Engagement in outreach services among persons experiencing unsheltered homelessness in a Southwestern Urban County: A spatial study

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Abstract

This study explored how engagement in street outreach services is impacted by the locations where structurally vulnerable individuals experiencing unsheltered homelessness enroll. Logistic regression models were applied to 2022 outreach service contact data to analyze spatial concentrations of engagement across 11 location types. The highest spatial concentration of outreach service contacts occurred in the downtown area of an urban city. Results showed that gender, race, and ethnicity moderated the relationship between engagement and locations where contacts occurred. Among racial and ethnic groups, American Indian/Alaska Native/Indigenous and Hispanic/Latino clients had significantly lower odds of outreach service contacts near the downtown area compared to White clients. In comparison, Black/African American/African and Asian/Asian American clients had higher odds. Additionally, Black/African American/African women had lower odds of outreach service contacts near the downtown area compared to White women. Women had higher odds of contacts near motels than men. High utilizers of outreach services had higher odds of contacts near the downtown area, with gender and race moderating this relationship. Spatial analysis is a novel approach to understanding geographic context where structurally affected individuals engage in services. These findings highlight the need to tailor outreach strategies better to serve diverse populations in different geographic contexts.

Introduction

According to the U.S. Department of Housing and Urban Development, the number of people experiencing literal homelessness increased 12.1% between 2022 and 2023 (Tanya de Sousa et al., 2023). Arizona has one of the highest homeless rates, with 19.2 people experiencing homelessness per 10,000 residents (Tanya de Sousa et al., 2023). The lack of affordable, stable, and safe housing is a well-documented social and structural determinant of health for this population (World Health Organization, 2018). Experiencing homelessness is linked to poorer health outcomes, limited access to care, and adverse health behaviors. This negatively affects physical and mental health, hinders personal and service-related recovery efforts, and increases morbidity within this population (Greene, 2024a; Henwood et al., 2015; Lifland et al., 2022).

Individuals experiencing homelessness (i.e., unsheltered persons) are structurally vulnerable due to factors that exacerbate housing instability, such as limited access to affordable housing and living wage employment, the cost of unexpected medical emergencies, and systemic issues like housing discrimination (Greene, 2024a). These circumstances contribute to significant personal shame and social stigma, perpetuating a socially constructed myth of “hard to reach” and “hard to serve” (Greene, 2024b; Shin, 2023). Greene (2024a) uses a framework of visibility to address the structural nature of homelessness, contextualizing visibility by where homelessness occurs and the social relations a person may engage in (or not) to access and engage in services (Greene, 2024a). These “aspects of visibility” categorize individuals as “most engaged and surveilled” (e.g., living in a shelter), “most visible and exposed (e.g., individuals experiencing unsheltered homelessness),” and “most hidden” (e.g., couch surfing) (Greene, 2024a, p. 109). Unsheltered homelessness is sleeping “outside, in a car, or places not meant for human habitation” (Shin, 2023, p. 693). In Arizona (AZ), more than 50% of people experiencing homelessness are unsheltered. Additionally, 21.5% of people experiencing homelessness in AZ meet the definition of chronic homelessness, which is having a disability and being homeless for 12 months or 4 times in the last three years (Tanya de Sousa et al., 2023). Given their vulnerability to harm, the severity of their needs, and the persistent nature of homelessness, reaching out to and engaging unsheltered persons is essential to helping them obtain access to stable housing (Greene, 2024a).

Outreach services target individuals affected by homelessness who are disconnected (e.g., lacking social support systems) and “at risk for adverse events or health outcomes” (Jiao et al., 2022, p. 9). Aligned with the visibility framework, outreach services address structural barriers by offering services in non-traditional settings and fostering social connections that help alleviate the “administrative burden” for this vulnerable population (Robinson et al., 2023, p. 1). Outreach service providers meet people where they are, building rapport and trust to establish a relationship that facilitates engagement in services (Jiao et al., 2022) or figuratively by providing support that is non-judgmental, supportive, and person-specific (Magwood et al., 2019). Olivet et al. (2010) found that outreach workers, acting as networkers, navigators, and advocates who respect and value unsheltered persons, help build trust and increase confidence in accessing and engaging in services. However, they argue that the relationship between outreach and engagement has not been fully explored in the literature, underscoring the difficulty quantifying the engagement process. One possible way to infer an individual’s response to outreach efforts is by measuring the number of outreach service contacts per person (e.g., whether they actively engage with an outreach worker). For example, in health care, utilization is typically measured by the frequency of acute service use within a specified timeframe (e.g., at least five visits in 12 months) or by a top percentile cutoff (Shukla et al., 2020). Given the limited research on quantifying utilization in homeless services, healthcare research provides various approaches to measuring, quantifying, and applying cost estimates to examine the acute healthcare needs of unsheltered persons (Szymkowiak et al., 2017; Wiens.

This study uses spatial analysis to examine how the engagement of unsheltered persons influences the locations of outreach services. Using spatial analysis to understand homelessness is a novel approach aimed at reaching individuals where they are and providing necessary support in a systematic way (Aasi, 2020; Ahasan et al., 2022; Rukmana, 2010; Semborski et al., 2022). One way to use data with spatial attributes, such as locations or distances, is by measuring individuals’ activity space. Activity space, the local areas where individuals move or travel within a specified timeframe, offers a way to measure behavior using spatial data (Semborski et al., 2022). Leopold et al. (2017) analyzed client addresses prior to entering homelessness and found that urban residents were more likely to become homeless, and suburban residents often moved to urban centers for housing services. Additionally, factors such as the availability of affordable rental housing, the percentage of minority households, and the proportion of single mothers were associated with community levels of homelessness (Leopold et al., 2017). Rowen (2017) investigated the locations where homeless women died using spatial clustering and found that deaths occurred in areas where services were concentrated. These analyses suggest that preventative efforts could be vital in reducing premature deaths among women experiencing homelessness in specific areas, offering opportunities for targeted outreach and services (Davidson et al., 2011). A review of the literature suggests that this study is the first to empirically examine how levels of engagement among unsheltered persons impact the location of outreach services and what factors moderate this relationship. Administrators and service providers can use results from this study to guide new and existing outreach efforts to target better and serve people experiencing unsheltered homelessness.

Methods

Researchers partnered with community stakeholders in Maricopa County, Arizona, and applied the principles of community-based participatory research to conduct spatial analysis of outreach contacts. This collaborative effort centered on developing the study's aims, engaging in analytical discussions, and partnering to disseminate the findings in ways beneficial to city and county stakeholders and the service community (Resnik & Kennedy, 2010).

This study uses 2022 Homeless Management Information System (HMIS) data from the Maricopa Association of Governments (MAG) (Maricopa Association of Governments, 2024). The Homeless Outreach Viewer is a tool created by MAG that displays HMIS street outreach service data reported by the Maricopa Regional Continuum of Care. Street outreach service contacts occur at the client level. Each contact includes the date, longitude, and latitude coordinates and is completed by outreach workers across providers in Maricopa County. Each contact also includes client demographic information. This study adhered to ethical guidelines for using secondary data, ensuring the confidentiality and anonymity of individuals and communities represented in the dataset provided by the MAG Homeless Outreach Viewer. This study was approved by the IRB # STUDY00014573.

The dataset consisted of 21,376 street outreach service contacts representing 8,237 unique clients. Less than 3% of the data contained missing client demographic information. These data were excluded from the analysis. Clients' levels of engagement were defined by using the 90th percentile as a threshold for the number of contacts made by outreach workers for each client. Based on this threshold, clients were categorized as "non-high utilizers of outreach services" or "high utilizers of outreach services" (see Fig. 1).

Four demographic characteristics were included in the analysis: gender, ethnicity, race, and veteran status. Gender was recoded into three categories: male, female, and other. The "other" category included transgender, female/transgender, questioning, non-binary/male/transgender, and man/non-binary identities. Race consisted of five categories: White, Black/African American/African (Black/AA/A), American Indian/Alaska Native/Indigenous (AI/AN/I), Asian/Asian American, or Native Hawaiian/Pacific Islander (NH/PI). Veteran status included "veteran" or "non-veteran." Ethnicity was represented by two categories: "Hispanic/Latino" or "Non-Hispanic/Latino."

This study used a hybrid approach to analyze the data, combining spatial and clustering techniques to identify outreach service contact patterns for unsheltered persons. First, a density map was created to visualize where contacts were concentrated (see Fig. 2). However, rather than focusing on specific geographical locations, the study examined the types of locations where contacts occurred, regardless of their actual spatial coordinates. To investigate these patterns further, K-means clustering (Lloyd, 1982; Macqueen, 1967) was applied separately to high utilizers and non-high utilizers of outreach services to identify patterns for each group. The optimal number of clusters for each group was determined using the silhouette score (Rousseeuw, 1987). This metric measures how well each data point fits within its cluster (i.e., cohesion) and how distinct the clusters are from each other (i.e., separation). The analysis identified 600 clusters for high utilizers and 530 clusters for non-high utilizers, comprising 50 or more contacts, allowing for precise location identification. By focusing on clusters with more than 50 contacts, the study identified the most common locations where street outreach service contacts occurred. These analyses were refined using OpenStreetMaps (OSM) (Open

Street Maps, n.d.). OSM is a collaborative project that provides a free, editable map of the world, offering detailed geospatial data from a global community of volunteers. The tagging system in OSM was used to automate assigning the location types above to raw geographic data, improving the analysis. This resulted in 12,509 (58.5%) contacts concentrated around 11 location types (see Table 1). The remaining contacts were classified as "other locations." Fig. 3 presents a graphical representation of the location types used in the study.

Table 1
Outreach service contact locations defined.

Location type	**Definition**
Downtown area	Area in downtown Phoenix with a high concentration of outreach contacts.
ES/TH	ES/TH locations provided by MAG. A contact is classified near an ES/TH if the contact location is less than 250 feet from the corresponding ES/TH location (only point locations are provided, not actual boundaries).
Park	OSM locations tagged with the key leisure = park or leisure = nature_reserve, including urban and rural parks and protected areas. A contact is classified near a park if the contact location is less than 50 feet from its boundary.
Fast food restaurant	OSM locations are tagged with the key amenity = fast_food, which indicates a facility where fast food is served. A contact is classified near a fast food restaurant if the contact location is less than 200 feet from its boundary.
Parking lot/garage	OSM locations tagged with the key amenity = parking, which includes facilities used by the public, customers, or other authorized users for parking motor vehicles, such as cars and trucks. Only dedicated parking buildings are considered, and parking lots are ignored. A contact is classified near a parking garage if the contact location is less than 200 feet from its boundary.
Gas station	OSM locations tagged with the key amenity = fuel, which indicates a facility where fuel, such as gasoline or diesel, is sold for vehicles. A contact is classified near a gas station if the contact location is less than 200 feet from its boundary.
Hotel	OSM locations tagged with the key tourism = hotel, which includes establishments that provide paid lodging, usually on a short-term basis. A contact is classified near a hotel if the contact location is less than 200 feet from its boundary.
Restaurant	OSM locations tagged with the key amenity = restaurant, which is applied to generally formal eating places with sit-down facilities selling full meals served by servers and often licensed (where allowed) to sell alcoholic drinks. A contact is classified near a restaurant if the contact location is less than 200 feet from its boundary.
Motel	OSM locations tagged with the key tourism = motel, which includes establishments that provide paid lodging, usually on a short-term basis, with convenient parking for motor cars at or close to the room. A contact is classified near a motel if the contact location is less than 200 feet from its boundary.
Place of worship	OSM locations tagged with the key amenity = place_of_worship, which includes all places of worship (buildings) independent of the religion or denomination. A contact is classified near a place of worship if the contact location is less than 200 feet from its boundary.
Post office	OSM locations tagged with the key amenity = post_office include facilities where letters and parcels may be sent or collected, and stamps may be bought. A contact is classified near a post office if the contact location is less than 200 feet from its boundary.

Logistic regression models for each location type were constructed at the client level and fitted using the simultaneous entry method, where all predictor variables were entered in a single step to assess the relationship between clients' characteristics and contact locations. Interaction terms were added to the models to explore interactions between predictors. For these analyses, "other" (n = 43 clients) consisting of 160 contacts was excluded due to its small sample size. Each client was assigned a location type where the majority of the contacts occurred, reducing potential selection bias related to multiple contacts per client. In cases where clients had the same number of contacts for more than one location, the least represented location type was assigned to the client to provide a balanced representation of where contacts occurred. From the total client sample (n = 8,237 clients), a subset of 5,023 (61.0%) clients were assigned to a location type different from "other location," and 299 (3.6%) clients had a tie situation. These steps uniquely classify each client into one location.

Findings

A total of 8,237 clients with 21,376 outreach service contacts were represented in this study. The sample consisted mainly of male (60.6%), non-veteran (94.5%), White (64%), and non-Hispanic/Latino (76.6%) clients. All racial groups, except Asian/Asian American and NH/PI, were overrepresented in the sample. Hispanics were not overrepresented. White, Black/AA/African, and AI/AN/I clients comprised 64%, 27%, and 8% of the sample, compared to their population proportions of 52%, 6%, and 1% in Maricopa County, respectively. Non-high utilizers comprised 7,250 (88%) clients with four or fewer contacts, and high utilizers comprised 987 (12%) clients with five or more contacts. Demographics by utilizer status are described in Table 2. Chi-square tests of independence showed statistically significant relationships between gender and utilizer status ($p = .001$), as well as between race and utilizer status ($p < .001$). Significant differences were also observed between ethnicity and utilizer status ($p < .001$). However, no significant differences were found between veteran status and utilizer status. The highest spatial concentration of contacts occurred in the downtown area of a city within Maricopa County. This area contained 6,129 contacts (28.7%). Of these, 3,139 contacts (51.2%) were from high utilizers, while 2,990 contacts (48.8%) were from non-high utilizers.

Table 2
Client demographics by utilizer status.

Demographics		High utilizer n (%)	Non-high utilizer n (%)	Total N
Gender	Male	548 (11.0%)	4,440 (89.0%)	4,988
	Female	430 (13.4%)	2,776 (86.6%)	3,206
	Other	9 (20.9%)	34 (79.1%)	43
Race	White	705 (13.4%)	4,569 (86.6%)	5,274
	Black/African American/ African	202 (9.1%)	2,020 (90.9%)	2,222
	American Indian/Alaska Native/Indigenous	65 (10.4%)	563 (89.6%)	628
	Native Hawaiian/Pacific Islander	10 (15.6%)	54 (84.4%)	64
	Asian/Asian American	5 (10.2%)	44 (89.8%)	49
Veteran status	Non-veteran	932 (12.0%)	6,849 (88.0%)	7,781
	Veteran	55 (12.1%)	401 (87.9%)	456
Ethnicity	Non-Hispanic/Latino	806 (12.8%)	5,501 (87.2%)	6,307
	Hispanic/Latino	181 (9.4%)	1,749 (90.6%)	1,930

Results from the logistic regression analyses are presented in Table 3. Analyses indicate that among racial and ethnic groups, AI/AN/I clients (OR = 0.72, $p < .05$) and Hispanic/Latino clients (OR = 0.77, $p < .001$) had significantly lower odds of contacts near the downtown area compared to White clients. However, Black/AA/African (OR = 1.27, $p < .01$) and Asian/Asian American clients (OR = 2.50, $p < .05$) had higher odds of contacts in the downtown area compared to White clients. Asian/Asian American clients also had higher odds of contacts near hotels (OR = 3.47, $p < .05$) than White clients. In comparison, Black/AA/African clients had lower odds of contacts near post offices (OR = 0.38, $p < .01$) than White clients. Veteran status was associated with contact locations. Veterans had higher odds of contacts near ES/TH (OR = 1.44, $p < .05$) and restaurants (OR = 2.16, $p < .001$) compared to non-veteran clients. The association between gender and location was also examined. Women had significantly higher odds of contacts near motels than men (OR = 1.69, $p < .05$). Additionally, Black/AA/African women had lower odds (OR = 0.71, $p < .01$) of contacts near the downtown area than White women.

Table 3. Logistic regression results of the associations between demographic characteristics and utilizer status by location types.

			Gender	Veteran Status
	Number of outreach service contacts N (%)	Number of clients N (%)	Female = 1 OR (95% CI)	Yes = 1 OR (95% CI)
Downtown area	6041 (28.5%)	2143 (26.2%)	0.92 (0.80, 1.05)	1.03 (0.83, 1.28)
ES/TH	2056 (9.7%)	524 (6.4%)	1.04 (0.86, 1.25)	1.44* (1.01, 2.04)
Park	1141 (5.4%)	649 (7.9%)	0.94 (0.79, 1.11)	0.68 (0.45, 1.02)
Fast food restaurant	586 (2.8%)	314 (3.8%)	0.97 (0.77, 1.22)	0.60 (0.32, 1.10)
Parking lot/garage	498 (2.3%)	286 (3.5%)	0.90 (0.70, 1.15)	0.93 (0.54, 1.59)
Gas station	412 (1.9%)	331 (4.0%)	1.04 (0.83, 1.31)	0.89 (0.53, 1.50)
Restaurant	334 (1.6%)	199 (2.4%)	0.82 (0.61, 1.11)	2.16*** (1.37, 3.41)
Hotel	325 (1.5%)	218 (2.7%)	1.23 (0.93, 1.62)	1.24 (0.71, 2.18)
Motel	260 (1.2%)	151 (1.8%)	1.69* (1.04, 2.74)	1.81 (0.95, 3.43)
Place of worship	239 (1.1%)	140 (1.7%)	0.77 (0.54, 1.10)	0.92 (0.44, 1.91)
Post office	145 (0.7%)	68 (0.8%)	1.21 (0.74, 1.97)	1.33 (0.52, 3.38)

* p < .05; * p < .01; * p < .001; † = Parsimonious model does not include interaction term; NC = Interaction term not computed due to insufficient data; OR = Odds ratio; 95% CI = confidence interval.

Table 3. Continued.

	Race				Ethnicity
	American Indian/ Alaska Native/ Indigenous = 1 OR (95% CI)	Asian/Asian American = 1 OR (95% CI)	Black/African American/African = 1 OR (95% CI)	Native Hawaiian/ Pacific Islander = 1 OR (95% CI)	Hispanic/Latino = 1 OR (95% CI)
Downtown area	0.72* (0.54, 0.95)	2.50* (1.22, 5.13)	1.27** (1.10, 1.48)	0.96 (0.43, 2.15)	0.77*** (0.67, 0.89)
ES/TH	0.77 (0.52, 1.14)	1.32 (0.46, 3.76)	1.02 (0.83, 1.27)	1.64 (0.73, 3.71)	0.84 (0.66, 1.06)
Park	1.21 (0.91, 1.62)	0.78 (0.24, 2.51)	0.95 (0.78, 1.15)	1.46 (0.66, 3.22)	1.03 (0.85, 1.25)
Fast food restaurant	0.87 (0.55, 1.37)	NC	1.00 (0.77, 1.30)	0.40 (0.06, 2.91)	0.89 (0.67, 1.19)
Parking lot/garage	1.19 (0.78, 1.83)	1.26 (0.30, 5.24)	1.00 (0.75, 1.33)	2.45 (0.97, 6.19)	1.29 (0.98, 1.70)
Gas station	1.27 (0.86, 1.87)	1.05 (0.25, 4.36)	1.07 (0.82, 1.39)	0.40 (0.06, 2.93)	1.07 (0.82, 1.39)
Restaurant	0.87 (0.50, 1.53)	0.75 (0.10, 5.53)	0.71 (0.49, 1.02)	1.09 (0.26, 4.50)	1.09 (0.78, 1.53)
Hotel	1.30 (0.81, 2.10)	3.47* (1.22, 9.82)	1.16 (0.85, 1.59)	1.25 (0.30, 5.18)	0.92 (0.65, 1.30)
Motel	1.84 (0.81, 4.18)	NC	1.40 (0.78, 2.50)	NC	1.23 (0.79, 1.93)
Place of worship	0.64 (0.30, 1.39)	NC	0.91 (0.61, 1.36)	0.85 (0.12, 6.24)	0.81 (0.53, 1.25)
Post office	0.81 (0.32, 2.04)	NC	0.38** (0.19, 0.78)	NC	0.56 (0.29, 1.07)

Table 3. Continued.

	High Utilizer (HU)	Gender x Race			
	Yes = 1 OR (95% CI)	Female x American Indian/Alaska Native/Indigenous OR (95% CI)	Female x Asian/Asian American OR (95% CI)	Female x Black/African American/African OR (95% CI)	Female x Native Hawaiian/Pacific Islander OR (95% CI)
Downtown area	1.44** (1.15, 1.81)	0.73 (0.47, 1.14)	1.33 (0.38, 4.64)	0.71** (0.56, 0.90)	0.88 (0.28, 2.84)
ES/TH	4.59*** (3.77, 5.58)	†	†	†	†
Park	1.44** (1.15, 1.80)	†	†	†	†
Fast food restaurant	1.31 (0.95, 1.80)	†	†	†	†
Parking lot/garage	0.81 (0.55, 1.21)	†	†	†	†
Gas station	0.30*** (0.17, 0.52)	†	†	†	†
Restaurant	1.20 (0.80, 1.81)	†	†	†	†
Hotel	0.82 (0.53, 1.29)	†	†	†	†
Motel	1.78 (0.84, 3.77)	0.76 (0.26, 2.20)	NC	1.47 (0.70, 3.10)	NC
Place of worship	1.77** (1.15, 2.71)	†	†	†	†
Post office	2.61*** (1.52, 4.47)	†	†	†	†

Table 3. Continued.

	Gender x HU	Race x HU			
	Female x HU OR (95% CI)	American Indian/Alaska Native/ Indigenous x HU OR (95% CI)	Asian/Asian American x HU OR (95% CI)	Black/African American/ African x HU OR (95% CI)	Native Hawaiian/ Pacific Islander x HU OR (95% CI)
Downtown area	1.55** (1.17, 2.07)	2.14** (1.20, 3.82)	0.12 (0.01, 1.28)	1.57* (1.11, 2.23)	1.90 (0.46, 7.80)
ES/TH	†	†	†	†	†
Park	†	†	†	†	†
Fast food restaurant	†	†	†	†	†
Parking lot/garage	†	†	†	†	†
Gas station	†	†	†	†	†
Restaurant	†	†	†	†	†
Hotel	†	†	†	†	†
Motel	1.04 (0.45, 2.40)	1.35 (0.41, 4.49)	NC	0.36 (0.10, 1.31)	NC
Place of worship	†	†	†	†	†
Post office	†	NC	NC	NC	NC

Table 3. Continued.

	Ethnicity x HU
	Hispanic/ Latino x HU OR (95% CI)
Downtown area	1.10 (0.76, 1.60)
ES/TH	†
Park	†
Fast food restaurant	†
Parking lot/garage	†
Gas station	†
Restaurant	†
Hotel	†
Motel	2.53* (1.07, 5.99)
Place of worship	†
Post office	†

High utilizers had higher odds of contacts near the downtown area ($OR = 1.44$, $p < .01$), ES/TH ($OR = 4.59$, $p < .001$), parks ($OR = 1.44$, $p < .01$), places of worship ($OR = 1.77$, $p < .05$), and post offices ($OR = 2.61$, $p < .001$) than non-high utilizers. However, high utilizers had lower odds of contacts near gas stations ($OR = 0.30$, $p < .001$). Analyses indicate client characteristics moderated the relationship between utilization status and contact location. Gender significantly moderated this relationship. Women with high utilization had higher odds of contacts near the downtown area than high-utilizing men (1.55, $p < .01$). High utilizers identifying as Black/AA/African ($OR = 1.57$, $p < .05$) or AI/AN/I ($OR = 2.14$, $p < .01$) also had higher odds of contacts near the downtown area compared to high-utilizing White clients. Additionally, high-utilizing Hispanic/Latino clients had higher odds of contacts near motels ($OR = 2.53$, $p < .05$) than high-utilizing non-Hispanic/Latino clients.

Limitations

One limitation of this study was that longitudinal data were analyzed as cross-sectional, potentially overlooking important temporal dynamics that could influence the findings. Furthermore, addressing bias related to multiple contacts at the client level may inadvertently introduce new biases. This occurs because the analysis focuses on the location type associated with the most client contacts, neglecting other contact location types for the same client. This approach limits a complete assessment of clients' experiences and interactions with various outreach services. Thus, these analyses limit deeper insights into patterns of unsheltered persons who are highly mobile (Semborski et al., 2022).

Another limitation of this study is the latitude and longitude coordinates of each outreach contact recorded in the Homeless Outreach Viewer. These coordinates were manually entered by outreach service workers, which raises concerns about potential inaccuracies in the reported locations. Furthermore, using community-driven maps can pose problems, as locations may be inaccurately tagged, potentially leading to misinterpretations of service engagement (Kilic et al., 2023). Researchers need to be aware of these biases to enhance the reliability and validity of spatial analyses.

Despite these limitations, this study makes significant contributions to the field. First, using a novel approach, this study examines the concept of visibility in the context of homelessness in a large urban county in the Southwest United States. Specifically, spatial analysis was used to understand how "visibility" is associated with where outreach service contacts occurred. Second, alternative distances were assessed to reduce bias related to the modifiable areal unit problem (Lobao & Murray, 2005). Third, outreach service contacts were examined at a small geographic level, which has been limited in studies investigating the geography of homelessness (Shin, 2023).

Discussion

By exploring an inherently spatial question, this study examined how visibility, defined by individuals' levels of engagement, influenced outreach service contact locations and the factors that moderated this relationship. Informed by Greene's (2024) visibility framework, this study has important implications for outreach services. Findings indicated that most outreach service contacts occurred in a concentrated downtown area surrounded by a geographic cluster of housing and social services. Research shows that individuals experiencing unsheltered homelessness are often concentrated in major downtown areas of major cities (Shin, 2023). According to Shin (2023), this concentration of people is known as a "zone of dependence," which helps explain the "spatial relationship between services and the homeless population" (Shin, 2023, p. 695). Although these clustered services may increase access and utilization of services, research suggests that they also concentrate a high number of vulnerable and high-need individuals in a specific geographic location (Semborski et al., 2022). High rates of community homelessness are also associated with increased alcohol consumption, infectious diseases, and greater use of emergency rooms for primary healthcare (Fargo et al., 2013). The implications show that migrating patterns of individuals experiencing housing instability to specific areas (e.g., downtown) and their service utilization ultimately affect their well-being (Semborski et al., 2022). Given the concentration of outreach service contacts in the downtown area, diversion efforts may be one strategy to facilitate a quick resolution to addressing housing instability among non-high utilizer clients, which made up almost half of outreach service contacts. On the other hand, multiple strategies may be needed to work with high utilizers. First, it is common for service outreach workers to meet and engage with an unsheltered person multiple times over weeks or months before they may agree to enroll in services. Over this period, it may be essential to consider the administrative burdens perpetuating disengagement, distrust, and stigma among this group. Robinson (2023) notes that these burdens, which have not been adequately considered in outreach services for unsheltered persons, "reinforce and promote" inequities among those who are in greatest need (p. 9).

Another implication of this study is the need to adopt a gendered perspective on homelessness, recognizing that men and women differ in both the circumstances that lead to homelessness and how they experience it (Rukmana, 2010). This perspective is often situated at the individual level, overlooking the social and structural context hindering an individual's engagement in outreach services. In this study, women were more likely to engage in outreach services near motels. Consistent with the framework of visibility, this finding may be explained by research suggesting that women are less likely to live on the streets, have more social contacts, and experience lower rates of chronic homelessness than men (Rukmana, 2010). Gender moderated the relationship between engagement (i.e., utilizer status) and location, specifically the downtown area. Contrary to prior research, this study found that women were more likely to engage in outreach services in the downtown area, where there was a large concentration of individuals experiencing unsheltered homelessness (Jiao et al., 2022; Lee & Donaldson, 2018). Both findings suggest that specialized outreach services for women may be necessary, considering both the circumstances that lead to homelessness and their experiences on the streets (Rowen, 2017). Furthermore, this highlights the potential need for differentiated practices tailored to women, men, and other gender-diverse populations.

Consistent with previous research, Black/AA/African and AI/AN/I clients experiencing unsheltered homelessness were overrepresented in this study (Neilsberg Research, 2024). Systemic racism and discrimination of racial and ethnic minority individuals contribute to the overrepresentation of these populations among those experiencing unsheltered homelessness, as well as disparities in access to care, service quality, and health outcomes. Implicit bias in medicine, behavioral health, and social services regarding "who is likely to receive help, who is dangerous, and who has a mental illness" (Lee & Donaldson, 2018, p.1182) exacerbates disparities in engagement and service utilization disproportionately affecting Black individuals, people of color, and Hispanic/Latino populations. These systemic issues foster pervasive mistrust within these communities, discouraging individuals from engaging with outreach teams (Lee & Donaldson, 2018). Findings from this study suggest that systemic barriers to outreach services exist in the downtown area for Black/AA/African women, AI/AN/I, and Hispanic/Latino clients. For AI/AN/I clients, the interplay between race and structural barriers impacting their homelessness is well documented, suggesting this subgroup has a disproportionate and more significant “aggregate number of barriers to services” than other subgroups (Greene, 2024b, p. 297). However, differences based on Native American tribes were not accounted for in these analyses, and a more nuanced analysis is recommended for future research. Interestingly, Asian/Asian Americans and Black/AA/Africans had higher odds of outreach service contacts near the downtown area. It is important to note the overrepresentation of White clients in this study, which may be specific to Maricopa County, where they comprise the racial majority. This trend can be attributed to the affordable housing crisis, which has led to increased homelessness among White individuals. While systemic issues generally impact racial minorities more significantly, specific populations of White individuals may also experience overrepresentation in specific contexts, particularly in areas where social, economic, and housing instability intersect.

Clients’ levels of engagement, particularly their high utilization of outreach services, were examined in relation to the locations where these services occurred to reach client groups that may benefit from specialized or targeted care. Findings indicate that high utilizers who identified as women, Black/AA/African, or AI/AN/I had higher odds of having street outreach service contacts near the downtown area. Implications for identifying locations where individuals access outreach services may facilitate broader efforts to improve service effectiveness. For instance, this can create opportunities to coordinate with community groups, businesses, and social service providers to support clients’ engagement and transition to stable housing (Semborski et al., 2022; Shin, 2023). In their research, Davidson et al. (2011) identified hotspots in Los Angeles for assessing local city policies, ranging from shelter to policing policies, to improve the efficacy of needle exchange services. These efforts, therefore, need to consider how services operate within the context of space and place (Laws, 1992). Laws (1992) also underscored how space and place are social constructions that reflect dominant ideologies. In this study, high utilizers were more likely to engage in outreach services near ES/TH, parks, places of worship, and post offices. Thus, addressing the political and ideological roles of individual agency, government intervention, and criminalization is important, particularly when considering specialized outreach services. Spatial analysis is a novel approach to understanding how service utilization is influenced by geographic context among structurally affected individuals. By examining individuals' levels of engagement within their specific geographic contexts, these findings contribute to valuable insights for implementing outreach services in a large urban county in the Southwest United States.

Conclusion

Spatial analysis is a relatively new tool for understanding the factors contributing to inequities in access and service utilization among individuals experiencing homelessness. This study applied spatial analysis to examine how clients' levels of engagement influenced the location of outreach service contacts and identified important implications for the delivery of outreach services. Given the inherently spatial nature of homelessness, this study discusses policy implications and future directions for improving access to outreach services among individuals experiencing unsheltered homelessness.

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Figures

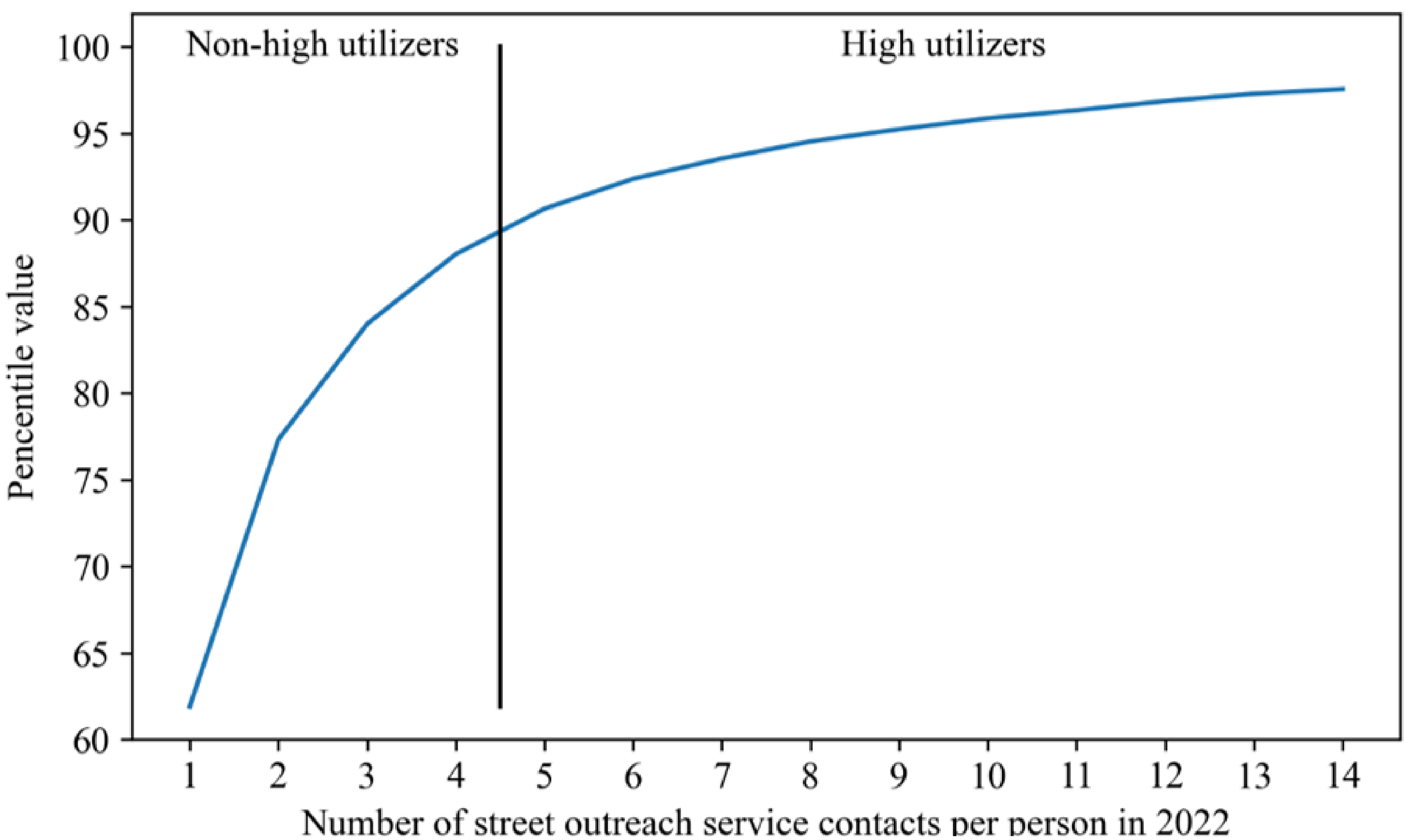

Figure 1

Distribution of contacts per person by utilizer status.

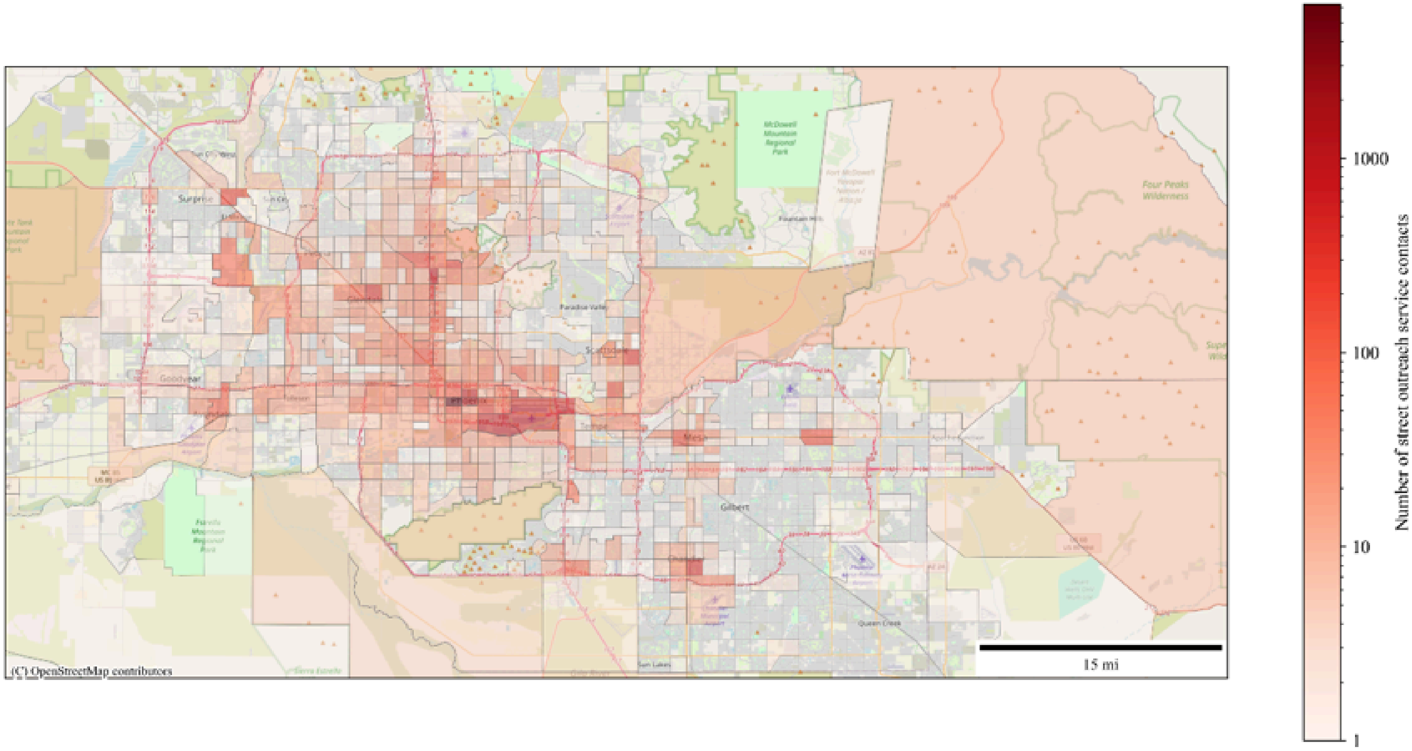

Figure 2

Service outreach contact density map, Census Tract level, 2022 only.

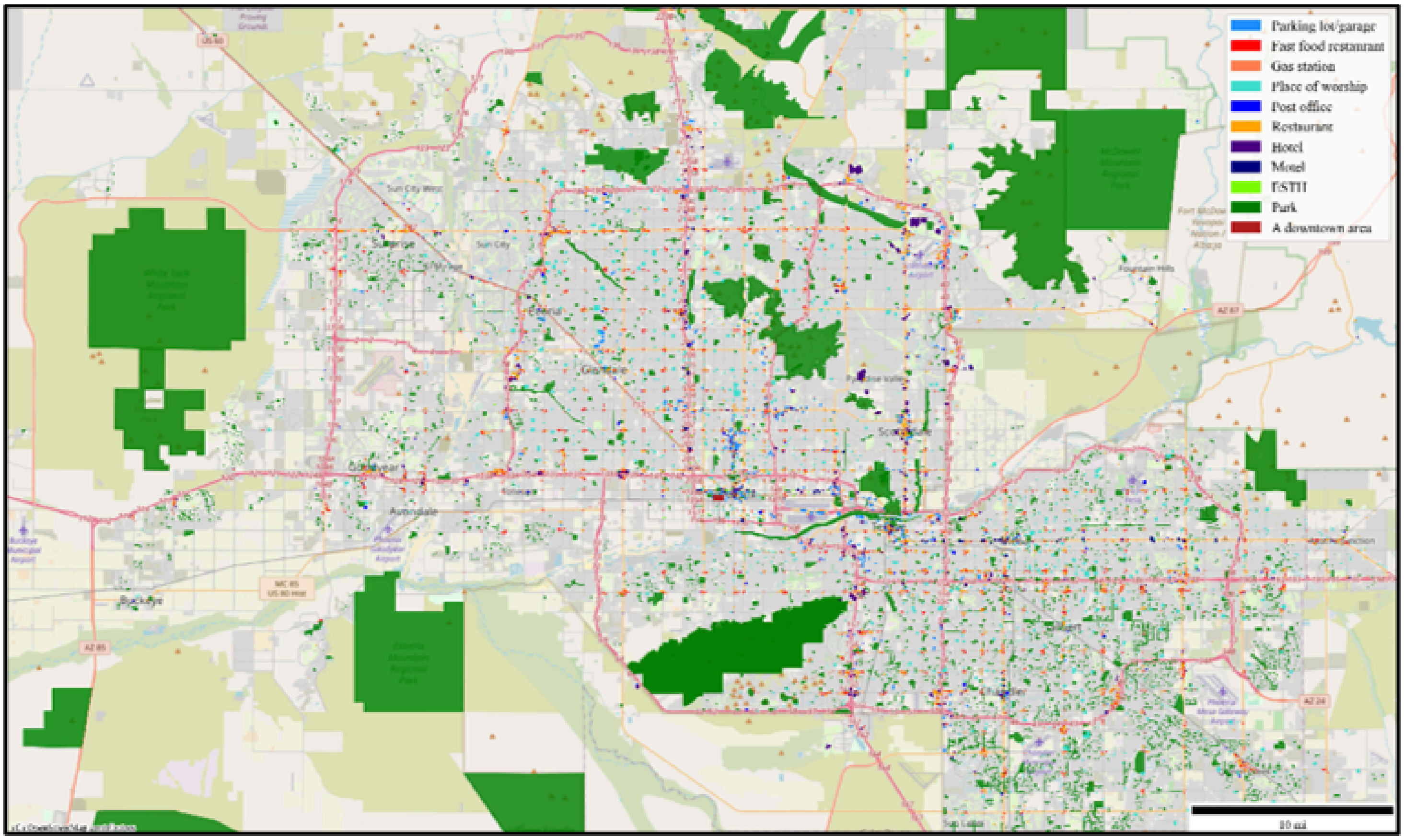

Figure 3

Map representation of location types, Maricopa County, Arizona.