the extent to which two or more groups are physically apart and is most commonly discussed in the context of residential segregation—systematic differences in where persons primarily reside [36,37]. Of note, residential segregation most commonly follows racial/ethnic or income lines but can involve any sociodemographic trait. The United States has a long history of profound residential racial segregation, and most communities in America show at least some degree of race- or income-based residential segregation [36,38]. However, the particular spatial patterns of residential segregation vary by location and result from long-standing patterns of discrimination—both individual and institutional—against particular groups [37,39]. For example, one heavily segregated locale may have members of one ethnic group clustered into pockets; in another locale, low-income residents may overwhelmingly live on one side of the city [40]. Regardless of the particular spatial patterns, residential segregation will produce systematic variations in the spatial distribution of a population. This sociodemographic variation in the spatial distribution of the study population can confound attempts to assess for treatment disparity when the outcome of interest is spatially-dependent.

Given the importance of minimizing time to treatment in AIS, we aimed to derive metrics of emergency medical transport time that can be calculated with readily available data and are amenable to comparison over time and space. We then characterized the performance of these metrics in a residentially segregated community. We hypothesized that spatially-dependent time metrics would be biased by sociodemographic variations in the spatial distribution of the patient population. As a case study in which to test this hypothesis, we used a large dataset documenting emergency medical transport times of suspected stroke patients in Austin, Texas, a city with a long history of residential racial segregation.

2. Materials and methods

2.1. Study setting

This was a retrospective study performed using a novel dataset from a public EMS in Central Texas with detailed temporospatial information on all ambulance runs for which a stroke alert was initiated between October 2010 and December 2018. Fig. 1 shows a map of the EMS service area with patient race and their locations at the time of EMS request for each ambulance run and clearly demonstrates residential racial segregation of the city's population. White patients are widely dispersed across the EMS service area, while Black and Hispanic patients are more tightly concentrated around the eastern aspect of Interstate 35 (a major highway running through downtown Austin, TX) (Fig. 1). Of note, the three comprehensive stroke care centers (CSC) within the EMS service area are all located in downtown Austin relatively close to Interstate 35. As mentioned above, we hypothesized that race-based variation in the geographic distribution of the study population would bias spatially-dependent metrics of emergency transport time. Lastly, though there are multiple stages of the pre-hospital timeline for suspected stroke patients, this analysis specifically examined emergency transport time from a patient's location to a hospital. The institutional review board at the University of Texas at Austin approved this study.

2.2. Study population

Each record in the dataset contained detailed demographic data along with sequential geographic coordinates and timestamps automatically recorded by a navigation device that documented the ambulance's route from time of dispatch to the patient's arrival at a hospital. To validate documented emergency transport times, we first calculated the Euclidean distance with Vincenty's ellipsoid formula between all serial geographic coordinates and the patient's location and hospital destination using Matlab version 9.0 (The MathWorks Inc., Natick, MA, USA). We then identified the latest time at which the ambulance was within a 10 m (m) radius of the patient's location as time of ambulance departure and the earliest time at which the ambulance was within a 10 m radius of the hospital as time of ambulance arrival; these times were used to calculate duration of transport. We included the 10 m buffer zone to account for systematic error in the positional accuracy of the ambulances' navigation systems [41].

Certain records had no documented temporospatial data for portions of the ambulances' routes. These data gaps often occurred as the ambulance was reaching its hospital destination. Most hospitals in the EMS service area were in urban settings; the surrounding infrastructure may have interfered with ambulances' navigation systems. To determine if there was racial variation in the distribution of data gaps, we implemented a one-way ANOVA and found that the length of the data gaps did not vary significantly by patient race ($F(4, 3854) = 0.597$, $p = 0.665$). This lack of race-based variation further suggests systematic error in the recording of ambulance routes.

We excluded 1332 entries missing temporospatial data for longer than one minute (Fig. 2). We additionally excluded 295 entries in which the ambulances' routes did not arrive within 100 m of either the patient's documented location at time of stroke or their hospital destination (Fig. 2). Patient race was either self-reported or documented by EMS providers during the encounter. Due to small sample sizes, patients whose race was listed as either "Native American" or "Pacific Islander" were recoded as "Other" for race; 435 patients with no documented race or ethnicity were excluded from the final analysis (Fig. 2).

2.3. Emergency transport time metrics

We defined four readily calculable emergency transport time metrics that could be used to compare ambulance runs of varying distances. Measured transport time (*mTT*) to hospital, the simplest metric, was calculated as duration in minutes between an ambulance's departure from the patient's location and its arrival at a hospital. To compare *mTT* with a patient's expected self-transport time (*eTT*), we estimated road travel time in minutes with ArcGIS Desktop version 10.8 (Environmental Services Research Institute, Redlands, CA, USA) using coordinates for the patient's location and their hospital destination. This estimation assumes average traffic speeds and does not account for routine traffic delays as these may change cyclically over varying time periods. Additionally, the route used by ArcGIS in its estimations can differ from that used by EMS personnel.

EMS personnel are given discretion to select routing and use special traffic permissions. Of note, EMS personnel may shorten their transport time in various ways: increasing travel speed, utilizing traffic permissions, or selecting alternate routes. However, the salient metric is hospital transport time irrespective of how transport time is shortened. To evaluate the effect and possible differential application of these traffic permissions, we calculated the difference between expected and measured transport times to a hospital (*dTT*):

$$dTT = eTT - mTT$$

To more readily compare the duration of EMS transport to expected duration of self-transport, we defined a factor μ that

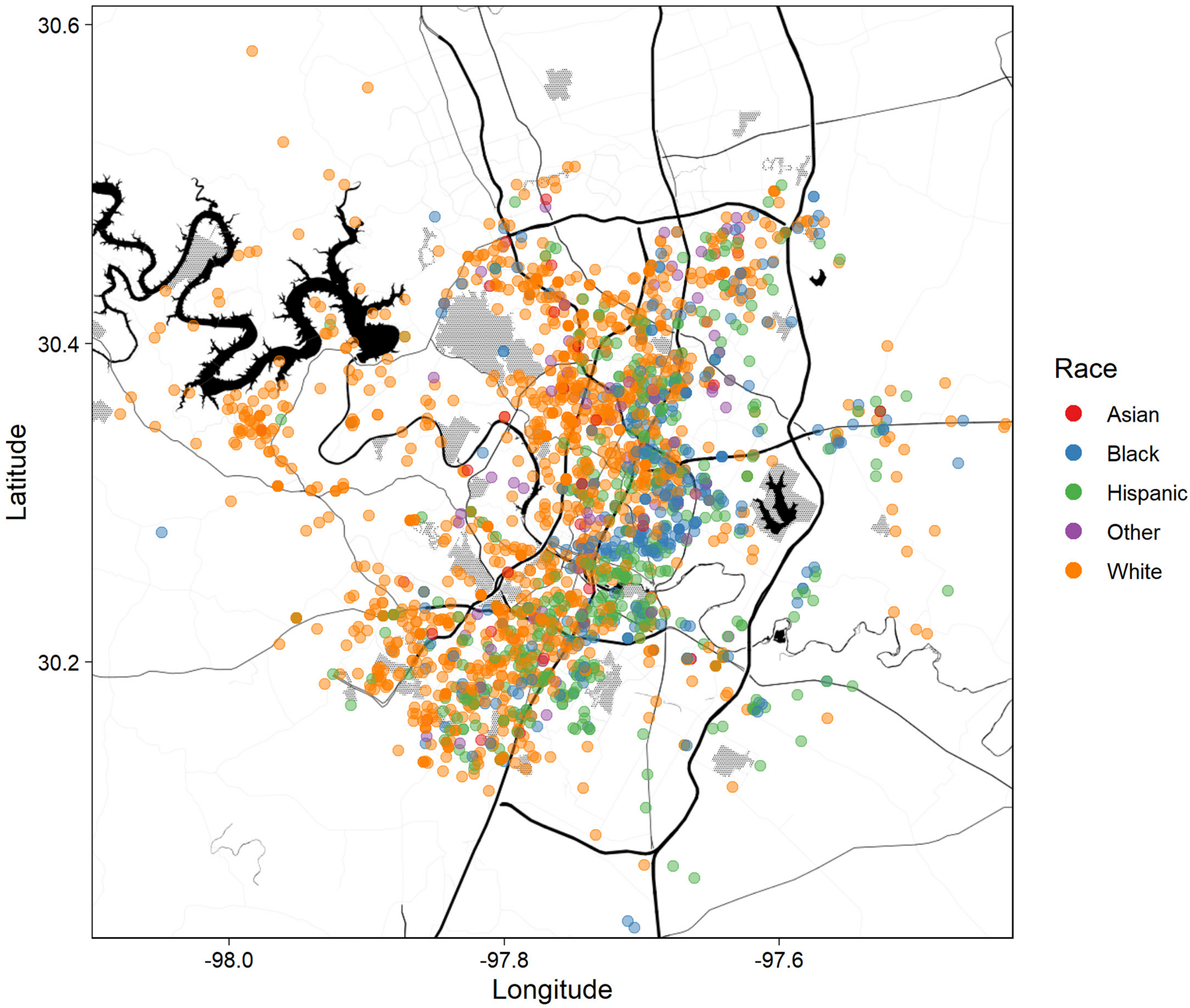

Fig. 1. A map depicting the location of each EMS call contained in the dataset colored by the patient's race/ethnicity. These data were derived from documented patient locations.

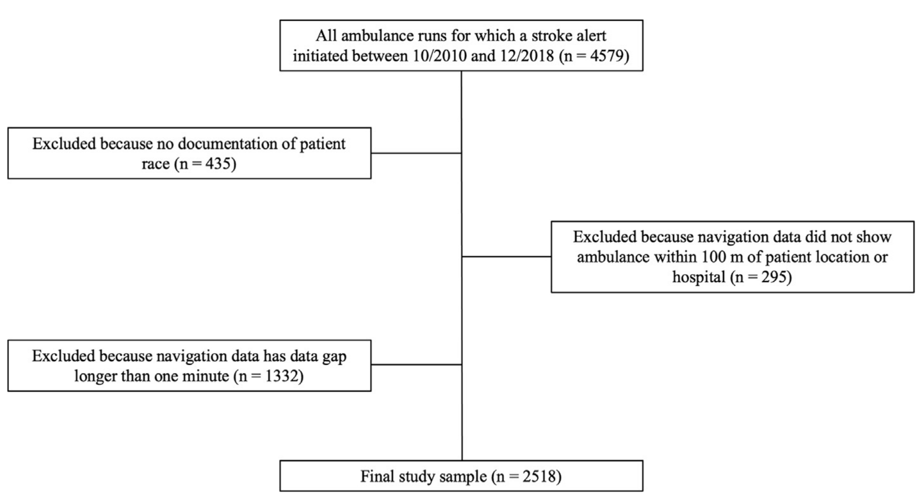

Fig. 2. Study exclusion criteria.

represents the ratio of EMS transport time to self-transport time. If S represents the speed at which the vehicles travel and D the road distance they travel:

$$S_{EMS} = \mu S_{self}$$

$$\frac{D}{mTT} = \mu \frac{D}{eTT}$$

$$\frac{1}{mTT} = \mu \frac{1}{eTT}$$

$$\mu = \frac{eTT}{mTT}$$

We can thus characterize μ as a novel, unitless index of emergency transport time urgency. Expected self-transport time (*eTT*) is generally longer than emergency transport time (*mTT*), so we expect that μ will be greater than one with larger numbers indicating more urgent transport. For example, if self-transport to the hospital takes 30 min but is completed by EMS in 20 min, μ will be 1.5.

Lastly, as emergency transport time is obviously dependent on a patient's physical distance from the hospital, we evaluated each metric's relationship with the patient's road distance from the hospital. To do this, we calculated hospital transport distance in kilometers (km) with ArcGIS using coordinates for the patient's location and the hospital to which they were transported. We then assessed the relationship between hospital transport distance and the emergency transport time metrics with Pearson's correlation coefficient.

2.4. Statistical analysis

By comparing mean emergency transport time metrics across racial groups, we can determine if EMS personnel differentially apply special traffic permissions. For example, consider two groups A and B with various distributions of a time metric. If there is a statistically significant difference between the average value of the time metric for groups A and B, we can conclude that the urgency of EMS transport is significantly different across groups. If there is no systematic difference in the urgency of EMS transport for each group, then the mean value of the time metric should be equivalent across groups. Thus, the test of equivalent group mean values of a time metric is an adequate test of the null hypothesis of no racial disparity in EMS transport.

To determine if the metrics of hospital transport time varied by patient race/ethnicity, we implemented one-way ANOVA tests with the various metrics of emergency transport time as outcomes and patient race as the covariate. Statistically significant omnibus tests were followed with post-hoc pairwise *t*-tests with Bonferroni-Holm adjustments [42,43]. All statistical analyses and figures were completed in R version 3.2 (R Foundation for Statistical Computing, Vienna, Austria).

Table 1
Sample characteristics of the dataset.

Demographics		Initial Sample		Final Sample	
		Count	Percent	Count	Percent
Race	Asian	69	1	40	2
	African-American	667	16	401	16
	Caucasian	2477	61	1505	60
	Hispanic	739	18	482	19
	Other	139	4	90	3
Gender	Female	2387	52	1323	53
	Male	2189	48	1192	47
Age	18 years and younger	25	1	6	1
	19 to 64 years	2058	45	1092	43
	65 years and older	2482	54	1417	56

Table 2
Summary statistics of all transport time metrics by patient race/ethnicity. These statistics represent the final dataset.

Race	mTT (min)		eTT (min)		dTT (min)		μ	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Asian	13.8	7.54	17.5	7.71	3.68	3.66	1.40	0.356
Black	10.9	5.48	14.3	6.27	3.36	2.49	1.39	0.488
Hispanic	12.1	5.36	15.8	6.06	3.64	3.28	1.36	0.310
Other	12	5.63	15.6	5.64	3.62	2.42	1.40	0.330
White	13.4	6.75	17.5	7.95	4.13	3.30	1.36	0.278

3. Results

3.1. Demographic characteristics of the study population

The final dataset included 2518 unique ambulance runs. Table 1 shows the demographic characteristics of the initial and final samples. The majority of patients in the dataset were White (60%). Black patients and Hispanic patients constituted 16% and 19% of the dataset respectively. More than half of the patients in the final dataset were female (53%). The majority of patients were over the age of 65 years (56%), and 43% of patients were between 19 and 64 years of age. Only six patients in the final dataset were younger than 18 years of age.

3.2. Primary outcomes of the ANOVA tests

Table 2 shows summary statistics for all transport time metrics grouped by patient race. One-way ANOVA tests showed that *mTT* varied significantly by race ($F(4, 2513) = 14.47$, $p < 0.0001$). Group means varied significantly for Asian and Black ($p = 0.036$), Hispanic and Black ($p = 0.031$), Black and White ($p < 0.0001$), and Hispanic and White patients ($p = 0.001$). Thus, average *mTT* was shortest for Black patients, then Hispanic patients, White patients, and longest for Asian patients (Table 2). *eTT* also varied significantly by patient race ($F(4, 2513) = 18.53$, $p < 0.0001$). Group means varied significantly for Hispanic and Black ($p = 0.018$), Black and White ($p < 0.0001$), and Hispanic and White patients ($p < 0.0001$). Though average *eTT* were slightly longer than average *mTT*, the same race-based pattern was observed in which the average *eTT* was shortest for Black patients, then Hispanic patients, White patients, and longest for Asian patients (Table 2). Thus, Asian and White patients had, on average, longer transport times to a hospital relative to Black and Hispanic patients.

dTT also varied significantly by patient race ($F(4, 2513) = 5.914$, $p < 0.0001$). Group means varied significantly for Hispanic and White ($p = 0.03068$) and Black and White patients ($p = 0.00015$). However, the race-based pattern seen for *mTT* and *eTT* was reversed for *dTT*; Black patients had the smallest average *dTT* followed by Hispanic patients, Asian patients, and then White patients with the largest difference (Table 2). Thus the difference between emergency transport time and estimated self-transport time was largest for White patients and smallest for Black patients. Finally, in contrast to the previous metrics, one-way ANOVA testing for μ ($F(4, 2513) = 0.883$, $p = 0.473$) was not statistically significant, indicating that the average value of μ did not vary significantly across racial groups.

3.3. Spatial dependency of emergency transport time metrics

Fig. 3 depicts the relationships between hospital transport distance and the four metrics of hospital transport time along with Pearson's correlation coefficient and associated *p*-value. *mTT* ($r = 0.89$, $p < 0.001$) and *eTT* ($r = 0.96$, $p < 0.001$) have a strongly positive correlation with hospital transport distance (Fig. 3A and B). *dTT* has a moderately positive correlation ($r = 0.43$, $p < 0.001$) with hospital transport distance (Fig. 3C), while μ has a weakly negative correlation ($r = -0.14$,

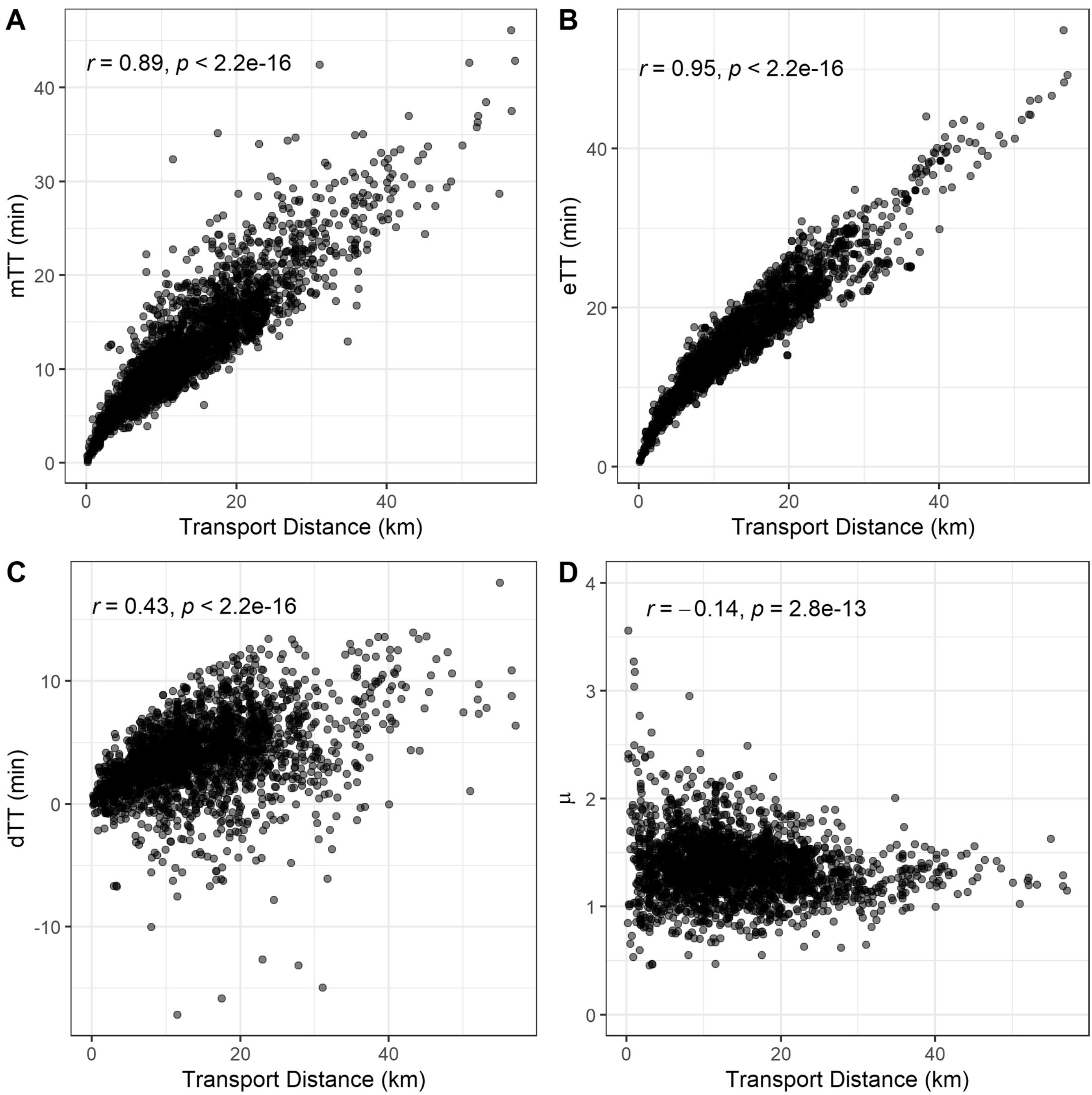

Fig. 3. Scatterplots depicting relationship between hospital transport distance (km) and the various hospital transport time metrics with Pearson's correlation coefficient and associated p-value. A) Measured hospital transport time (min). B) Expected hospital transport time (min). C) Difference in expected and measured hospital transport time (min). D) μ, a spatially-independent metric of transport urgency.

$p < 0.001$) with hospital transport distance (Fig. 3D). Notably, μ shows greater variation over shorter hospital transport distances (Fig. 3D). Lastly, Fig. 4 shows the spatial density—as estimated by a bivariate normal kernel—of the patient population across the EMS service area subset by patient race.

4. Discussion

We investigated the performance of four emergency transport time metrics in assessing for racial disparities in emergency transport of suspected stroke patients in the setting of stark residential racial segregation (Figs. 1 and 4). We hypothesized that time metrics most strongly correlated with distance would be most sensitive to group-level variations in the spatial distribution of the patient population. Additionally, previous studies demonstrated that road distance from a patient's location to a hospital can significantly impact patient outcomes, so it is essential to control for hospital transport distance when assessing for transport disparity [44,45]. However, hospital transport distance will vary systematically by sociodemographic characteristics in a residentially segregated community; patients of particular sociodemographic groups may live, on average, further or closer to a hospital relative to patients of other sociodemographic groups. Thus

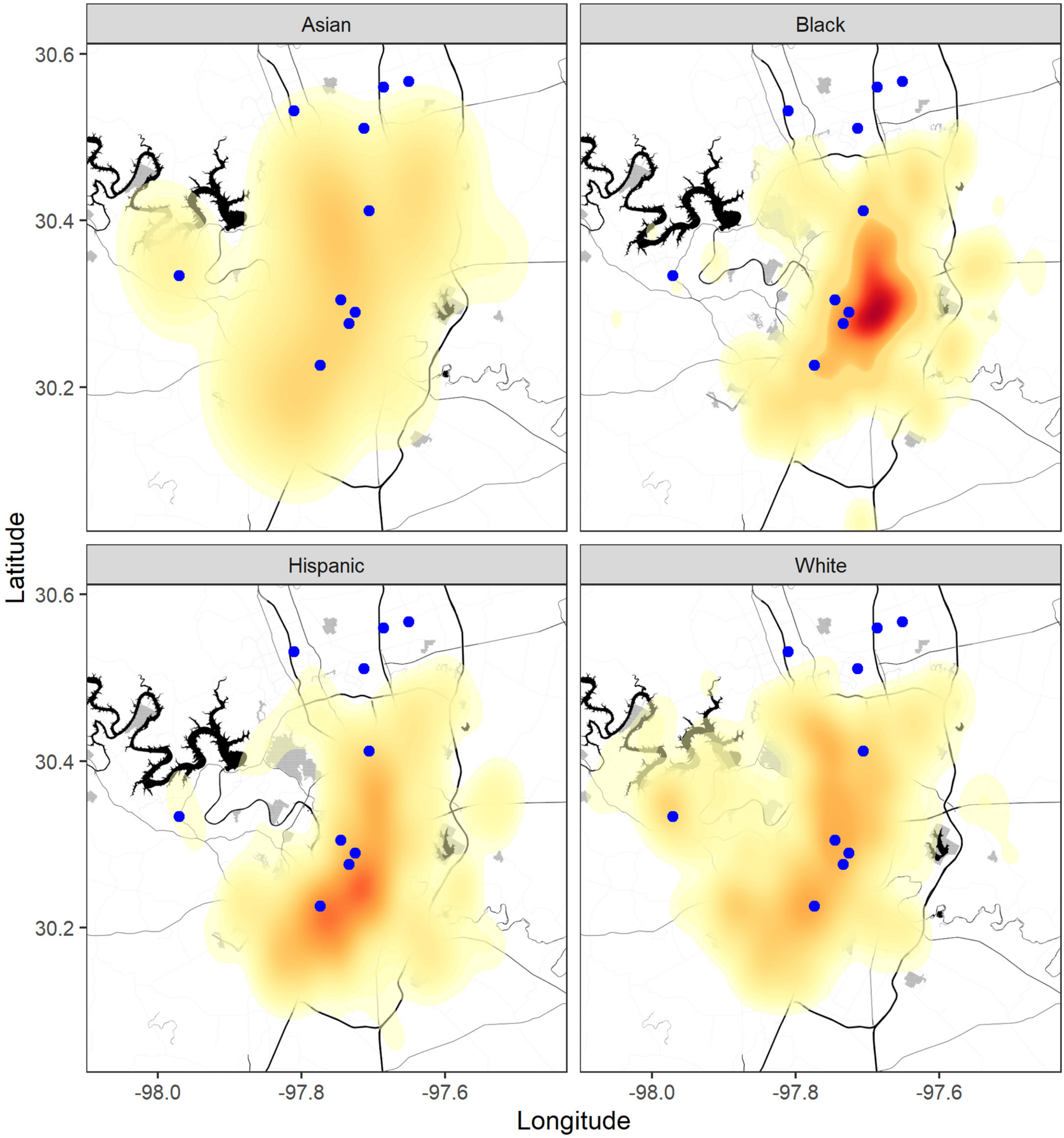

Fig. 4. Density plots depicting the spatial distribution of each racial group with darker colors indicating greater population density. Blue points indicate major hospitals. These data were derived from documented patient locations.

transport time metrics that strongly correlate with transport distance have minimal utility in a residentially segregated community, as the spatial concentration of population subgroups relative to hospital location will bias these metrics.

Both *mTT* and *eTT* strongly correlate with hospital transport distance (Fig. 3A and B); this is to be expected, as the strongest determinant of transport time is transport distance. Thus, in the presence of group-level variation in hospital transport distance—as is seen in Austin, Texas—both *mTT* and *eTT* are not readily comparable metrics of emergency transport time. *dTT* also substantially correlates with transport distance (Fig. 3C) because the possible range of *dTT* varies with hospital transport distance. As hospital transport distance increases, the potential time saved by emergency transport relative to self-transport also increases. Over short transport distances, *dTT* is necessarily constrained, as EMS personnel have less distance over which to exercise special traffic permissions. Notably, the impact of *dTT* varies by transport duration; a

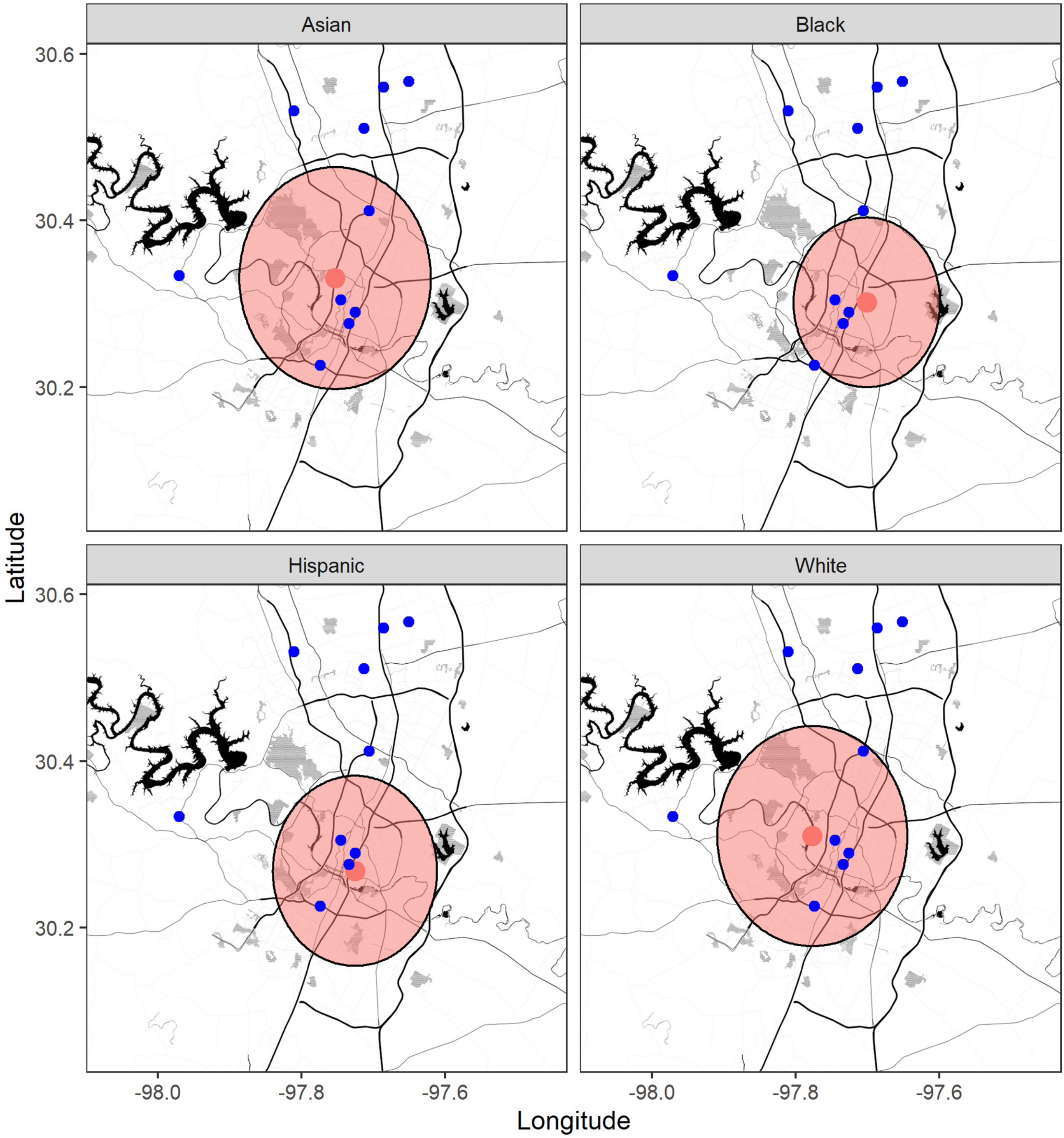

Fig. 5. Maps depicting the standard distance (transparent circle with black outline) and mean center (opaque point) of each racial/ethnic group. Red points indicate major hospitals. These data were derived from documented patient locations.

dTT of 5 min is more impactful for a 10-min trip than for a 30-min trip. Thus *dTT* does not permit ready comparison of trips of varying hospital transport distances.

Because it can be defined as a unitless index of the ratio of *eTT* to *mTT*, we described μ as representative of emergency transport urgency, the factor by which emergency transport time differs from expected duration of self-transport. In contrast to *mTT*, *eTT*, and *dTT*, μ is minimally correlated with hospital transport distance (Fig. 3D). It is thus less sensitive to the group-level variation in spatial distributions that would be seen in residentially segregated populations and readily permits comparison of trips of varying distances.

Fig. 4 clearly demonstrates group-level variation in the spatial distribution of our study population. Asian and White patients are most widely dispersed across the EMS service area, while Hispanic and Black patients are most geographically concentrated and appear to have their highest population density adjacent to the CSCs in downtown Austin (Fig. 4). The significant differences in *mTT* and *eTT* by patient race suggest that White and Asian patients had significantly longer emergency medical transport times relative to Hispanic and Black patients (Table 2). However, analysis of time saved by utilization of EMS special traffic permissions—as represented by *dTT*—exhibited an inverse pattern wherein Black and Hispanic patients seemed to have significantly less time saved by emergency transport relative to White and Asian patients (Table 2). Thus, it would seem that these results discord insofar as Black patients received less advantage from these traffic permissions relative to White patients, while White patients had longer average transport times to the hospital relative to Black patients.

We posit that these discordant results actually reflect substantial race-based variation in patient location across the EMS service area which preferentially biases spatially-dependent metrics of emergency transport time. The significant differences in *mTT* and *eTT* by race reflect strong race-based variation in the spatial distribution of our patient population. Moreover, because the spatial dispersion of Asian and White patients is much greater (Fig. 4), EMS personnel have more road time over which to utilize special traffic permissions; this explains the greater *dTT* for Asian and White patients relative to Black and Hispanic patients. The significant differences between mean *dTT* by patient race thus reflect the spatial dependence of *dTT* (Fig. 3) and the substantial group-level variation in our patient population.

The spatially-independent metric μ did not vary significantly by patient race suggesting no racial disparity specifically in emergency transport urgency of suspected stroke patients in Austin, Texas. Though we demonstrate how use of a spatially-independent transport time metric contextualizes results initially suggestive of profound race-based disparity, we cannot exclude other disparities in emergency medical transport. Additionally, racial segregation has been shown to produce unique socio-ecological environments that drive exposure to environmental risk factors and reflect varying levels of access to healthcare [46-49]. In short, geography strongly influences health behaviors, disease risk, and access to care, but its influence is deeply tangled with race and socioeconomic status; these complicated relationships further emphasize the importance of careful documentation of spatial distributions [50]. Furthermore, residential segregation is present in almost all communities in America and causes significant group-level variation in patients' spatial distributions by the relevant sociodemographic characteristics [51].

Analyses that concern spatial relationships should be sensitive to group-level variation in the spatial distribution of the study population, as group-based differences in patient location can mask evidence of disparate care or create the false appearance of equity. By adequately characterizing how spatial distributions vary across population subgroups of interest, researchers can provide the necessary context for appropriate interpretation of results. As an example of best practices for spatial data characterization, Fig. 5 demonstrates a comprehensive visual depiction of group-level variation in the spatial distribution of our patient population by documenting geometric mean and standard distance, the primary center and dispersion parameters for most spatial distributions, for each population subgroup along with relevant geographic landmarks. We advise researchers using geographic data to conduct detailed exploratory analyses, carefully describe spatial variations in their features of interest, and use spatially-independent metrics. Given the long history of race- and income-based segregation in the United States, investigations of healthcare disparities that involve spatial relationships should begin with careful attention to the methodological challenges produced by the geographic concentration of underserved populations.

To our knowledge, this is the first study to derive and implement a spatially-independent metric of emergency transport time. By comparing measured emergency transport time with the expected duration of self-transport, μ permits comparison of varying trips even in the absence of detailed data on infrastructure—not only do traffic patterns, roads, and other infrastructure considerations change over time, they are difficult to accurately operationalize. Given the heterogeneity in emergency medical services across the country, our focus on one community highlights the importance of local analyses, as national-level data may conceal significant regional variation in emergency medical care [52]. Furthermore, our study uses individual incidence and destination coordinates which permits more accurate estimation of travel times [44,53,54].

However, the use of μ assumes that relative change between *mTT* and *eTT* reflects only the urgency of EMS transport. Thus μ does not account for disparity in EMS evaluation of a patient nor in the selection of a hospital destination. Moreover, the heteroskedasticity in μ when predicted by hospital transport distance likely reflects the outsize impact of small changes in transport time for short trips (Fig. 3D); this suggests that μ is not an ideal metric for communities in which patients live immediately adjacent to hospitals. Important data limitations include systematic error in the recording of timestamps and patient demographic information.

Current models of health inequity consider not only individual characteristics such as race and SES but also the larger context of a patient's location [55]. Further research should address the myriad ways in which patient location influences health outcomes in time-sensitive conditions. Disparities in the placement of hospitals or EMS stations and urban-planning decisions such as the placement of roads may also influence access to healthcare. Lastly, a large proportion of Americans do not call emergency medical services [56,57]. Racial minorities have been found to be less likely to call EMS [58]. Further research should investigate barriers to EMS usage and variation in outcomes between patients who utilize EMS and those who do not.

5. Conclusion

Given the importance of minimizing time to treatment in AIS, we aimed to derive simple, easily calculable metrics of emergency medical transport time and then characterize the performance of these metrics in a residentially segregated community. For a case study in which to test this hypothesis, we used a large dataset documenting emergency medical transport times of suspected stroke patients in Austin, Texas, a city with a long history of residential racial segregation. We found that spatially-dependent metrics were more sensitive to the group-level variation in the spatial distribution of the patient population that is seen in residentially segregated communities. We additionally described the performance of a spatially-independent metric and proposed best practices for working with spatial data in the setting of residential segregation.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Prior presentations

A poster describing the results of this study was presented at the 2021 International Stroke Conference.

Ethics approval

This was an entirely retrospective study conducted with data obtained from an external organization. The Institutional Review Board of the University of Texas at Austin approved this study.

Declaration of Competing Interest

None.

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