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Spatiotemporal dynamics of ethnoracial diversity and segregation in Los Angeles County: Insights from mobile phone data

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ABSTRACT

Ethnoracial segregation persists as a pressing issue in American cities. Understanding these issues is crucial for promoting social equity and justice, and planning more inclusive cities. Prior research has predominantly emphasized residential ethnoracial diversity but has often overlooked or inadequately addressed ethnoracial diversity and segregation in individuals' daily activities and places they visit, due in part to data limitations. This study leverages a dynamic measure of ethnoracial diversity and dominance at the finest spatial scale, specifically at the Points of Interest (POI) level and various temporal contexts. Using one month of privacy-enhanced mobile phone location data in Los Angeles County, California, this study explores ethnoracial diversity and spatial segregation simultaneously in POI visits in LA County. Our findings confirm that individuals' daily mobility in urban areas enhances ethnoracial mixing at activity locations. Empirical results indicate that the diversity of visitors to a POI is significantly higher than the neighborhood diversity where the same POI is located. A significant positive linear relationship was found between the neighborhood diversity of POIs and the diversity of visitors. About 34 % of the variance in the diversity of visitors to POIs can be explained by the neighborhood diversity of POIs. Our results also suggest significant spatial clusters of isolated/integrated areas regarding ethnoracial mixing in people's daily activity locations. Notably, the Hispanic or Latino population tends to stay in their own communities and experiences a higher level of segregation in their daily activity locations. The findings have significant implications for urban planners and policymakers to design targeted solutions and policies to promote social equity, integration, and equal access to public amenities and opportunities in urban spaces.

1. Introduction

The persistence of ethnoracial segregation in residential spaces remains a critical concern as urbanization and suburbanization continue to expand in the United States (Wright et al., 2014). Ethnoracial segregation, especially affecting marginalized communities or disadvantaged groups, is closely linked to adverse consequences in education, housing, employment, poverty, public safety, environmental justice, and access to healthcare resources (Brazil, 2022; Grady, 2006; Hall & Stringfield, 2014; Massey et al., 1987; Perlin et al., 2001). Gaining insights into socio-spatial segregation is imperative for city planners to promote social integration via creating opportunities and local environments that foster more inclusive interactions between a diverse range of people (Jones & Pebley, 2014; Moro et al., 2021; Perlin et al., 2001). Promoting social integration can foster positive urban interactions with socially heterogeneous individuals, contributing to personal integration into a community and enhancing social cohesion more broadly, which, in turn, leads to increased solidarity, trust, pro-social behavior, well-being, and reduced violence and crime in society (Phillips et al., 2021; Putnam, 2007).

The prevailing body of research has traditionally centered on residential diversity and segregation, primarily drawing from static census data (Holloway et al., 2012; Lichter et al., 2015; Wright et al., 2014). While these census-based studies have provided valuable insights into residential segregation and its implications for ethnoracial stratification, they overlook the multifaceted dimensions of ethnoracial diversity and segregation within individuals' daily lives and their interactions with various places beyond their residences. Indeed, research has shown that individuals travel to, and spend a sizeable portion of waking hours outside their residential environments (Hamermesh et al., 2005; Putnam, 1995). As such, some scholars have argued that segregation is a dynamic phenomenon that evolves across both spatial and temporal

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dimensions, suggesting the need to extend the study of segregation beyond the residential context (Candipan et al., 2021; Moya-Gómez et al., 2021; Park & Kwan, 2018; Phillips et al., 2021; Silm & Ahas, 2014; Wong & Shaw, 2011; Wu et al., 2023). Nevertheless, many of these efforts face constraints, often characterized by either restricted sample sizes, especially when employing conventional travel diaries to document individuals' daily activities (Park & Kwan, 2018; Wong & Shaw, 2011), or issues related to data representativeness and demographic bias when utilizing georeferenced social media posts (Phillips et al., 2021; Wu et al., 2023).

The advent of Location-Aware Technologies (LATs) has ushered in an era of abundant movement data, encompassing diverse temporal granularities and collected through various means. Among the various data sources, mobile phone data have become increasingly popular in segregation studies due to their extensive spatial and temporal coverage, large sample size, and cost-effective data collection. These data provide an unprecedented opportunity for understanding human behavior and researching diversity and segregation across finer spatial and temporal scales beyond residential perspectives (Abbiasov et al., 2024; Cook et al., 2024; Järv et al., 2021; Moya-Gómez et al., 2021; Nilforoshan et al., 2023; Xu, 2022; Yabe et al., 2023).

Diversity and segregation are not opposites but rather interconnected aspects of social dynamics. Researchers argue that ethnoracial diversity and segregation should be understood together, given the increasingly multiracial nature of urban life, especially in many multiracial U.S. cities (Dmowska & Stepinski, 2022; Holloway et al., 2012). Studying them simultaneously enables us to move beyond a binary perspective of the "majority-minority divide" and treat all social groups equally. This research leverages massive mobile phone location data to explore dynamic ethnoracial diversity and segregation simultaneously in individuals' visits to places at the finest spatial scale. Specifically, we explore shared visits (i.e., co-location or encounters) of individuals at the Points of Interest (POIs) level, considering various temporal contexts and different types of activities. POIs represent activity locations, wherein individuals engage throughout their daily activities (Cagney et al., 2020). Examples of POIs include restaurants, grocery stores, drugstores, hospitals, entertainment establishments, and more. Our research questions are: How do patterns of ethnoracial diversity and dominance at daily activity locations vary over time and across different POI types? Is the racial diversity of visitors to a POI different from the racial diversity of the residents in the neighborhood where the POI is located?

The contributions of this study are threefold. First, this study contributes to a growing interest in exploring dynamic ethnoracial diversity using massive mobile phone location data at the most granular spatial resolution currently available, specifically at the level of POI visits, which directly represents the ethnoracial composition of individuals' daily activity locations. Secondly, our research unveils the dynamic diversity and dominance patterns in POI visits considering activity types across diverse social groups and temporal contexts, which has been largely understudied to date. Third, it compares the neighborhood diversity surrounding POIs with the diversity of visitors to the same POIs, emphasizing the importance of considering everyday population dynamics in segregation research. The findings have significant implications for urban planners and policymakers to design targeted solutions and policies to promote social equity, social integration, and equal access to public amenities and opportunities in urban spaces (Johnston et al., 2014; Orfield & Lee, 2005).

2. Background

2.1. Measures of diversity and segregation

Segregation has been studied extensively (e.g., see the reviews by Yao et al. (2019) and Müürisepp et al. (2022)). There has been a debate about conceptualizing segregation (Massey & Denton, 1988). For instance, Massey and Denton (1988) suggested five dimensions of segregation: evenness, exposure-isolation, concentration, centralization, and clustering. Some researchers, though, argued that these can be simplified into evenness-clustering and exposure-isolation (Reardon & O'Sullivan, 2004), or evenness-concentration and clustering-exposure (Brown & Chung, 2006). Another perspective combines aspects into two broader categories: separateness (which includes evenness, isolation, and clustering) and location (which includes concentration and centralization) (Johnston et al., 2007). Of the dimensions mentioned above, evenness and exposure/isolation are the most commonly discussed and mutually complementary aspects in segregation studies.

To measure the evenness aspect of segregation, the most widely used measurement might be the dissimilarity index based on proportions of two population groups (Duncan & Duncan, 1955). Some extended the index by incorporating spatial relationships between population groups (e.g., distance or adjacency relationships between spatial units) (Reardon & O'Sullivan, 2004; White, 1983; Wong, 2005). Besides the similarity-based measures, there has been a growing focus on entropy-based methods, which can assess the level of ethnoracial diversity in residential areas or activity spaces and are adaptable to situations involving more than two ethnoracial groups (Catney et al., 2021; Dmowska & Stepinski, 2022; Ellis et al., 2018; Holloway et al., 2012; Müürisepp et al., 2023; Theil, 1972; Wright et al., 2014). Although it does not directly measure segregation, the diversity measure can complement our understanding of the complex racial structure of metropolitan neighborhoods.

Another major dimension of segregation, exposure-isolation, often takes a people-based approach by considering social proximity or the potential for interactions between individuals (Johnston et al., 2007). Conventional methods rely on exposure and isolation indices (Bell, 1954; Lieberson, 1969; Lieberson & Carter, 1982a, 1982b; Massey & Denton, 1988), which measures the extent to which members of one group (e.g., a specific ethnoracial group) are exposed to members of another group in a given area or neighborhood. Beyond residential exposure and isolation, several researchers argued that an individual's experience of segregation is shaped by their daily activities across multiple locations and interactions with various individuals (Athey et al., 2021; Jones & Pebley, 2014; Park & Kwan, 2018; Schnell & Yoav, 2001; Wong & Shaw, 2011; Yabe et al., 2023). For example, Wong and Shaw (2011) extended the original exposure index to accommodate all individuals' daily activity locations beyond residences based on the concept of activity space (Golledge, 1997).

2.2. Activity space segregation and mobile phone location data

Socio-spatial segregation is a multifaceted phenomenon experienced across spatial and temporal contexts. Until recently, its study has been restricted by the use of static data that fail to record spatiotemporal behaviors of individuals (Müürisepp et al., 2022). As such, empirical research has been centered around the study of residential segregation that quantifies the degree of heterogeneity among residents of a given neighborhood from different social groups. At the same time, it has been recognized that experiences of segregation and social isolation are registered beyond the residential context and are replicated within places of activity and along their course of daily mobility (Jones & Pebley, 2014; Schnell & Yoav, 2001; Wong & Shaw, 2011). However, activity place segregation constitutes numerous conceptual distinctions that make difficult its study using static data (Li & Wang, 2017). Most pertinent is the requirement to account for multiple contexts, as activity spaces are numerous and varied in function, the dynamic nature of activity spaces and their changing characteristics over time, and the critical inclusion of a time dimension as individuals visit spaces at different times and for varying durations (Kwan, 2013; Le Roux et al., 2017; Wang et al., 2012).

The emergence of mobile phone location data has facilitated the advanced study of segregation beyond the residential context and into

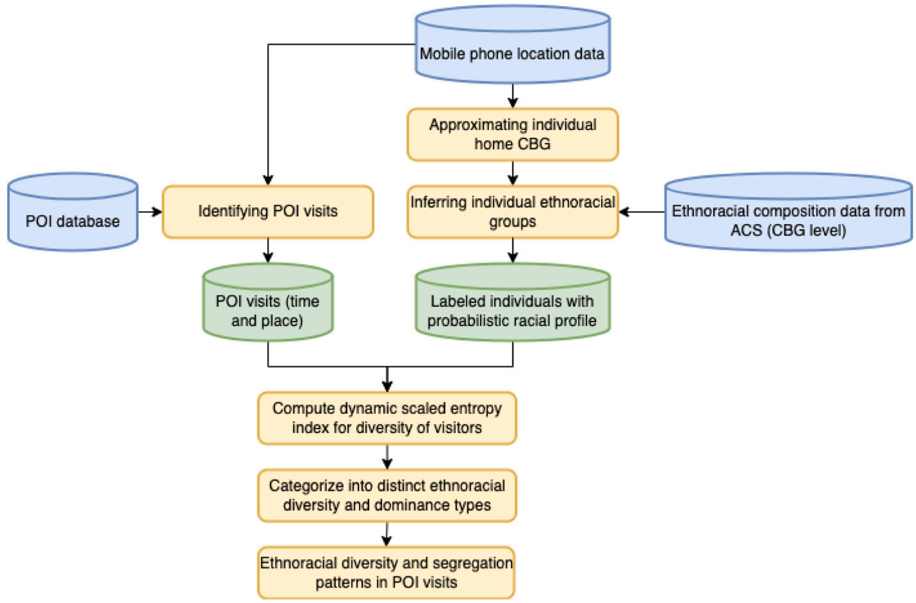

Fig. 1. Framework of mobile phone data processing and analysis for ethnoracial diversity of visitors to POIs.

activity spaces (Müürisepp et al., 2022). Derived from mobile phones and smart devices with GPS capabilities, these data capture high-resolution spatiotemporal footprints of users previously absent from traditional data. With this information, it is possible to detect co-locations of individuals within an activity space at a given time (Dodge et al., 2021; Su et al., 2022), enabling quantification of socio-demographic diversity in day-to-day locations (Athey et al., 2021; Müürisepp et al., 2023; Östh et al., 2018; Toomet et al., 2015). Furthermore, the temporal information included within these data allows for a comparison of segregation metrics across various times of day (Cai et al., 2024), or between different periods (Li et al., 2022; Müürisepp et al., 2023). Within this study, we leverage the spatiotemporal information to quantify the extent of ethnoracial diversity in POIs.

As the study of activity space segregation has developed, two major distinct strands have emerged with a different analytical focus. The first recognizes how segregation in activity space is a personal experience and seeks to measure the segregation experienced by an individual or a social group with an exposure-based calculation that considers the actual encounters or co-locations with different other social groups. This people-based perspective is dominant (see a review by Müürisepp et al. (2022)), as evidenced by extensive segregation studies (Järv et al., 2015; Li & Wang, 2017; Nilforoshan et al., 2023; Wang et al., 2018; Wang & Li, 2016). In contrast, the second strand is a place-based perspective that focuses on understanding the degree of segregation at a given place (such as work and school locations) or spatial unit (Müürisepp et al., 2023; Östh et al., 2018; Phillips et al., 2021; Silm et al., 2018). To our knowledge, a place-based approach that dynamically quantifies the extent of racial diversity within daily activity locations remains under-studied. We address this research gap by leveraging spatiotemporal footprint data from mobile phones to analyze the co-location of different racial groups at specific POIs considering different activity types. This dynamic approach allows us to assess the diversity of visitors to various places, capturing the nuances of potential social interactions and socio-spatial segregation patterns in various types of activity locations and times.

3. Study area and data

The study area is Los Angeles County, California, the most populous county in the United States with an estimated population of 10,105,518 according to the 2017–2021 American Community Survey (ACS) 5-Year Estimates. LA County is characterized by a large, dense, and diverse urban population (Johnston et al., 2006), set across an expansive territory. According to the 2017–2021 American Community Survey 5-Year Estimates, the Hispanic or Latino population in LA County constitutes 48.64 % of the total population. Among the non-Hispanic or Latino population, 25.92 % are White, 14.58 % are Asian, 7.76 % are Black, 0.19 % are American Indian, and 2.91 % belong to other races (we will discuss in detail the ethnoracial configuration and segregation patterns in LA's residential neighborhoods in Section 5.1). LA has long been characterized by high levels of residential segregation, particularly affecting Black and Latino communities (Massey & Denton, 1993). Over the last few decades, Los Angeles County has experienced significant demographic changes mainly due to Hispanic and Asian immigration, impacting residential segregation patterns. For example, Ong et al. (2016) found that while Black-White segregation has gradually declined, it remains relatively high. Hispanic-White segregation is the second highest and has increased, while Asian-White segregation is the lowest. However, many Asians and other minority groups still live in spatially concentrated, segregated neighborhoods. From the activity space segregation perspective, researchers found that people's daily activity spaces in LA County exhibit greater racial heterogeneity compared to residential diversity (Jones & Pebley, 2014). Using Twitter data, Wu et al. (2023) found that experienced isolation occurs across all ethnoracial groups. Among these groups, Latinos or Hispanics experience the highest levels of exposure to their own group, while Asians are the most diverse in their interactions with other groups. Additionally, individuals from higher socioeconomic backgrounds tend to experience lower diversity in their interactions with other social groups during their daily activities (Browning et al., 2017; Wu et al., 2023).

The mobile location records used in this study are obtained from Cuebiq,[1] a location data intelligence company, that provides anonymized, privacy-enhanced, and high-resolution mobile location pings of millions of users in the United States. Cuebiq collects mobility data through its software development kit that is integrated into various mobile applications and services in smartphones (e.g., maps, navigation, weather, and geo-specific retail), all while maintaining strict privacy adherence.[2] The data collection relies on the voluntary sharing of

[1] https://www.cuebiq.com/
[2] https://www.cuebiq.com/privacypolicy/

location by device owners through a process compliant with the General Data Protection Regulation and the California Consumer Privacy Act compliant frameworks. Cuebiq mandates application partners to disclose their relationships with Cuebiq in their privacy policies. The mobile phone location data used in this study encompasses the daily movement data of 283,556 anonymized individuals (more than one billion location records) during March 2019, comprising 21 weekdays and 10 weekend days. The weekday data contain 2,963,269 POI visit records (34,205 unique POIs) from 242,108 distinct individuals, while the weekend data comprise 1,617,700 records (31,382 unique POIs) from 226,710 distinct individuals over the entire month. The difference in the number of POIs between weekdays and weekends is reasonable as certain businesses may be closed partially or completely during the weekend (e.g., banks, schools, government offices, some restaurants, and small local businesses). This sample represents approximately 3 % of the total population in LA County. Previous studies have discussed the representativeness of Cuebiq data and found that, overall, the mobile phone location data collected by Cuebiq provide a good representation of the adult population at the CBG scale (Yabe et al., 2023). Each entry in the mobility data includes an anonymized person identifier, location coordinates (in longitude and latitude), and timestamp. The month of March was selected for our research because it does not include any special holiday seasons, making it a suitable representation of typical human activity patterns before the COVID-19 pandemic.

The unique individuals in our data are not only from LA County but from across the entire state of California. It's reasonable to assume that individuals who live close to LA County may have a more significant impact on the dynamics of ethnoracial diversity in POI visits in LA County compared to individuals residing elsewhere in California. In Section 5.3, we will discuss the disparities when considering different populations, such as those residing within the Greater LA region as opposed to the visitors from the entire California. We examine the Greater LA region rather than solely LA County because it is common in California, especially among residents in the Greater LA region, to commute from neighboring counties to LA County for work or other purposes. The Greater Los Angeles region encompasses Ventura County in the west, extending to San Bernardino County and Riverside County in the east, with Los Angeles County at its center, Kern County in the north, and Orange County to the south. By focusing on individuals whose home locations are situated in the Greater LA region, the new weekday dataset comprises 2,907,007 POI visit records (34,172 unique POIs) from 226,170 unique individuals, while the weekend dataset consists of 1,569,466 POI visit records (31,315 unique POIs) from 210,377 unique individuals.

4. Methodology

4.1. Data processing

As shown in Fig. 1, to prepare the data for the main ethnoracial diversity analysis, several essential data processing steps are conducted using the Cuebiq curated mobile phone location data. These steps include: (1) approximating the home census block group (CBG) of each individual based on mobile phone pings, (2) inferring individual ethnoracial groups based on their home CBG's ACS data, and (3) identifying their POI visits based on mobile phone pings and POI data. Among these, steps (1) and (3) are already automated and incorporated in Cuebiq data. Our code for data processing and the main analysis is available on GitHub.[3]

4.1.1. Approximating individual home CBG

In order to preserve privacy, Cuebiq provides the approximate home location at the CBG level for each individual using their most recurring location between 10 p.m. and 6 a.m. every week.[4] According to the US Census Bureau, CBGs generally have a population of 600 to 3000 individuals with similar socio-demographic characteristics, ensuring data privacy. Specifically, Cuebiq utilizes raw mobile phone pings to generate three variables: the duration of stay in a particular location within the past month, the average number of hours spent daily in that location, and the time of day visited that location. These variables are used to calculate a score, which indicates the likelihood of a location being considered home. Subsequently, the location with the highest score is determined as the individual's home location. To ensure privacy protection, the specific home locations are obfuscated by mapping the latitude and longitude coordinates of each home location to the corresponding CBG. This home location identification algorithm runs daily to confirm or update the inferred home CBG as Cuebiq observes new data. We use the identified home locations on March 1st, 2019 to align with the study period for this analysis (the whole month of March 2019).

4.1.2. Inferring individual ethnoracial groups

Since mobile phone pings do not capture the ethnoracial characteristics of individuals, a common approach is to infer an individual's ethnoracial group based on the ethnoracial composition of their home CBG (Athey et al., 2021; Xu, 2022). Following the same approach, we infer individual ethnoracial groups based on home CBG's ethnoracial composition collected from the 2017–2021 American Community Survey (ACS) 5-Year Estimates.[5] We categorize six ethnoracial groups based on the ACS classification. These groups are: Hispanic or Latino ("Latino" herein), Black or African American ("Black" herein), American Indian and Alaska Native ("American Indian" herein), Asian American and Pacific Islander ("Asian" herein), White, and "Other" (encompasses all other ethnoracial groups that do not belong to the above five groups, such as multiracial and multiethnic groups). For simplicity, note that in this study, these six ethnoracial groups are mutually exclusive. For example, someone who identifies as White is not counted as Latino (i.e., the person is non-Latino White). Instead of assigning a single distinct ethnoracial group to each individual, we compute the individual's probabilities of belonging to each of the six groups according to its home CBG's ethnoracial compositions from the ACS data. For example, for an individual with an identified home located in a CBG with 60 % White, 30 % Latino, 6 % Black, and 4 % Asian, the probability of this individual belonging to White is 0.6, Latino 0.3, Black 0.06, Asian 0.04, American Indian 0, and Other 0.

4.1.3. Identifying POI visits

Cuebiq offers POI visit data that is generated through a spatial join between stops and nearby POIs (Xiang et al., 2016). The POI dataset is also curated by Cuebiq in compliance with its Sensitive Points of Interest Policy.[6] Each POI represents a point with an attribute indicating its geographic boundary when available; otherwise, a spatial buffer is assigned based on the POI type. For instance, airports and malls have a larger radius (500 m and 300 m, respectively), while others such as bus stops have a smaller radius (5 m). For a more accurate estimation of POI visits, the geographic boundaries or spatial buffers of the POI, the open hours of the POI, and the minimum and maximum dwell time are all taken into account in this procedure.[7] Each POI visit entry encompasses a unique and anonymized person identifier, a POI identifier, a POI type according to 4-digit Standard Industrial Classification (SIC) codes,[8] and

[3] https://github.com/move-ucsb/racialdiversity

[4] See the details in the Cuebiq documentation: https://docs.spectus.ai/Getting%20Started/User_Guides/Data_Assets/Device_Recurring_Areas_and_Sensitive_Locations/

[5] https://www.census.gov/programs-surveys/acs

[6] https://www.cuebiq.com/spoi-policy/

[7] See the details in the Cuebiq documentation: https://docs.spectus.ai/

[8] https://www.osha.gov/data/sic-manual

start and end time of the visit. The average dwell time for the POI visits in this study is 43 min, with a median dwell time of 21 min. Note that casual or random passing by a POI is not considered a meaningful visit in this study and is therefore not included in the analyses. The POI visit data are subsequently utilized to calculate the ethnoracial diversity of visitors at various types of places. In addition to the overall ethnoracial diversity at activity locations, we further explore several essential urban amenities as significant places in people's daily activities. These include the locations of restaurants (e.g., coffee shops, restaurants, bakeries), healthcare, drugstores, entertainment (e.g., amusement parks, bowling centers), grocery stores, and service establishments. These are key places that individuals may visit frequently in their daily routines, excluding their homes, workplaces, and study locations (Abbiasov et al., 2024; Cook et al., 2024; Moreno et al., 2021). We categorize POIs into these six types according to their SIC code (see Table A.5 in Appendix A). These six categories account for approximately 40 % of the total POIs in our data.

4.2. Place-based ethnoracial diversity computation

This study examines place-based diversity by analyzing both the ethnoracial makeup of the neighborhoods where the POIs are located and the demographic compositions of their visitors.

4.2.1. Neighborhood ethnoracial diversity index

A widely used measure for assessing place-based ethnoracial diversity is the *scaled entropy index*, which is formally defined as follows (Farrell & Lee, 2011; Holloway et al., 2012; White, 1986).

$$E_\alpha = \frac{\sum_{j=1}^{n} p_{\alpha,j} ln\left(1 / p_{\alpha,j}\right)}{ln(n)} \tag{1}$$

where E_α is the scaled entropy index of the spatial unit α (e.g., census tract, CBG, grid cell, etc), $p_{\alpha,j}$ denotes a studied ethnoracial group j's proportion of the total population observed at the spatial unit α, and n is the total number of ethnoracial groups. In this study, n equals six ethnoracial groups. This index is widely used to assess residential ethnoracial diversity based on ethnoracial composition from census data. The scaled entropy index falls within the range of 0 to 1. A value of 0 signifies no diversity, indicating the presence of only one ethnoracial group at the spatial unit α. Conversely, a value of 1 indicates maximum diversity, suggesting that all ethnoracial groups are equally represented.

We utilize Eq. (1) to calculate the neighborhood ethnoracial diversity at the CBG level using the ACS data. In essence, the ethnoracial composition at the CBG level, as obtained from the ACS data, corresponds to $p_{\alpha,j}$ and can be used for calculating the scaled entropy index for each CBG. Subsequently, the neighborhood diversity of each POI corresponds to the neighborhood diversity of the CBG where the POI is located.

4.2.2. Dynamic visit-based ethnoracial diversity index

We extend the scaled entropy index to assess ethnoracial diversity at the POI level, which can be considered the finest spatial resolution for capturing urban encounters or social interactions. This extension accounts for the spatiotemporal dynamics of individuals' daily activities and their visits to these locations. The *visit-based scaled entropy index* at the POI level can be formalized as follows. Essentially, the index measures the diversity of visitors to each POI. Note that the terms "visit-based scaled entropy index", "visit-based diversity" and "diversity of visitors to POIs" are used interchangeably in this article.

$$E(l,t) = \frac{\sum_{j=1}^{n} p_j(l,t) ln\left(1 / p_j(l,t)\right)}{ln(n)} \tag{2}$$

where $E(l,t)$ is the scaled entropy index of the visitors to POI l at time t, $p_j(l,t)$ denotes ethnoracial group j's proportion of the total individuals who visited POI l at time t. The interpretation of $E(l,t)$ values is the same as E_α.

For each POI, the ethnoracial group composition is quantified based on the inferred race groups of individuals, which is determined according to the ethnoracial configuration of their home CBGs as illustrated in Section 4.1.2. To ensure sufficient POI visit records for computing the visit-based scaled entropy index, we aggregate POI visits for the entire month of March 2019, distinguishing only between weekdays and weekends. Subsequent analyses are performed separately for these two datasets.

We calculate the diversity of visitors for each POI based on two different temporal aggregations: 1) weekdays versus weekends (considering all activities between 0 and 11:59 pm) and 2) four distinct time periods of the day, including morning (6–10:59 am), noon (11 am - 1:59 pm), afternoon (2–5:59 pm), and evening (6–11:59 pm). The period after midnight (0–5:59 am) is excluded from the analysis due to the sparse number of POI visits observed during these hours. It is worth noting that the visit-based scaled entropy index is flexible enough to be calculated at any temporal resolution (e.g., hourly) as long as a sufficient number of POI visits are available at the given temporal aggregation. In Eq. (2), the variable t can be used to represent the sequence of time periods within a given temporal analysis unit, such as the four distinct time periods of the day. The premise is that people of different ethnoracial groups might tend to or prefer visiting certain POIs in certain neighborhoods at different times during the day. For example, Black, Latino, or White groups might prefer certain and different POIs in their own neighborhood for socializing after work hours, while they tend to visit other POIs in other neighborhoods more during the day. Similarly, certain groups might avoid certain POIs at nighttime due to concerns for safety or perceived risks.

4.2.3. Accounting for sampling bias

To deal with the potential sampling bias issues in mobile phone location data, we apply a post-stratification technique. Post-stratification is a well-known sampling tool, commonly employed to investigate the influence of sampling biases in mobile phone location data or geo-tagged social media data on a wide range of subsequent data analyses (Salganik, 2019). Specifically, each individual's POI visit count is weighted by an expansion factor (Yabe et al., 2023) which is the ratio of the population of their home CBG (based on the 2017–2021 American Community Survey 5-Year Estimates) to the number of individuals observed in the same CBG from the mobile phone data. Subsequently, the ethnoracial group j's proportion of the population who visited POI l during time t can be calculated as follows.

$$p_j(l,t) = \frac{\sum_i w_i \rho\left(i \in G_j\right)}{\sum_i \sum_{j'=1}^{n} w_i \rho\left(i \in G_{j'}\right)} \tag{3}$$

where w_i denotes the expansion factor of person i who visited POI l at time t, $\rho\left(i \in G_j\right)$ denotes the probability of person i belonging to ethnoracial group G_j (the probability is inferred based on their home CBG's ethnoracial configuration as described in Section 4.1.2). To avoid the potential bias caused by small samples, the POIs with fewer than ten visit counts over the entire study timeline are excluded from this measure.

4.3. Ethnoracial diversity and dominance classification

Following Holloway et al. (2012)'s approach, we further adopt a classification framework to differentiate different types of ethnoracial diversity for POI visits. This approach incorporates a multiplicity of ethnoracial groups, moving beyond the focus on single-group numerical dominance or even pairs of groups (Holloway et al., 2012; Wright et al., 2014). It is done by first distinguishing three levels of diversity including *low*, *moderate*, and *high diversity*, and subsequently subdividing by a dominant ethnoracial group. Specifically, a *low diversity* POI is one with

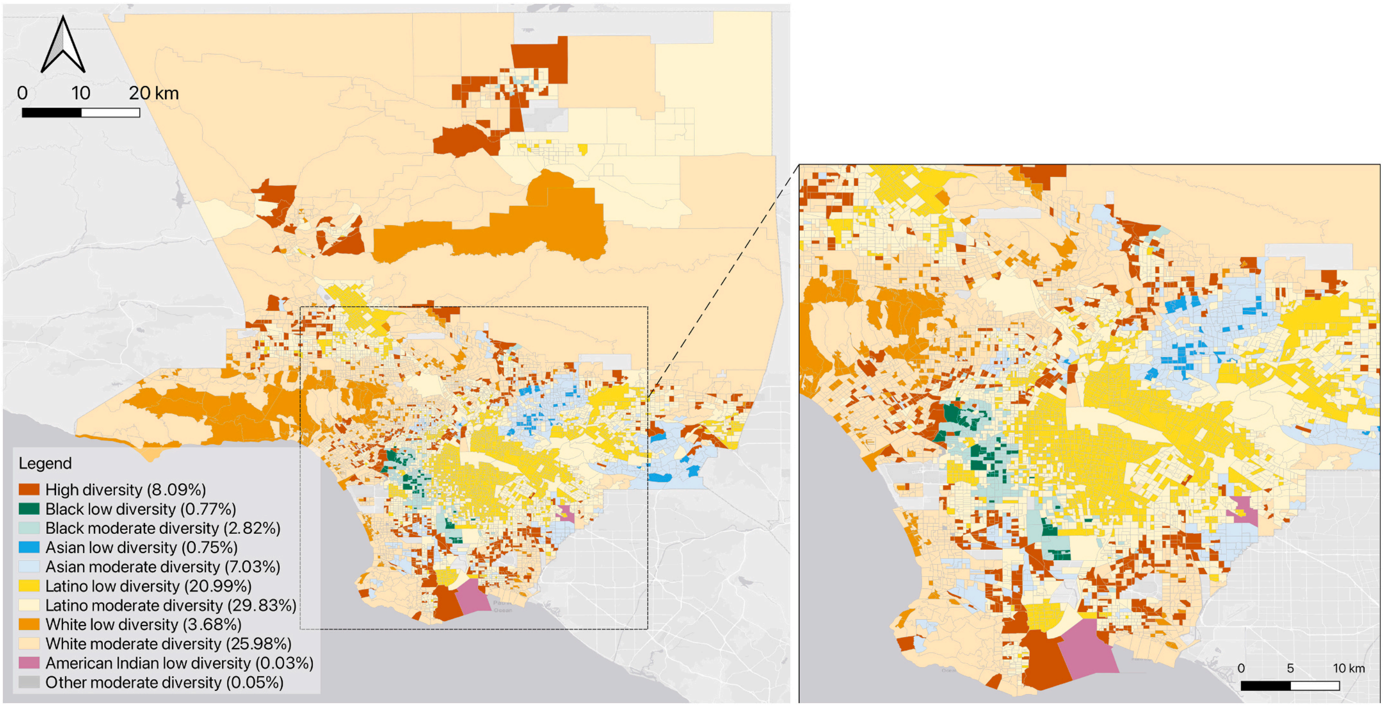

Fig. 2. Los Angeles County's census block groups (n = 6,425 CBGs) classified by residential ethnoracial diversity and dominance based on ethnoracial composition from the 2017–2021 American Community Survey 5-Year Estimates. An interactive version of the map is available at https://rongxiangsu.github.io/files/CBG_diversity.

scaled entropy values less than or equal to 0.3707 (this is the maximum entropy when one of the six ethnoracial groups constitutes 85 % of the population) or when one group makes up more than 80 % of the total population. A POI with *high diversity* is characterized by scaled entropy values greater than or equal to 0.7414, and no single group constituting more than 45 % of the total population (this ensures that the third and fourth-ranked groups maintain significant representation). Other POIs that do not fall into either the low or high diversity categories are classified as POIs with *moderate diversity*. In general, a low diversity level indicates an isolated (segregated) racial setting with one or two dominant ethnoracial groups. This may also suggest that the community has stronger social ties within itself. In contrast, a high diversity level indicates an integrated racial setting with a balanced presence of various ethnoracial groups, with no single group dominating.

Subsequently, the three levels of diversity are further categorized based on the predominant ethnoracial group. In essence, there could be 13 distinct types of ethnoracial diversity and dominance for each POI in this study: Latino-dominated low diversity, Latino-dominated moderate diversity, Asian-dominated low diversity, Asian-dominated moderate diversity, Black-dominated low diversity, Black-dominated moderate diversity, White-dominated low diversity, White-dominated moderate diversity, American Indian-dominated low diversity, American Indian-dominated moderate diversity, Other-dominated low diversity, Other-dominated moderate diversity, and High diversity. Note that the High diversity category is not further classified by a distinct ethnoracial group because, by definition, a CBG with High diversity has no dominant ethnoracial group. The reader may refer to Holloway et al. (2012) for details of the classification criteria.

4.4. *Identifying significant clusters of ethnoracial diversity at activity locations*

We apply Local Indicators of Spatial Association (LISA) analysis (Anselin, 1995), specifically, Local Moran's *I* on the visit-based scaled entropy index to assess spatial segregation in terms of the ethnoracial diversity of visitors to POIs. This additional analysis allows us to pinpoint significant cold spots and hot spots of ethnoracial mixing in people's daily activity locations. Local Moran's *I* is a widely used tool for identifying spatial concentrations of high values or low values, and spatial outliers.

Table 1
The average ethnoracial composition for each residential diversity and dominance type (n = 6,425 CBGs) in Los Angeles County.

Residential diversity type	Black	Latino	American Indian	Asian	White	Other
Black low diversity (n = 49)	**84.65 %**	9.01 %	0.09 %	1.81 %	1.89 %	2.55 %
Black moderate diversity (n = 180)	**57.69 %**	27.04 %	0.23 %	3.14 %	6.38 %	5.51
American Indian low diversity (n = 2)	0	0	**100 %**	0	0	0
Asian low diversity (n = 48)	0.62 %	10.23 %	0.04 %	**82.31 %**	5.71 %	1.09 %
Asian moderate diversity (n = 449)	2.82 %	21.55 %	0.26 %	**55.42 %**	15.67 %	4.28 %
Latino low diversity (n = 1,342)	4.08 %	**88.97 %**	0.12 %	2.70 %	3.46 %	0.67 %
Latino moderate diversity (n = 1,907)	9.05 %	**60.30 %**	0.21 %	11.97 %	15.18 %	3.29 %
White low diversity (n = 235)	1.01 %	6.02 %	0.17 %	4.37 %	**85.25 %**	3.17 %
White moderate diversity (n = 1,664)	3.52 %	17.73 %	0.18 %	11.91 %	**59.05 %**	7.60 %
High diversity (n = 517)	12.06 %	28.04 %	0.41 %	20.53 %	**28.54 %**	10.42 %
Other moderate diversity (n = 3)	2.81 %	10.25 %	0	11.80 %	32.90 %	**42.24 %**

Notes: The largest ethnoracial group within each residential diversity type is in bold.

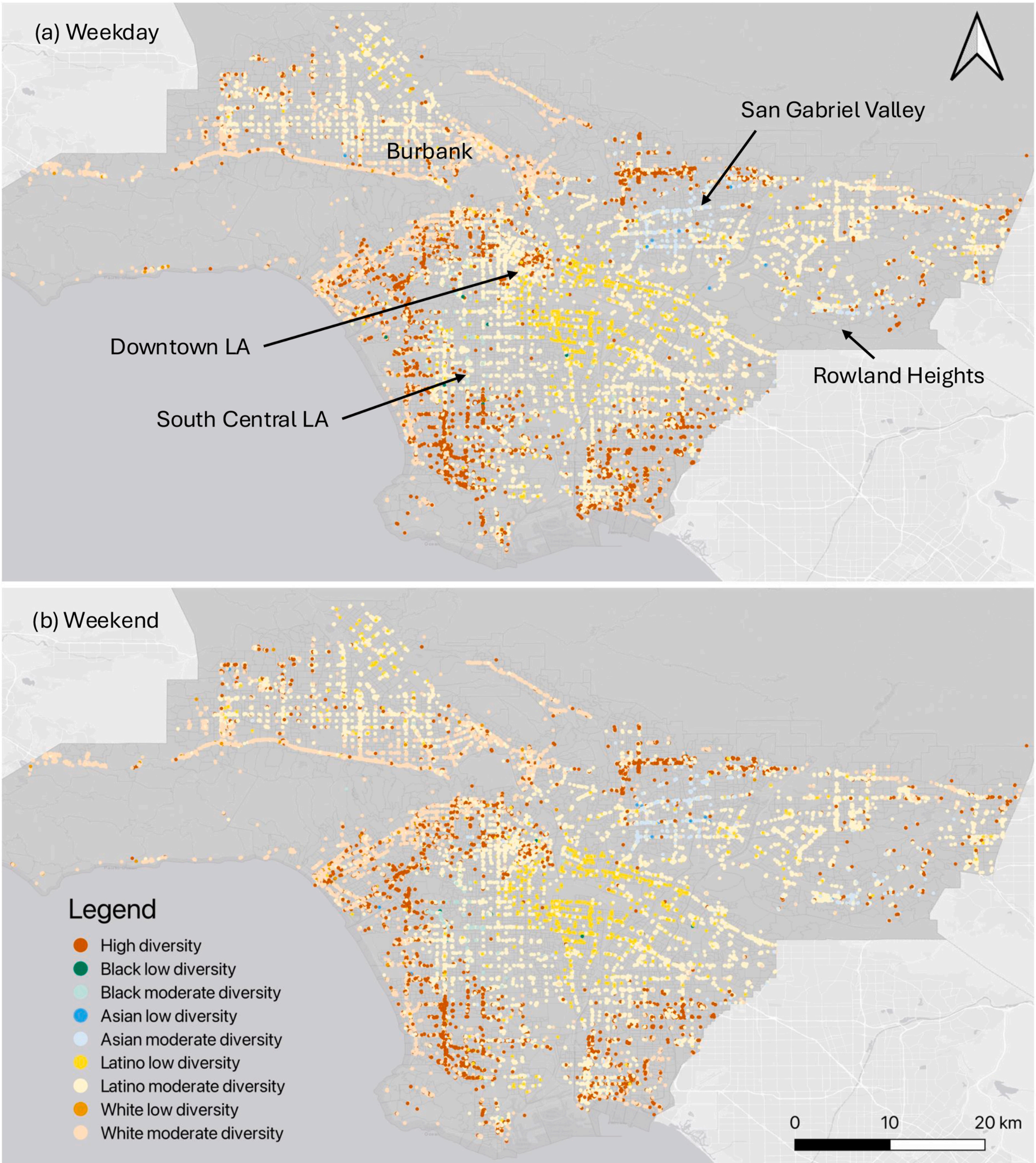

Fig. 3. Spatial distribution of ethnoracial diversity and dominance categories of POI visits on (a) weekdays ($n = 34{,}205$ POIs) and (b) weekends ($n = 31{,}382$ POIs) in Los Angeles County based on visitors' home CBGs and mobile phone location data collected in March 2019. The map cropped out the northern suburban and less densely populated areas with fewer POIs, to better display the distribution of POIs in the main LA County areas. An interactive version of the map is available at https://rongxiangsu.github.io/files/POI_diversity/.

In this study, the spatial weight matrix is constructed using the K-nearest neighbors (KNN) method, with each point considering its eight nearest neighboring POIs. A significance level of 0.05 is used to identify significant spatial clusters. In the context of our study, the outcomes of Local Moran's I indicate four types of significant spatial associations: *high-high clusters*, representing POIs with high diversity of visitors spatially clustered with neighboring POIs showing high diversity of visitors; *low-low clusters*, indicating POIs with low ethnoracial diversity

Table 2
Percentage composition of visit-based ethnoracial diversity types on weekdays and weekends.

POI diversity type	Weekday	Weekend
Latino moderate diversity	47.11 %	45.11 %
White moderate diversity	23.62 %	24.83 %
High diversity	20.43 %	19.25 %
Latino low diversity	5.28 %	6.55 %
Asian moderate diversity	2.68 %	2.88 %
Black moderate diversity	0.68 %	0.89 %
White low diversity	0.15 %	0.39 %
Asian low diversity	0.03 %	0.05 %
Black low diversity	0.02 %	0.04 %
Total number of POIs	34,205 (100 %)	31,382 (100 %)

spatially clustered with POIs with low ethnoracial diversity; *high-low clusters*, indicating POIs with high ethnoracial diversity surrounded primarily by POIs with low ethnoracial diversity; *low-high clusters*, denoting POIs with low ethnoracial diversity surrounded primarily by POIs with high ethnoracial diversity.

We are particularly interested in *low-low* and *high-high clusters*, as they may indicate the presence of spatial isolation (segregation) and integration areas in terms of ethnoracial mixing. Low-low clusters may need special attention from city planners because they represent areas predominantly visited or used by mainly one or two ethnoracial groups. Such segregation might hinder social mixing and the benefits that come with diverse interactions. Policymakers can enhance the configuration or types of POIs in these areas to encourage visits from more diverse groups. Identifying these clusters can help in developing targeted interventions to promote inclusivity and integration in these places. On the other hand, high-high clusters suggest areas where different ethnoracial groups are present and potentially interact more frequently, indicating the potential for positive social outcomes at more inclusive places.

5. Results

5.1. Residential ethnoracial diversity

Fig. 2 (all the maps in this study were generated using Esri ArcGIS Pro v3.1.2 software) illustrates the spatial distribution and percentage composition of census block groups of LA County ($n = 6{,}425$ CBGs) classified by residential ethnoracial diversity and dominance using the 2017–2021 American Community Survey 5-Year Estimates. In general, the percentage composition of CBGs aligns with the ethnoracial configuration of LA County from the ACS data, where the Latino population made up 48.64 %, Whites 25.92 %, Asians 14.58 %, Blacks 7.76 %, American Indians 0.19 %, and Other races 2.91 %. Furthermore, these dominant residential ethnoracial groups are spatially segregated. For example, many White-dominated CBGs (i.e. CBGs with White low or moderate diversity) are concentrated along the coast and in suburban and remote mountain areas. Latino-dominated CBGs are away from the coast and more prevalent in downtown LA and its surrounding areas, as well as suburban areas to the west of Burbank city and several neighborhoods in the eastern part of LA County. Black-dominated CBGs cluster primarily in South Central Los Angeles. Asian-dominated CBGs are predominantly located in neighborhoods such as Chinatown, Koreatown, Torrance City, San Gabriel Valley, and Rowland Heights. Table 1 summarizes the average ethnoracial composition for each residential diversity and dominance type in LA County. The average ethnoracial composition of each residential diversity type aligns well with our definitions outlined in Section 4.3.

5.2. Ethnoracial diversity of visitors to POIs

Next, we evaluate the dynamic diversity of visitors to POIs by considering the spatiotemporal dynamics of individuals' activities and visits to various types of places. Fig. 3 shows the spatial distribution of ethnoracial diversity and dominance types of visitors to POI locations on weekdays and weekends. We also compute the dynamic diversity of visitors for four distinct time periods throughout the day (morning, noon, afternoon, and evening) as described in Section 4.2.2. These results are available on our GitHub repository.[9] Table 2 summarizes the percentage composition of POI ethnoracial diversity types during weekdays and weekends. On both weekdays and weekends, the majority of POI visits display Latino-dominated moderate diversity, followed by White-dominated moderate diversity, High diversity, Latino-dominated low diversity, and Asian-dominated moderate diversity. Other visitor diversity types account for less than 1 % of the total. When compared to the percentages of ethnoracial diversity types in residential CBGs, as depicted in Fig. 2, Latino-dominated moderate diversity and White-dominated moderate diversity continue to be the top two types. The average visit-based scaled entropy index is 0.66 on weekdays but slightly drops to 0.64 during the weekend. A Mann-Whitney U test indicates a significant difference between the two values ($p < 0.01$). This implies a significantly higher level of ethnoracial diversity in POI visits on weekdays compared to weekends in LA County. This finding is consistent with existing literature (Silm & Ahas, 2014). One plausible explanation is that on weekends, individuals may prefer to socialize with their family and members of their own social group, but on weekdays they might be exposed more to other groups based on their work locations and the location and nature of their weekday activities.

The overall geographic distribution of various POI ethnoracial diversity types closely mirrors the established residential ethnoracial diversity of the CBGs, as depicted in Fig. 2. Presumably, individuals of the same ethnoracial background tend to visit similar places or places similar to their own neighborhoods. A similar finding was reported by (Wu et al., 2023). Black-dominated POIs cluster primarily in South Central Los Angeles. Latino-dominated POIs are distributed widely across LA County. White-dominated POIs are predominantly located in coastal areas and along major freeways. Asian-dominated POIs are concentrated in several Asian-populated neighborhoods, such as San Gabriel Valley and Rowland Heights. Comparing Figs. 2 and 3, it is worth noting that the High diversity POIs display a noticeably wider geographical distribution compared to the High diversity CBGs of LA residents. Notably, the High diversity category constitutes 8 % of the total CBGs, while there are nearly 20 % High diversity POIs. These observations may imply that individuals' daily mobility in urban areas enhances ethnoracial mixing, particularly at these POIs characterized by a diverse mixing of races and ethnicities. A similar finding by (Jones & Pebley, 2014) suggests that people's daily activity spaces in LA County display greater racial diversity than in residential areas.

5.2.1. Correlation between neighborhood and visit-based diversity

We further explore whether the racial diversity of visitors to a POI differs from the racial diversity of the residents in the neighborhood where the POI is located. To do this, we use the scaled entropy index of the CBG in which each POI is located as the neighborhood diversity for each POI. The Pearson correlation coefficient (r) between the neighborhood diversity of POIs and the diversity of visitors to POIs on weekdays ($n = 34{,}205$ POIs) is 0.58 ($p < 0.01$), indicating a strong positive linear relationship between the two variables. The R^2 value is 0.34 ($p < 0.01$), suggesting that approximately 34 % of the variance in the diversity of visitors to POIs can be explained by the diversity of the residents in the neighborhood where the POI is located. On weekends (n

[9] https://github.com/move-ucsb/racialdiversity/tree/master/figure

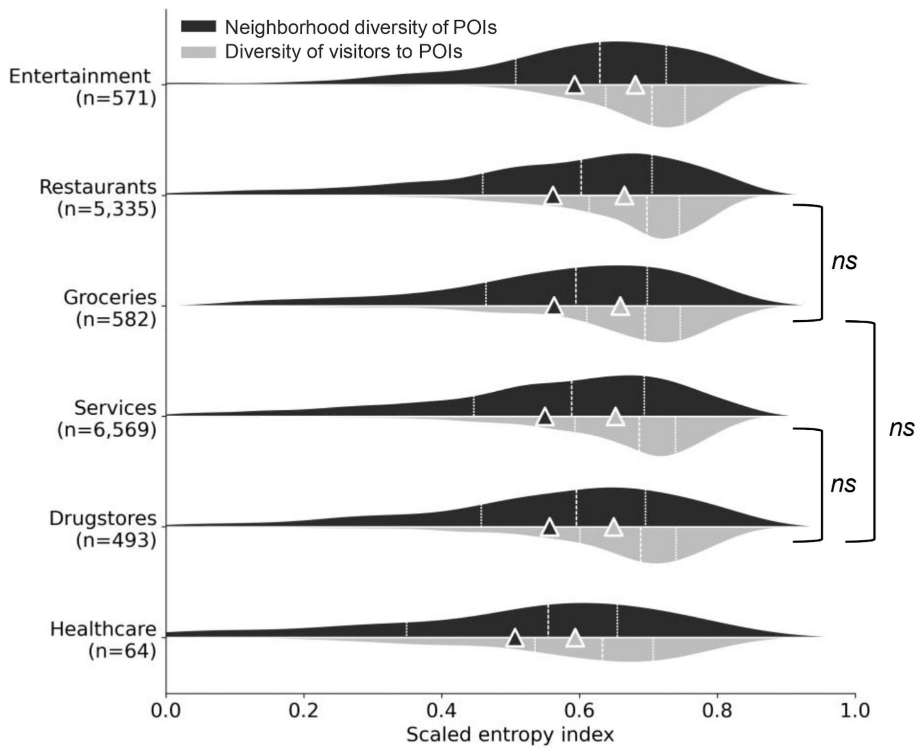

Fig. 4. Neighborhood diversity of POIs (shown in black) and diversity of visitors to POIs (shown in gray) on weekdays by six major POI business categories. The POI count of each category is in parentheses on the y-axis. Triangles represent the mean. Violin plots are sorted by the average diversity of visitors. *ns* indicates no significant difference in the diversity of visitors between the two POI groups according to the Mann-Whitney U test ($p > 0.1$).

= 31,382 POIs), the Pearson correlation coefficient is 0.57 ($p < 0.01$), with an R^2 of 0.33 ($p < 0.01$), indicating a similarly strong positive relationship. The fitted linear graphs are shown in Fig. A.8 in Appendix A. The mean values for neighborhood and visit-based diversity on weekdays are 0.56 and 0.65, respectively. The Wilcoxon signed-rank test indicates that the diversity of visitors to POIs is significantly higher than the neighborhood diversity of POIs ($p < 0.01$). The same pattern is also observed on weekends. These observations reinforce our finding that individuals' daily mobility contributes to greater ethnoracial mixing in activity locations.

We then associate both the neighborhood and visit-based diversity indices with their corresponding POI business categories to further examine the observed discrepancies between the neighborhood and visit-based diversity. As described in Section 4.1.3, we focus on six essential urban amenities: entertainment establishments, restaurants, grocery stores, services, drugstores, and healthcare. Fig. 4 summarizes the discrepancies between neighborhood diversity and visit-based diversity on weekdays by the six POI categories. In general, visit-based

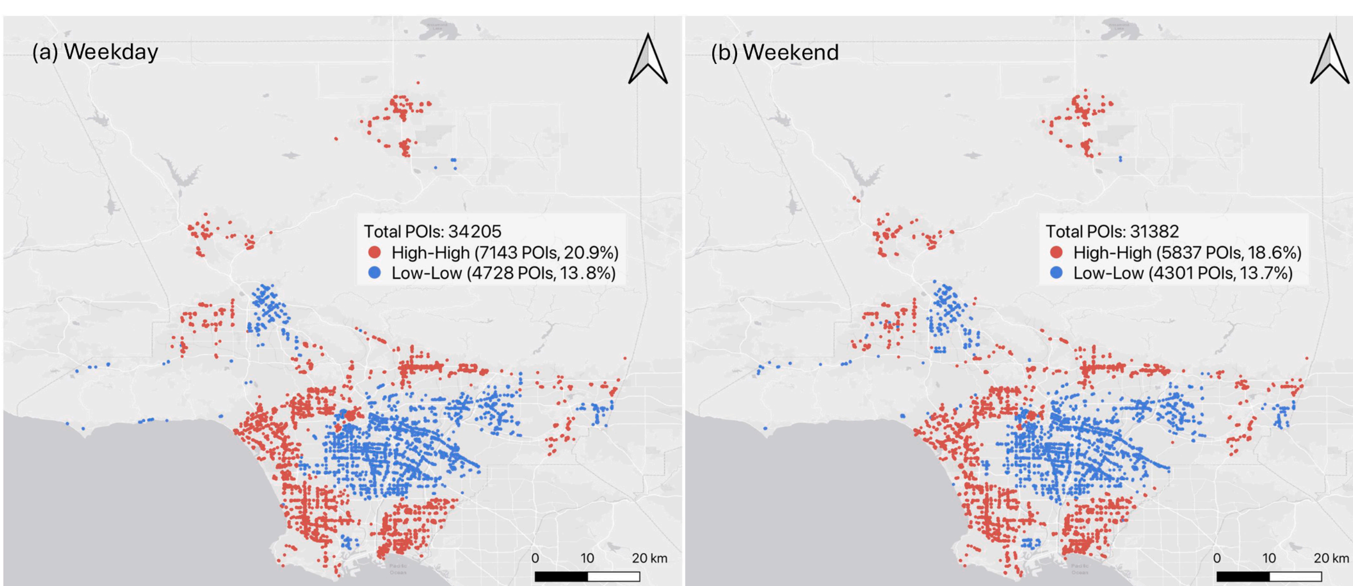

Fig. 5. Significant high-high clusters (in red) and low-low clusters (in blue) of ethnoracial diversity of visitors to POIs on (a) weekdays and (b) weekends using Local Moran's I ($p < 0.05$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

diversity significantly surpasses neighborhood diversity of POIs across all six POI business categories, as indicated by the Wilcoxon signed-rank test results ($p < 0.01$). This suggests that visitors contribute to the ethnoracial mixing in these particular types of POIs. Similar trends are observed on weekends (see Fig. A.9 in Appendix A).

We then compare the diversity of visitors across the six POI categories. Based on mean values, entertainment establishments exhibit the highest diversity (mean = 0.68), followed by restaurants (0.67), groceries (0.66), services (0.65), and drugstores (0.65). Healthcare-related POIs show the lowest diversity (0.59). Further analysis using the Mann-Whitney U test reveals no significant differences in the diversity of visitors to restaurants and groceries, groceries and drugstores, or services and drugstores ($p > 0.1$). Overall, the differences in the diversity of visitors to these essential urban amenities are relatively small, except for healthcare-related POIs. This may be due to people's tendency to visit healthcare facilities close to their residences. As previously reported, Los Angeles County exhibits notable residential segregation, which may contribute to the lower diversity observed in healthcare visits. In contrast, for the other five types of activities, there is usually no racial specificity. Individuals are more likely to travel outside their neighborhoods to access entertainment, dining, service, drugstore, and grocery options and be exposed to more diverse social groups.

5.2.2. Spatial clusters of ethnoracial mixing at activity locations

Fig. 5 depicts the spatial distribution, counts, and percentages of significant high-high (shown in red) and low-low clusters (shown in blue) of ethnoracial diversity of POI visits during weekdays and weekends ($p < 0.05$), as analyzed using Local Moran's I through Esri ArcGIS Pro v3.1.2. The decrease in the percentage of high-high clusters from weekdays to weekends further reinforces our previous analysis that the average visit-based diversity is lower during weekends. The high-high clusters indicate places where higher levels of ethnoracial mixing occurred, whereas the low-low clusters may suggest more isolated areas where only one or very few ethnoracial groups are predominantly present. The high-high clusters tend to be close to coastal regions, suburban areas, and major freeways, while the low-low clusters predominantly concentrate in inland areas. In general, there is no significant variation in the spatial segregation of high and low ethnoracial diversity observed between weekdays and weekends.

These high-high clusters and low-low clusters are subsequently associated with their respective ethnoracial diversity and dominance categories (see Fig. 3). Table 3 summarizes the POI count and percentage of each POI ethnoracial diversity type in high-high and low-low clusters. As expected, more than half of the POIs in high-high clusters are intrinsically High diversity types in terms of ethnoracial mixing. The rest of the POIs at least exhibit a moderate level of ethnoracial diversity. In the weekday subset, within the 4728 POIs classified into low-low clusters, two major Latino-dominant types emerge: 3065 (64.83 %) POIs exhibit Latino moderate diversity, and 1552 (32.83 %) POIs display Latino low diversity. In other words, approximately one-third of the POIs in low-low clusters are primarily or, at times, almost exclusively visited only by the Latino population. This suggests that the Latino population tends to encounter primarily other Latinos and experience a higher level of segregation/isolation in their daily activities, which is consistent with previous findings (Jones & Pebley, 2014; Wu et al., 2023). A primary reason for Latino isolation in LA County is that they are the largest ethnic group in the area. Similar to the observation on weekdays, on weekends, more than half of the total number of POIs within high-high clusters exhibit High diversity, followed by Latino moderate diversity, White moderate diversity, Asian moderate diversity, and Black moderate diversity. In terms of low-low clusters on the weekend subset, Latino moderate diversity and Latino low diversity remain the two predominant types. The proportion of POIs categorized as Latino low diversity increases compared to weekdays, indicating that the Latino population is more likely to engage with their own communities during weekends.

5.2.3. Time of day variation in diversity of visitors to POIs

The same six essential urban amenities frequently visited in people's daily lives which may provide opportunities for social interaction are selected to examine further the time-of-day variation in the ethnoracial diversity of visitors to POIs. Our focus is on examining two key aspects: 1) whether the diversity of visitors to these six types of POIs significantly differs from the diversity of the neighborhoods in which these POIs are located, and 2) whether the variation in diversity of visitors to POIs across different times of the day is significant. The box plots in Figs. 6 and 7 illustrate the time of day variation in the diversity of visitors (i.e., scaled entropy index) to restaurants (in total 8874 POIs), grocery stores (779 POIs), and entertainment establishments (886 POIs) in LA County on weekdays in March 2019 (the graphs of weekend subset are available on the GitHub repository[9]). These POIs are grouped according to the neighborhood diversity and dominance type of the CBG in which the POI is located. POI groups with less than ten observations are excluded from this figure and subsequent analysis. The box plots to the left of the vertical dashed line illustrate the distribution of neighborhood diversity of POIs. This can be considered a default diversity level for each POI without considering people's daily movements and activities. The box plots labeled “Morning”, “Noon”, “Afternoon”, and “Evening” illustrate the distribution of the diversity of visitors for the same POI groups as in the “neighborhood diversity” group. The Mann-Whitney U test results indicate that most of the changes in the diversity of visitors from the morning, noon, afternoon, and evening, compared to the neighborhood diversity of corresponding types of POIs, are statistically significant ($p < 0.01$). Exceptions include grocery POIs located in Black-dominated moderate diversity neighborhoods, where changes during the day are not significantly different from the neighborhood diversity ($p > 0.1$); drugstore POIs in Asian-dominated moderate diversity neighborhoods, where morning and evening changes are not significant; and healthcare POIs in Latino-dominated moderate diversity neighborhoods, where all changes from morning to evening are not significant compared to the neighborhood diversity.

At the start of the day, we observe a significant rise in the diversity level of POIs located in low diversity CBGs ($p < 0.01$), including those dominated by Black, Asian, Latino, and White populations. For restau-

Table 3
POI count and percentage of each POI ethnoracial diversity type in high-high and low-low clusters.

POI diversity type	Weekday		Weekend	
	High-high	Low-low	High-high	Low-low
High diversity	4480 (62.72 %)	0	3471 (59.47 %)	0
Latino moderate diversity	1620 (22.68 %)	3065 (64.83 %)	1340 (22.96 %)	2479 (57.64 %)
White moderate diversity	946 (13.24 %)	–	906 (15.52 %)	–
Asian moderate diversity	77 (1.08 %)	–	106 (1.82 %)	–
Black moderate diversity	20 (0.28 %)	–	14 (0.24 %)	–
Latino low diversity	0	1552 (32.83 %)	0	1736 (40.36 %)
Total number of POIs	7143 (100 %)	4728 (100 %)	5837 (100 %)	4301 (100 %)

Notes: The dash indicates below 1 %. Other types in low-low clusters less than 1 % are omitted in this table.

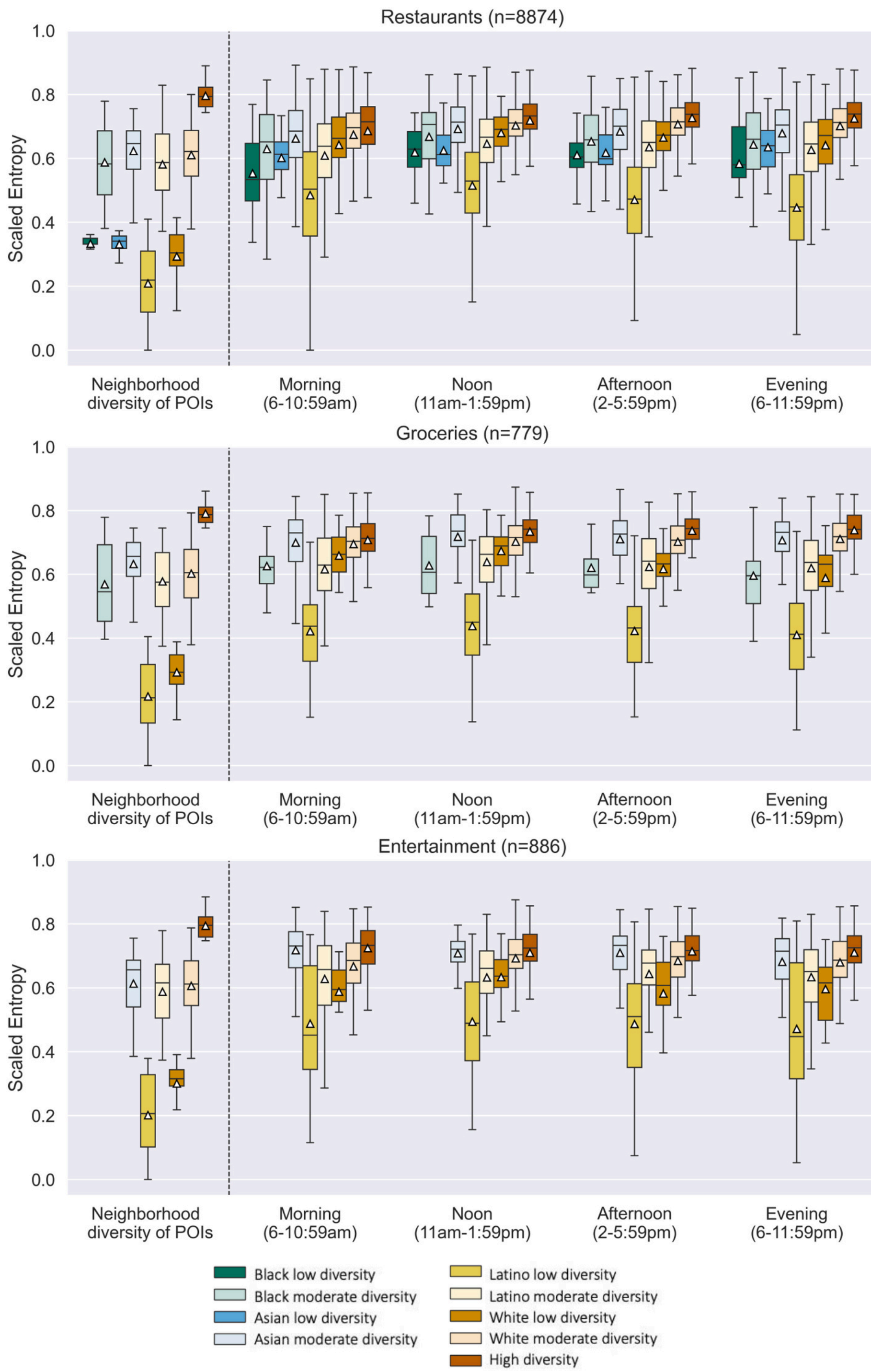

Fig. 6. Time of day variation (to the right of the vertical dashed line) in the diversity level of visitors to restaurants, grocery stores, and entertainment establishments in LA County on weekdays in March 2019, grouped by neighborhood diversity and dominance type where each POI is located. The triangles represent the mean values. Box plots with less than ten observations are excluded from this figure.

rants, on average the Black-dominated low diversity group increases from 0.33 (default neighborhood diversity level) to 0.59 (daily average of the four diversity levels of morning, noon, afternoon, and evening), Asian-dominated low diversity increases from 0.33 to 0.62, Latino-dominated low diversity increases from 0.21 to 0.48, and White-dominated low diversity increases from 0.29 to 0.66. This suggests that despite these restaurants being situated in areas with low diversity, daily mobility and activities of individuals contribute to more ethno-racial mixing. Note that the average rise of the diversity level in the Latino-dominated low diversity group is the least (+0.27) among these four low diversity groups. Presumably, Latino-dominated low diversity areas are more preferred by the Latino population. The average increase in the White-dominated low diversity group is the biggest (+0.37) which may suggest that restaurants operating in White-dominated low diversity areas attract the most racially diverse population. According to the one-way ANOVA test, the changes in the diversity of visitors to restaurants across morning, noon, afternoon, and evening are not significant ($p > 0.1$) only for three POI groups: Black low diversity, Black moderate diversity, and Asian low diversity. Likely, restaurants in these neighborhoods are primarily frequented by specific racial groups, such

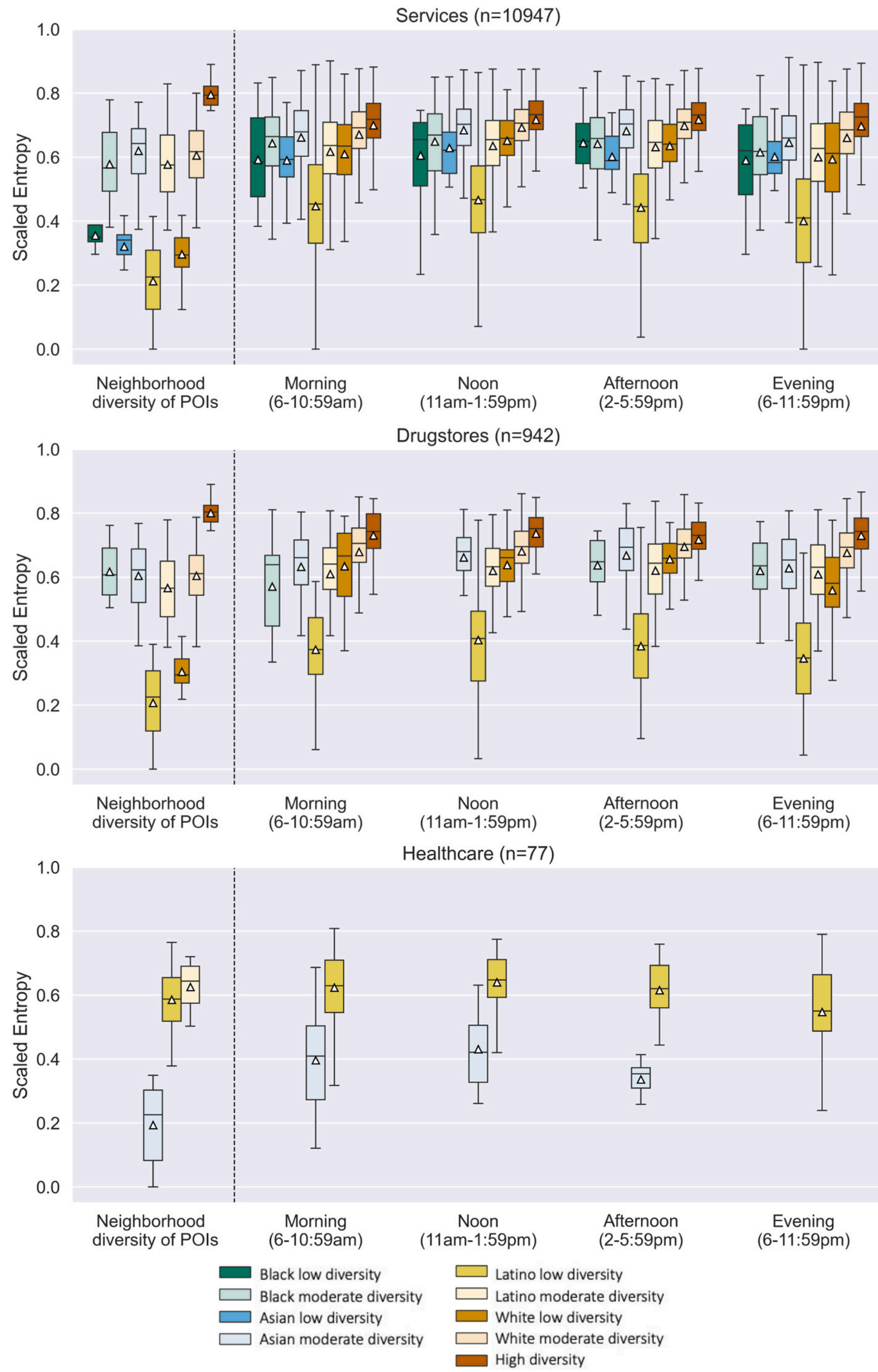

Fig. 7. Time of day variation in the diversity level of visitors to service, drugstores, and healthcare establishments. Box plots with less than ten observations are excluded from this figure.

as the dominant Black and Asian residents in these areas.

In terms of grocery visits, among the grocery POIs located in low diversity neighborhoods dominated by Latino or White groups, we observe the following significant changes: the Latino-dominated low diversity POI group increases from 0.22 (default neighborhood diversity level) to 0.42 (daily average), and the White-dominated low diversity group increases from 0.29 to 0.63. The increase in the diversity of visitors to grocery stores of the Latino-dominated low diversity group is smaller than the White-dominated low diversity group. Presumably, grocery stores near Latino neighborhoods are more attractive to the Latino population. In contrast, grocery stores in White-dominated low diversity areas might not have the same racial specificity as those in Latino-dominated low diversity areas, such as Mexican-specific grocery stores. Based on the one-way ANOVA test results, the changes in the diversity of visitors to grocery stores across morning, noon, afternoon, and evening are only significant for White low diversity ($p < 0.05$) and High diversity ($p < 0.01$) groups. However, the differences are relatively small. This is not surprising, as the likelihood of buying groceries at

Table 4
Descriptive statistics and Mann-Whitney U test results for the visit-based diversity index of the Greater LA subset and the entire California sample.

Period	The Greater LA			The entire California			Difference
	POI count	Mean	S.D.	POI count	Mean	S.D.	
Weekday morning	29,502	0.626	0.15	29,584	0.627	0.149	−0.001
Weekday noon	31,831	0.645	0.136	31,891	0.647	0.135	−0.002
Weekday afternoon	32,600	0.642	0.139	32,655	0.643	0.138	−0.001
Weekday evening	27,220	0.625	0.152	27,275	0.626	0.152	−0.001
Weekend morning	23,888	0.603	0.165	24,051	0.606	0.164	−0.003*
Weekend noon	28,287	0.626	0.152	28,393	0.628	0.151	−0.002**
Weekend afternoon	28,330	0.629	0.149	28,416	0.631	0.148	−0.002*
Weekend evening	22,178	0.614	0.159	22,288	0.616	0.158	−0.002*

Notes: *$p < 0.1$; **$p < 0.05$.

different times of the day should be generally similar across racial groups.

Regarding entertainment visits, we also observe a substantial increase in diversity level for the POIs located in Latino-dominated low diversity and White-dominated low diversity CBGs when considering people's activities compared to the neighborhood diversity ($p < 0.01$). However, according to the one-way ANOVA test, no significant changes in the diversity level throughout the day are observed for any POI diversity groups at the 0.01 significance level. For services, drugstores, and healthcare POIs, we also find a significant rise in diversity levels for the POIs located in low diversity CBGs compared to their neighborhood diversity ($p < 0.01$). In terms of the time of day variation patterns over the four distinct periods, the changes in the diversity of visitors to service POIs across morning, noon, afternoon, and evening are only not significant for Black low diversity, Black moderate diversity, and Asian low diversity groups ($p > 0.1$). Regarding drugstore visits, the time of day variation is only significant for the POIs located in the White low diversity CBGs at the 0.05 significance level. For healthcare visits, the time of day variation is only significant for the Latino moderate diversity group.

5.3. Comparison between the Greater LA and the entire California

Previous analyses of ethnoracial diversity in POI visits focused on individuals from across the entire state of California, including those residing in LA County, who visited POIs in LA County. This section explores the disparities in ethnoracial diversity when examining populations within the Greater Los Angeles region as opposed to visitors from the entire California. Table 4 summarizes the descriptive statistics and Mann-Whitney U test results for the visit-based diversity index of the Greater LA subset and the entire California sample. This comparison is made for weekdays and weekends across four distinct periods. We also break down the analysis by more than 160 POI categories according to SIC code instead of using all POIs in the significant tests; however, no significant differences were found for any POI category. As indicated in the table, the diversity of visitors tends to be lower during weekends compared to weekdays. Specifically, weekend mornings exhibit the lowest diversity level, followed by weekend evenings, weekend noons, and weekend afternoons. On weekdays, the lowest diversity level is observed during the evenings, followed by mornings, afternoons, and noons. The overall diversity index suggests a decrease of 0.001 to 0.003 when only considering the Greater LA subset compared to the entire California sample. The diversity index for all periods on weekends, as observed in the Greater LA subset, exhibits a significant decrease compared to the entire California sample ($p < 0.1$). However, no significant differences are observed during weekdays ($p > 0.1$). These findings suggest that individuals from regions outside the Greater LA areas in California contribute positively to ethnoracial diversity observed in POI visits in LA County during weekends. Presumably, individuals visiting from outside Greater LA during weekends are often tourists, and they are likely to come from more diverse ethnoracial backgrounds.

6. Discussion and conclusions

Leveraging one month privacy-enhanced mobile phone location data collected in Los Angeles County, this study explored the ethnoracial diversity and spatial segregation in POI visits in LA County. The main contributions of this study are threefold: (1) our work goes beyond the simplistic “majority-minority” perspective of segregation by extending the method proposed by Holloway et al. (2012) to examine segregation in activity locations through the lenses of racial diversity and dominance; (2) it explores dynamic, visit-based diversity and dominance at the POI level, which has been largely understudied to date; and (3) it compares the neighborhood diversity surrounding POIs with the diversity of visitors to those same POIs, highlighting the importance of considering everyday population dynamics in segregation research.

Empirical results from LA County showed a significantly higher level of ethnoracial diversity of visitors to POIs during weekdays compared to weekends. The outcomes suggest a notable spatial segregation in the ethnoracial diversity and dominance in POI visits within LA County. The overall geographic distribution of various POI ethnoracial diversity types closely mirrors the patterns of residential ethnoracial diversity. This suggests that individuals of the same ethnoracial background tend to visit similar places or places similar to their own neighborhoods, aligning with previous findings (Wu et al., 2023). Notably, POIs classified under the High diversity category exhibit a more extensive geographic presence when compared to High diversity census block groups. This observation suggests that individuals' daily mobility in urban areas enhances exposure to diversity, particularly at these POIs characterized by a diverse mixing of races and ethnicities. Consistent with our results, Jones and Pebley (2014) also found that people's daily activity spaces in LA County exhibit greater ethnoracial heterogeneity compared to residential diversity.

In addition, our findings provide new insights into the population dynamics in segregation research. We identified a strong positive linear relationship between the diversity of visitors to a POI and the neighborhood diversity where the POI is located. We found that about 34 % of the variance in the diversity of visitors to POIs can be explained by the neighborhood diversity of POIs. The diversity of visitors is significantly higher than the neighborhood diversity of POIs, which reinforces our finding that daily mobility in urban areas improves ethnoracial mixing at activity locations. By examining six local amenities as proxies for different activity types (entertainment, restaurants, grocery stores, services, drugstores, and healthcare), we found that the differences in the diversity of visitors among these activities are generally minor, except for healthcare-related POIs, which exhibit the lowest level of ethnoracial mixing. These new findings contribute to our understanding of the heterogeneous segregation and diversity patterns at different types of daily activity locations that individuals may visit frequently in their daily routines, excluding their home, work, and study locations. While the analysis reported here is based on visit counts, we also weighted the diversity measure using the duration of individual activity spent at each POI. However, no significant differences were observed.

Moreover, a Local Moran's *I* analysis suggests significant high-high and low-low clusters in POI's ethnoracial diversity. The outcomes reveal that the high-high clusters tend to be close to coastal regions, suburban areas, and major freeways, while the low-low clusters predominantly concentrate in inland areas. Approximately one-third of the POIs in low-low clusters are primarily or, at times, almost exclusively visited only by the Latino population. This suggests that the Latino population tends to encounter primarily other Latinos and experience a higher level of segregation/isolation in their daily activities, which is consistent with previous findings that the Latino group has the highest exposure to its own group in daily activities in LA (Jones & Pebley, 2014; Wu et al., 2023). This might also indicate that Latino communities have stronger internal social ties and prefer businesses that cater to or represent their population. Most of the changes in the diversity of visitors from the morning, noon, afternoon, and evening, compared to the neighborhood diversity where the POIs are located, are statistically significant. However, we found a few exceptions including grocery stores located in Black moderate diversity neighborhoods, drugstores in Asian moderate diversity neighborhoods, and healthcare establishments in Latino moderate diversity neighborhoods. These places are likely frequented primarily by population groups similar to those residing in the neighborhoods where the POIs are located. Regarding the time of day variation, the changes in the diversity levels of visitors to restaurants and service establishments are generally significant, while those for grocery stores, entertainment venues, and drugstores are mostly not significant throughout the day. This is not surprising, as the latter typically do not cater to any specific ethnoracial group. Lastly, a comparison between visitors from the Greater LA region and the entire state of California identifies a significant decrease in ethnoracial diversity in POI visits on weekends when focusing solely on the Greater LA sample. This implies that individuals from outside the Greater LA region in California have a positive impact on the ethnoracial diversity observed in visits to POIs on weekends in LA County.

Several limitations need further investigation. One limitation associated with mobile phone data is its potential inability to reflect the true population and social interaction accurately. The data also have inevitable uncertainty issues during the data collection process such as positional uncertainty or errors. Although the number of unique mobile phone users in this study is 283,556, which is considerably large compared to traditional survey-based data, this sample represents only about 3 % of the total population in LA County. Even though we reweighted the sample to match the population distribution from the American Community Survey, as with many other segregation studies using mobile phone data (Athey et al., 2021; Xu, 2022; Yabe et al., 2023), it is crucial to carefully examine potential sample bias in generating the findings. Also, it may be difficult to discern the purpose of visits or the types and quality of social interactions. For example, the visits do not represent whether they involve strangers co-locating randomly in these places without meaningful social interactions or friends catching up. Hence, the ethnoracial diversity metrics computed in our study should be regarded as a proxy for all meaningful social interactions.

Second, similar to many existing studies, individual probabilistic ethnoracial profiles were inferred based on the demographic composition of their home CBG (Athey et al., 2021; Xu, 2022). This method assumes that all individuals within a CBG share the same ethnoracial composition as the aggregate statistics, which may oversimplify the actual diversity within a CBG. As a result, individuals might be misrepresented, especially in more diverse CBGs where no single group is dominant. This limitation should be further examined when interpreting the findings from mobile phone data in future research.

Third, our primary focus is on the dynamics of ethnoracial diversity within activity locations. It is also important to consider people-based perspectives, such as the experienced diversity of individuals as they visit different POIs throughout the day (Athey et al., 2021; Park & Kwan, 2018; Wu et al., 2023). Future research could explore experienced diversity at the POI level along individual travel paths to complement our current analysis, providing deeper insights into patterns of ethnoracial diversity and segregation within people's daily activity spaces. This approach could also enable correlations with individual socioeconomic/sociodemographic characteristics and more variables, helping to understand how various factors influence segregation or diversity levels in activity space contexts. It would also be valuable to consider the distance traveled to various POIs to understand whether individuals travel further to experience more or less diversity.

CRediT authorship contribution statement

Rongxiang Su: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Niall Newsham:** Writing – review & editing, Validation, Investigation. **Somayeh Dodge:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors have no conflict of interest in this research.

Data availability

Our code for data processing and the main analysis is available on GitHub (https://github.com/move-ucsb/racialdiversity). The mobile phone location data supporting the findings of this study are available from Cuebiq, but access is restricted due to licensing agreements, making these data not publicly accessible. However, aggregated data used in this study can be obtained from the authors upon reasonable request and with permission from Cuebiq. Additional data used in the study comes from the 2017–2021 American Community Survey 5-Year Estimates, which is publicly available.

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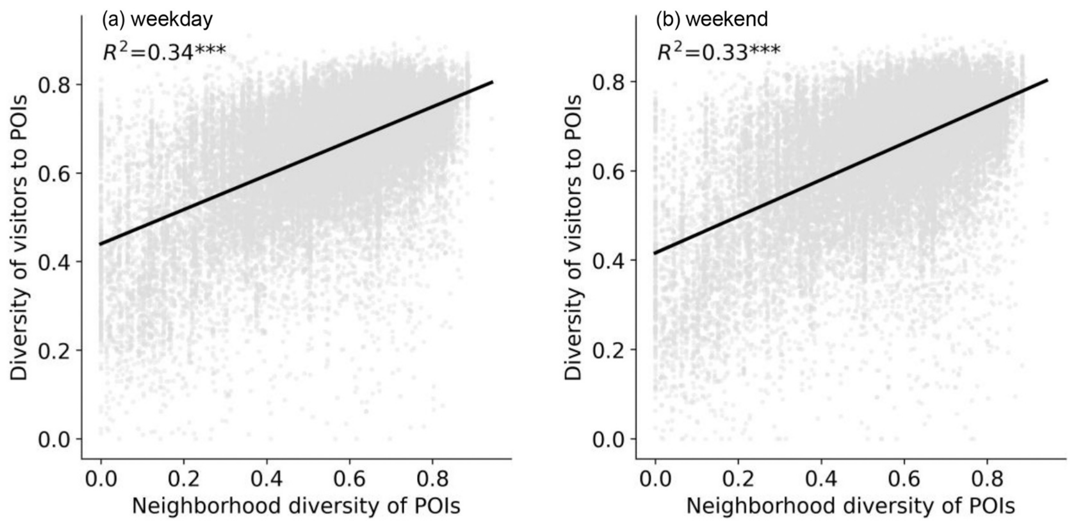

Fig. A.8. The relationship between the neighborhood diversity of POIs and the diversity of visitors to POIs. The R^2 is derived from a linear least-squares regression for the two diversity indices.

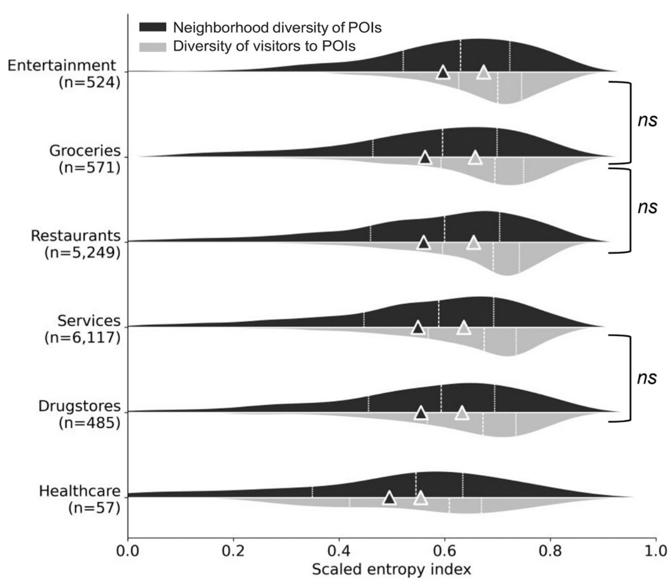

Fig. A.9. Neighborhood diversity of POIs (in black) and diversity of visitors to POIs (in gray) on weekends by six major POI business categories. The POI count of each category is in parentheses on the y-axis. Triangles represent the mean. Violin plots are sorted by the mean diversity of visitors. *ns* indicates no significant difference in the diversity of visitors between the two POI groups according to the Mann-Whitney *U* test ($p > 0.1$). The Wilcoxon signed-rank test results suggest that the diversity of visitors to a POI is significantly higher than the neighborhood diversity where the POI is located across all six POI business categories ($p < 0.01$).

Table A.5
SIC codes by category of essential urban functions.

POI category	4-Digit SIC code
Healthcare	80xx (health services)
Drugstores	5122 (drugs, drug proprietaries, and druggists' sundries), 5912 (drug stores and proprietary stores)
Restaurants	5461 (retail bakeries), 5812 (eating places), 5813 (drinking places)
Groceries	5141 (groceries, general line), 5411 (grocery stores)
Entertainment	79xx (amusement and recreation services)
Services	4311 (united states postal service), 60xx (depository institutions), 72xx (personal services), 73xx (business services)

Notes: Detailed description of each SIC code can be found at https://www.osha.gov/data/sic-manual

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