



# Spatial equity implications and neighborhood indicators of ridehailing trip frequency and vehicle miles traveled in the phoenix metro region

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## Abstract

Early optimism for ridehailing services to complement existing public transit services and offer individuals another shared mobility service with reduced travel costs and improved travel times have largely proven to be unsubstantiated. This unwelcomed outcome, in part due to the popularity of ridehailing services among wealthier populations and restrictions on the less-expensive ridesharing service in some urban settings, has likely instead resulted in heightened disparities in access to this on-demand mobility option for historically-marginalized populations and under-resourced communities. This hypothesis is examined by estimating the macro-level socioeconomic and built environment determinants of ridehailing pick-ups and drop-offs in the Phoenix metro region with spatial lag of X modeling. A geographically weighted regression (GWR) model of vehicle miles traveled was then estimated using route-level ridehailing data from a third-party mileage tracking app to identify zonal attributes associated with this measure of vehicle-based exposure. Together, study findings highlight the benefits and drawbacks of greater ridehailing service activity, identifying a need for programs and interventions that safeguard and improve access to affordable high-quality mobility options for transportation disadvantaged neighborhoods.

**Keywords** Ridehailing · Ridesourcing · Transportation network company (TNC) · Spatial equity · Geographically weighted regression

## Introduction

### Study context

In the decade prior to the onset of the Covid-19 pandemic, ridehailing services emerged as a competitive alternative to more established mobility options. The convenience for

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individuals to schedule a reliable on-demand service from their home, workplace, or elsewhere held promise as a panacea for lowering travel costs, reducing congestion, and improving travel times, if these services were shared with other passengers (Chan and Shaheen 2012). Ridehailing services in the United States instead arose as a predominantly single-party mobility service (Gehrke et al. 2021), raising alarming sustainability concerns including higher travel costs (Young et al. 2020), increased traffic volumes (Erhardt et al. 2019), and replacement of public transit services (Gehrke et al. 2019). These results have likely exacerbated existing disparities in mobility access for individuals who cannot afford relatively expensive ridehailing services or reside in neighborhoods where decreased transit ridership revenue and increased roadway congestion due to ridehailing service popularity have weakened the availability and quality of more affordable public transit services.

Social distancing and government-mandated stay-at-home orders in response to public health risks of Covid-19 disease transmission have further destabilized public transit systems, highlighting the systemic inequalities in mobility access for poor and historically disadvantaged residents (Monahan and Lamb 2022). Although ridehailing activity similarly diminished, the substitution of ridehailing services for public transit adoption brought on by changing consumer preferences and declines in service quality has continued during the pandemic, with evidence suggesting neighborhoods of greater affluence and transit service availability had higher substitution rates (Meredith-Karam et al. 2021). Acknowledging that trends in public transit decline and single-party ridehailing popularity are likely to resume once Covid-19 health risks have been assuaged, the identification of where spatial disparities in ridehailing activity exist becomes necessary toward informing transportation policies and programs that help ensure under-resourced communities have equitable access to emergent mobility services that have adversely impacted more accessible travel options.

This study aims to identify features of neighborhoods which have observed a disproportionate share of the benefits (and disadvantages) from greater ridehailing utilization and activity. Specifically, this study analyzes a cross-section of multiyear ridehailing data collected for a major United States metro region to estimate the macro-level socioeconomic and built environment features associated with ridehailing service pick-up and drop-off frequencies as well as ridehailing-related vehicle miles traveled (VMT). By doing so, this study seeks to identify communities and contexts where ridehailing service demand was greatest and those neighborhoods where an increased adoption of ridehailing services unfavorably affected residents via exposure rather than improved access to a multimodal transportation system. This multifaceted examination of ridehailing activity seeks to bring greater attention to the spatial equity implications of these services and supply evidence for new interventions that seize a second opportunity to define who can access ridehailing services once the pandemic subsides, and their popularity inevitably rebounds.

## Ridehailing and socioeconomic context

Ridehailing studies continue to suggest that significant associations exist between the adoption of these car-based services and individuals of certain socioeconomic backgrounds and mobility profiles. In the United States, younger, more educated, and wealthier adults appear most likely to adopt ridehailing services (Alemi et al. 2018a; Gehrke et al. 2019; Loa and Habib 2021). In an early survey-based study, Rayle et al. (2016) found that 60% of ridehailing passengers in San Francisco were male and 75% of respondents were younger than 35 years. Ridehailing passengers also seem more likely to adopt non-car travel modes including public transit (Conway et al. 2018; Grahn et al. 2019; Sikder 2019; Das 2020),

with technological aptitude also identified as an indicator of ridehailing adoption (Lavieri and Bhat 2019).

Equitable access of ridehailing services among individuals identifying as a racial or ethnic minority has also been associated with service utilization in significant, albeit divergent ways. Clewlow and Mishra (2017) identified Black/African American individuals in Chicago as more likely to use ridehailing services compared to similarly historically-marginalized populations, whereas Di et al. (2019) found areas with more White residents to have disproportionately higher levels of adoption. Studying ridehailing and traditional taxi services, Pan et al. (2020) found in New York City, equitable access to these competing services for unemployed residents increased over time and after ridehailing service introduction.

Access to fewer vehicles has been correlated with an increased likelihood of adopting ridehailing services and other shared mobility options including public transit (Circella and Alemi 2018; Grahn et al. 2019; Sikder 2019; Young and Farber 2019). Clewlow and Mishra (2017), however, found minimal differences in auto ownership rates between transit- or ridehailing-only households and car-centric households. Regarding household structure, households without children are generally more likely to adopt ridehailing services (Alemi et al 2019). Analyzing National Household Travel Survey data, Conway et al. (2018) reported that higher-income households adopted ridehailing services at a disproportionately higher rate than households in lower-income cohorts. However, conflicting findings in certain contexts have been reported (Gehrke et al. 2019); with suggestions that ridehailing service adoption is popular on both ends of the income spectrum (Alemi et al. 2018a).

Examining neighborhood-level sociodemographic and economic context, Gehrke (2020), in a study of Uber service area expansion in three metropolitan areas, found that San Francisco neighborhoods with a higher share of young adults and zones with a greater share of adults with advanced college degrees were positively connected to expanded service areas. Brown (2019) echoed these findings in a Los Angeles study where areas with a higher percentage of young adults and auto-less households were associated with increased Lyft trip frequency, while also noting that neighborhoods with Hispanic or Asian majorities were negatively associated with ridehailing trip frequency. Whether studied at the individual or neighborhood unit, the above research suggests that significant variations in ridehailing demand exist across social equity indicators. However, differences in study findings are related to study area, data source, and analytic design decisions, leaving planners and decisionmakers with an unclear understanding of the transportation equity problems created with the emergence of ridehailing services (Jiao and Wang 2021).

## Ridehailing and built environment

Areas with more activity opportunities are observed to produce higher ridehailing service adoption rates. Studying seven major metropolitan regions, Clewlow and Mishra (2017) found 29% of respondents in urban areas had adopted ridehailing services, while only 7% of suburban residents reported the same behavior, suggesting greater ridehailing service viability in neighborhoods with greater population and employment densities. Studies into the role that ridehailing services play in bridging local accessibility gaps have found improvements in equitable access after service introduction in more suburban settings outside regional cores (Acheampong et al. 2020; Abdelwahab et al. 2021). However, ridehailing services tend to favor urban areas disproportionately due to the inherent demand provided by their greater

activity densities (Dey et al. 2021), which is also associated with shorter travel and wait times as well as decreased costs (Conway et al. 2018).

Yu and Peng (2019) further underscored how built environments conducive to high-quality transit service are also likely to be catalysts for ridehailing activity, finding that greater land use entropy in addition to transit stop and sidewalk density were associated with greater ridehailing service utilization. Greater land use mixing as well as stronger local and regional accessibility have been found to predict ridehailing service use elsewhere (Sabouri et al. 2020). Although other studies have found residents in areas of greater mixed-use favor active transportation modes over ridehailing services (Alemi et al. 2018b), ridehailing service use continues to be linked to walkable neighborhoods (Malik et al. 2021) characterized by greater intensities of restaurants, cafes, and points of interest near an individual's residence (Dey et al. 2021).

Regarding travel patterns, a positive association has been consistently found between ridehailing adoption and higher VMT totals than would be observed without its availability (Henao and Marshall 2019; Tirachini and Gomez-Lobo 2019; Das 2020). An outcome likely attributed to deadheading, which is defined as the miles that a ridehailing driver travels without a passenger inside their vehicle (Nair et al. 2020). This commonly occurs when ridehailing drivers travel between a trip's destination and the origin of their next pick-up, with this phenomenon found to have contributed to an additional 70 percent of VMT by ridehailing drivers (Henao and Marshall 2019). While studies have started to associate increased ridehailing demand with dense and walkable neighborhoods that also promote efficient transit systems, there is scant evidence describing neighborhood attributes associated with ridehailing travel between trip origins and destinations (Marquet 2020).

## Study contributions

This study advances a growing evidence base by addressing two identified research gaps. First, this study investigates ridehailing activity patterns in the Phoenix, Arizona urbanized area, a populous, southwestern region of the United States that has to-date been underreported in the literature. A Phoenix case study is of particular interest given that cost-efficient pooling services have yet to be offered by either Uber or Lyft in this region, which also has an extensive bus system but limited light rail transit services. Thus, individuals in areas where ridehailing activity has flourished are likely to have replaced an established shared mobility option with a more expensive, exclusive travel alternative. A second study contribution is the quantification of revenue-producing trip distances that were used to identify ridehailing VMT and examine its association with spatial equity-related and environmental determinants of this less-understood measure of ridehailing activity in addition to the frequency of ridehailing pick-ups and drop-offs. By analyzing the socioeconomic and built environment determinants of these three ridehailing outcomes with spatial econometric modeling techniques, this study helps to offer new insights into the potential for social inequities in ridehailing activity and travel patterns after accounting for spatial variations in this transportation-land use interaction.

## Data

### Study area

For this study, the Phoenix metro region refers to the Census-defined urbanized area of Phoenix and Mesa that is found within Maricopa County, Arizona (Fig. 1). Per 2015–2019 American Community Survey estimates, this definition of the Phoenix region houses over 3.92 million residents, with Phoenix accounting for more than two-fifths of the region's population (1.63 million residents), followed by the City of Mesa (499,720 residents) bordering to its east. The next four largest cities within the region (Chandler, Scottsdale, Glendale, and Gilbert) are comparable in population, ranging from 252,692 to 243,254 residents. Tempe, home to Arizona State University's main campus, is the region's seventh largest city with 187,454 residents and its densest with 7.29 residents per acre.

In terms of travel, the percentage of workers over 16 years old in the Phoenix metro region who commute by automobile (alone or pooled) generally exceeds the national average (85.3%), with 86.1% of workers in the Phoenix-Mesa region commuting by car, truck, or van and only 1.8% commuting by public transit (excluding taxis). Unfortunately, ACS ridehailing commute mode share data are not available, as the Census defines ridehailing services in a catchall category that includes taxicabs, motorcycles, bicycles, and other means. However, using 2015–2019 ACS data as a top-end estimate of ridehailing mode shares, Tempe (3.1%), Scottsdale (2.2%), Phoenix (2.0%), and Glendale (2.0%) can be observed as having the potentially highest modal splits for this emergent mobility service

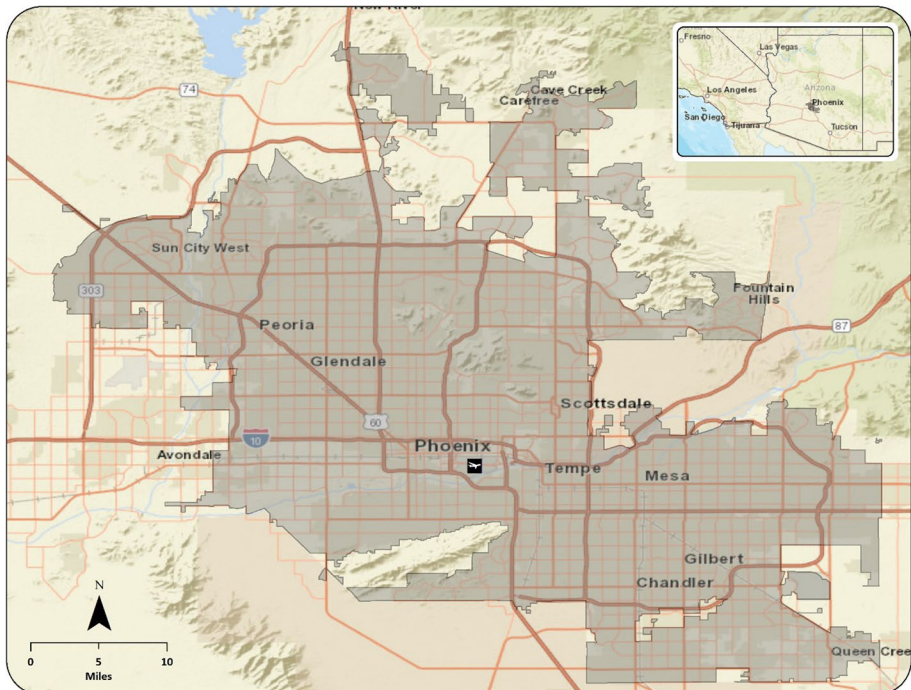


Fig. 1 Phoenix-Mesa, Arizona urbanized area

in the region. Assessing 2017 NHTS data, Conway et al. (2018) noted roughly 15% of adults living in the Phoenix-Mesa-Scottsdale metropolitan area adopted a ridehailing service (not traditional taxi service) in the past month. Herein, while ridehailing adoption and utilization trends for the Phoenix metro region are comparatively low, it must be noted that neither Uber nor Lyft offer their passengers the less expensive and often more efficient pooled ride option.

To investigate local variations in ridehailing travel patterns and spatial determinants of ridehailing trip frequency and VMT in this understudied metro region, a zonal system of 2673 one-mile hexagons was casted across the study area. Hexagonal sampling areas have been adopted in previous studies to allow for a consistent spatial distribution of zones across study areas, with the desirable property that the centroids of all neighboring hexagons have identical Euclidean distances between them (Liao 2021; Jiao et al 2021). However, one must recognize that the choice of any artificial boundary for spatial analysis is likely to result in potential measurement errors attributed to the Modifiable Areal Unit Problem (Openshaw 1984). The decision herein to choose a one-mile hexagon zonal system was made after also investigating the adoption of a two-mile diameter and determining the former sampling area better captured the heterogeneity in zonal socioeconomic context and built environment data while maintaining a reasonable connection between neighborhood contexts and summarized information of ridehailing pick-ups, drop-offs, and VMT (Wang and Noland 2021).

## Ridehailing travel data

Ridehailing trip data were provided by the third-party ridehailing driver assistant app, SherpaShare, which aids drivers in their accounting of vehicle mileage and passenger escorting activities. The complete data set contained 87,124 GPS traces of single-party ridehailing trips that originated and terminated in the Phoenix metro region; collected for each October between 2015 and 2019. The month of October was selected due to data availability limitations, with the calendar month adequately exemplifying typical travel conditions in the region as there are no observed holidays, schools are in session, and weather conditions are generally mild. The data set was aggregated to a cross-section of all observed GPS traces and trip end points from the five Octobers, permitting a more stable and robust statistical examination of ridehailing travel patterns. Every ridehailing trip in the final data set originated in the region's inner core, approximately bounded by a semi-belt formed by Arizona State Highway 101 (AZ-101 or Pima Freeway) to the north and Arizona State Highway 202 (AZ-202 or South Mountain Freeway) to the south, and terminated anywhere within the Phoenix metro region. These data were filtered to exclude ridehailing travel classified by the driver to have been conducted for personal rather than business purposes, resulting in a removal of 17,304 records. One last data set reduction step was performed to eliminate traces that could not be map-matched to the street network—described in more detail below, which resulted in a final study sample size of 65,240 trips.

Although ridehailing traces given by SherpaShare roughly aligned with the street network, a map-matching process was undertaken to attribute network characteristics and more precise trip lengths to the ridehailing data set. GraphHopper, an open-source Java library and web-based routing service, was used for this map-matching process that tested the vertices along the recorded route against potential 'correct' candidate points on the OpenStreetMap (OSM) network (Ramm 2017). The Viterbi algorithm, a generalized predictive method of generating the most likely hidden path for a series of observations

(Newson and Krumm 2009), was adopted to sequence potential matches based on the provided vertex along the route and routing distances between consecutive map-matched candidates on the OSM network. Ridehailing trips marked as ‘unmatchable’ by this map-matching algorithm were then passed onto a map-matching algorithm powered by Google Directions API as a second attempt to align trip routes onto the street network, with ride-hailing trips map-matched by either process constituting the final sample.

Table 1 provides a summary of the ridehailing travel data set used in this study, after aggregating trip ends to a one-mile hexagon system and generating zonal frequencies of pick-ups and drop-offs as well as calculating the vehicle mileage of the recorded ridehailing trips in each hexagon. In reviewing the annual count of zones with ridehailing activity and VMT averages, variation in the data set was observed. A decrease in ridehailing VMT from October 2015 to October 2016 occurred, followed by an increase over the next three Octobers and a second ridehailing activity decrease observed between the final 2 months. Period-to-period variation was confirmed after conducting a Kruskal–Wallis test on ridehailing VMT that found statistically significant differences ( $\chi^2 = 80.15, p < 0.01$ ). Similarly, further Kruskal–Wallis tests found statistically significant differences across the five Octobers for trip generation ( $\chi^2 = 51.74, p < 0.01$ ) and trip attraction ( $\chi^2 = 64.52, p < 0.01$ ) activity. This variation is most likely an artifact of the sampled data set being obtained from a private company that encounters peaks and valleys in its market penetration as it competed with opposing mileage-tracking services rather than any waxing or waning in the adoption of ridehailing services, which likely experienced positive year-to-year growth.

While not shown in Table 1, these ridehailing travel data also provided useful summary statistics regarding the time these trips occurred and their average distance. Of the 65,240 ridehailing trips originating in the Phoenix region’s inner core, over 23% were found to have occurred during peak travel periods, with 9.13% starting in the morning peak (6–9 am) and 14.02% taking place during the evening peak (4–7 pm). This finding of significant ridehailing adoption during the most congested periods of the week is consistent with previous ridehailing

**Table 1** Descriptive statistics for ride-hailing trips

Variable	Trip origins	Trip destinations	Vehicle miles traveled
2015			
Zones	952	1193	1991
Mean	8.21	5.04	52.05
SD	18.43	15.46	125.02
2016			
Zones	1112	979	2673
Mean	7.75	4.86	50.61
SD	16.49	11.90	121.56
2017			
Zones	922	1263	2081
Mean	7.63	4.68	55.79
SD	15.13	10.39	120.65
2018			
Zones	1039	942	2116
Mean	7.63	4.80	61.31
SD	16.76	11.77	123.09
2019			
Zones	950	1217	2118
Mean	8.21	5.03	53.56
SD	19.22	12.59	111.81

survey findings (Gehrke et al. 2019). In this sample, the most popular time for ridehailing travel was during mid-day (9 am–4 pm) on Mondays through Fridays in which 32.22% of all trips were observed, followed by travel during any time on Saturday or Sunday (29.52%). Fewer ridehailing trips were recorded during weekday evenings (7 pm–12 am) or early mornings (12–6 am), with shares of 6.43% and 8.69% trips, respectively. In general, these temporal shares of ridehailing activity were constant across the five periods, with a modest increase in mid-day shares occurring from October 2015 (5.59%) to October 2019 (7.26%) that was accompanied by a two-percent decrease in weekend activity shares from October 2015 (7.64%) to October 2019 (5.38%). In the pooled sample, the average trip distance was 7.20 miles, ranging from 6.64 miles per trip in October 2015 to 8.20 miles per trip in October 2018.

## **Socioeconomic context and built environment data and measures**

Socioeconomic context metrics were calculated using population estimates provided by the 2015–2019 ACS and employment figures derived from the 2018 Longitudinal Employer-Household Dynamics (LEHD) data sets. These data were collected at US Census geographies—ranging in size from blocks to tracts—that were then summarized to one-mile hexagons using an area-based apportionment process to generate a robust set of area-wide characteristics based on person- and household-level attributes. Variables at the former level describe the share of residents within a hexagon classified by different Census-designated categories of sex, age, education, race/ethnicity as well as immigrant and work status. These metrics were complemented with household-level variables related to annual income, poverty status, housing unit tenure, vehicle ownership, and Internet access as well as a zone's percentage of residents employed in low- (\$15,000 or less annually), medium- (\$15,001 to \$39,999 annually), or high-wage (more than \$40,000 annually) occupations.

Built environment measures selected for this study span three distinct categories: land development patterns, urban design, and transportation systems (Frank and Engelke, 2001). Land development pattern measures, including population, employment, and activity (sum of population and employment) density as well as jobs-population ratio, were constructed using the ACS and LEHD data sources. The share of workers in a hexagon across different categories contains the same wage breaks as the socioeconomic metrics but instead describes the area's workforce and its businesses. Urban design and transportation system variables were constructed from OSM data. Three metrics—intersection density, connected node ratio, and beta index (the number of links divided by number of vertices)—define the overall connectivity of a hexagon's street network (Levinson 2012; Gehrke and Welch 2017), while the percentage of primary, secondary, tertiary, and residential roads was calculated using OSM's highway tags and describes an area's predominant road infrastructure. Finally, the percentage of a hexagon's area that lies in a one-half-mile areal buffer of a Valley Metro light rail transit station was created as another independent variable to test in the statistical modeling process. Table 2 summarizes these built environment and socioeconomic context variables at a one-mile hexagon geography for all regional (destination) zones and zones located within the origin area.



**Table 2** Descriptive statistics for neighborhood-level characteristics

Variable	All zones				Origin zones			
	Mean	SD	Min	Max	Mean	SD	Min	Max
<i>Socioeconomic context</i>								
Sex: Male	0.49	0.05	0.00	1.00	0.49	0.05	0.00	1.00
Sex: Female	0.50	0.05	0.00	0.64	0.50	0.05	0.00	0.64
Age: Less than 18 years old	0.23	0.09	0.00	0.46	0.23	0.08	0.00	0.46
Age: 18–34 years old	0.21	0.10	0.00	0.86	0.24	0.10	0.00	0.86
Age: 35–44 years old	0.12	0.04	0.00	0.23	0.13	0.03	0.00	0.21
Age: 45–64 years old	0.26	0.07	0.00	0.50	0.25	0.06	0.00	0.43
Age: 65 years old or more	0.18	0.15	0.00	0.90	0.14	0.10	0.00	0.83
Education: High school or less	0.62	0.19	0.00	1.00	0.66	0.20	0.00	1.00
Education: Bachelors or some college	0.23	0.11	0.00	0.46	0.21	0.11	0.00	0.46
Education: Masters of PhD	0.14	0.09	0.00	0.37	0.13	0.09	0.00	0.37
Race/ethnicity: Asian	0.04	0.04	0.00	0.33	0.04	0.04	0.00	0.33
Race/ethnicity: Black/African American	0.04	0.05	0.00	0.30	0.05	0.05	0.00	0.30
Race/ethnicity: Hispanic/Latinx	0.17	0.16	0.00	0.85	0.21	0.18	0.00	0.85
Race/ethnicity: White, Non-Hispanic	0.62	0.26	0.00	1.00	0.52	0.27	0.00	0.97
Immigrant status: Population foreign-born	0.12	0.07	0.00	0.48	0.14	0.08	0.00	0.48
Household income: Less than \$35,000	0.21	0.13	0.00	0.78	0.26	0.14	0.00	0.78
Household income: \$35,000–\$74,999	0.28	0.10	0.00	0.66	0.30	0.10	0.00	0.66
Household income: \$75,000–\$149,999	0.30	0.10	0.00	0.57	0.28	0.10	0.00	0.55
Household income: \$150,000 or more	0.21	0.17	0.00	1.00	0.16	0.14	0.00	0.66
Poverty status: Families below poverty line	0.11	0.10	0.00	0.80	0.14	0.11	0.00	0.80
Employment: Share of low-wage workers	0.19	0.03	0.00	0.33	0.19	0.03	0.13	0.33
Employment: Share of mid-wage workers	0.30	0.10	0.00	0.60	0.33	0.10	0.15	0.60
Employment: Share of high-wage workers	0.50	0.12	0.00	0.68	0.48	0.12	0.19	0.68
Work status: Adult unemployment	0.02	0.02	0.00	0.20	0.03	0.02	0.00	0.20
Internet access: Household subscriptions	0.88	0.12	0.00	1.00	0.85	0.13	0.00	1.00
Tenure: Homeowners	0.70	0.21	0.00	1.00	0.62	0.21	0.00	1.00
Tenure: Renters	0.29	0.20	0.00	1.00	0.37	0.20	0.00	1.00
Car ownership: 0	0.02	0.03	0.00	0.18	0.03	0.03	0.00	0.18
Car ownership: 1	0.19	0.11	0.00	0.71	0.22	0.11	0.00	0.71
Car ownership: 2	0.44	0.11	0.00	1.00	0.41	0.09	0.00	0.65
Car ownership: 3 or more	0.35	0.13	0.00	0.75	0.34	0.12	0.00	0.75
<i>Built environment</i>								
Persons per acre	4.15	3.88	0.00	23.70	5.43	4.14	0.00	23.70
Jobs per acre	2.04	4.40	0.00	109.84	3.04	5.35	0.00	109.84
Persons and jobs per acre	6.20	6.50	0.00	117.57	8.48	7.16	0.02	117.57
Share of low-wage workplaces	0.22	0.10	0.00	0.66	0.21	0.09	0.00	0.66
Share of mid-wage workplaces	0.35	0.10	0.00	1.00	0.35	0.10	0.00	0.73
Share of high-wage workplaces	0.40	0.15	0.00	1.00	0.42	0.16	0.00	1.00
Jobs-population ratio	1.25	18.20	0.00	788.00	1.72	22.40	0.00	788.00
Intersections per acre	0.69	0.61	0.00	4.00	0.80	0.57	0.00	4.00
Connected node ratio	0.92	0.26	0.00	1.00	0.96	0.20	0.00	1.00
Beta index	0.93	0.26	0.00	2.00	0.96	0.21	0.00	2.00

Table 2 (continued)

Variable	All zones				Origin zones			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Share of primary roads	0.06	0.24	0.00	1.00	0.07	0.25	0.00	1.00
Share of secondary roads	0.04	0.20	0.00	1.00	0.04	0.19	0.00	1.00
Share of tertiary roads	0.02	0.15	0.00	1.00	0.02	0.14	0.00	1.00
Share of residential roads	0.67	0.47	0.00	1.00	0.68	0.47	0.00	1.00
Half-mile light rail transit shed	0.02	0.14	0.00	1.00	0.03	0.18	0.00	1.00

## Methods

### Ridehailing trip frequency

To identify a set of spatial predictors of ridehailing trip frequency, base negative binomial (NB) models of the count of ridehailing trips that originated and terminated within each one-mile hexagon were estimated using cross-sectional data of all ridehailing trips sampled for each October between 2015 and 2019. An NB modeling approach was adopted for this first analysis since the travel outcome recorded in each zone is a non-negative integer and overdispersion is likely to exist in its distribution. The ability of this model structure to relax the equidispersion assumption, stating that an equality in conditional mean and variance functions must exist, which is inherent to a Poisson count model is a clear advantage for selecting a negative binomial model structure that will default to the Poisson model structure if overdispersion is not present in the data set.

When analyzing ridehailing trip generation and attraction data aggregated to a geographic unit of analysis, unobserved spatial correlations may be present. As such, a global Moran's  $I$  statistic (Moran 1950; Anselin 1995) was estimated to determine whether spatial autocorrelation, which would introduce bias to the base NB model estimates, exists.

$$I = \frac{\sum_i \sum_j w_{ij} z_i \times z_j / S_0}{\sum_i z_i^2 / n} \quad (1)$$

where,  $w_{ij}$  represents the elements of a spatial weight matrix,  $S_0 = \sum_i \sum_j w_{ij}$  is the sum of the weights, and  $n$  is the number of zones (one-mile hexagons). This formulation shows Moran's  $I$  to be a cross-product statistic between a variable and its spatial lag (the average value of that variable in neighboring hexagons), with the statistic expressed in terms of deviations from the mean. In testing the null hypothesis that trip end counts exhibit spatial randomness, the estimated Moran's  $I$  statistic and significance of its accompanying test enabled the null hypothesis to be rejected, with the spatial distribution of high and low trip end values per hexagon determined to be more clustered than would be expected in a spatially random distribution of these ridehailing travel metrics.

If spatial autocorrelation in these outcomes was found, the estimation of the spatial lag of X (SLX) model (Vega and Elhorst, 2015) was performed to account for any spatial spillover effects related to the count of ridehailing trip origins and destinations in

neighboring one-mile hexagons that was not accounted for in the base NB model specifications. Controlling for these spillover effects in the SLX model is accomplished by the addition of a spatially lagged explanatory variable, presented in the following form:

$$Y_i = \rho W_y + \beta x_i + \epsilon_i \quad (2)$$

where,  $\rho$  is the spatial autoregressive coefficient and  $W_y$  is the spatially lagged dependent variable. The parameterization of  $W_y$  used a queen-contiguous spatial weight matrix in which immediate hexagons were weighted with a value of one.

Model specification was pursued by adopting a multistep approach of stepwise and least absolute shrinkage and selection operator (lasso) variable selection techniques (Tibshirani 1996). Initially, a single-variable model was estimated for all neighborhood socioeconomic and built environment predictors of trip frequency at the origin and destination zone, separately, with predictors found to be marginally significant ( $p < 0.10$ ) retained. Second, the unadjusted correlations between these remaining independent variables were assessed and, of those that were moderately correlated, the variable with the weaker association with the travel outcome was removed from further consideration. Third, using this reduced set of noncorrelated and statistically significant predictors of trip frequency, a lasso modeling approach, which uses regularization penalties on the overall model fit to minimize empirical errors and produce a sparse and potentially more interpretable specification, was implemented (Tibshirani 1996; Zhao and Yu 2006). In this approach, a further reduced set of predictors was identified by forcing some predictors in the model to have a regression coefficient of zero after imposing a constraint on the model parameters. If the resulting model specification produced non-significant coefficient estimates, then each non-significant predictor was iteratively removed via a backwards elimination process until all remaining model predictors produced statistically significant coefficient estimates.

## Ridehailing vehicle miles traveled

Beyond estimating SLX models of trip frequency, the data set collected for this study is unique in its ability to allow for an investigation of ridehailing VMT accrued by drivers. Like the investigation of ridehailing trip end activity, this analysis explored the impact of socioeconomic context and built environment metrics operationalized at one-mile hexagon zones across the Phoenix metro region on ridehailing VMT aggregated to the same spatial scale. An ordinary least squares regression was estimated for this initial analysis, with the VMT outcome log transformed to improve linearity and stabilize variances in the produced coefficient estimates of the various independent variables. The specification of this base VMT model was obtained by following a similar multistep process to which was conducted for the NB models.

While estimation of a base VMT model can offer insights on the spatial determinants of ridehailing VMT, a global model will likely be insufficient for examining spatial heterogeneity (or nonstationarity) in which zonal attributes vary over space rather than being constant across a study area (Fotheringham 2009). The identification of spatial autocorrelation in the VMT variable and many hexagon-level socioeconomic context and built environment variables was determined by estimating the aforementioned global Moran's  $I$  statistic. In testing the null hypothesis that VMT values exhibit spatial randomness, the estimated Moran's  $I$  statistic and significance of its accompanying test enabled the null hypothesis to be rejected, as was also found with the two ridehailing trip frequency outcomes. Accordingly, a geographically weighted regression (GWR) model for VMT was supported, which

provides local coefficient estimates for each spatial unit by using a set of spatial weight matrices based on a given hexagon and its neighboring zones. The GWR model structure is presented as (Brundson et al. 1996):

$$y_i = a_{i0} + \sum_{k=1,m} a_{ik}x_{ik} + \varepsilon_i \quad (3)$$

where,  $a_{ik}$  is the value of the  $k$  th parameter at hexagon  $i$  and the remaining components of Eq. (4) are found in a simple linear regression model:  $y_i$  is the  $i$  th observation of the dependent variable  $y$ ,  $x_{ik}$  is the  $i$  th observation of the  $k$  th independent variable, and  $\varepsilon_i$  is the normally distributed error term for the  $i$  th observation. Since the hexagonal units are evenly distributed over space, a Gaussian weighting function with a fixed bandwidth was adopted in this GWR application (Wang and Noland 2021). This function is expressed as (Fotheringham 2009):

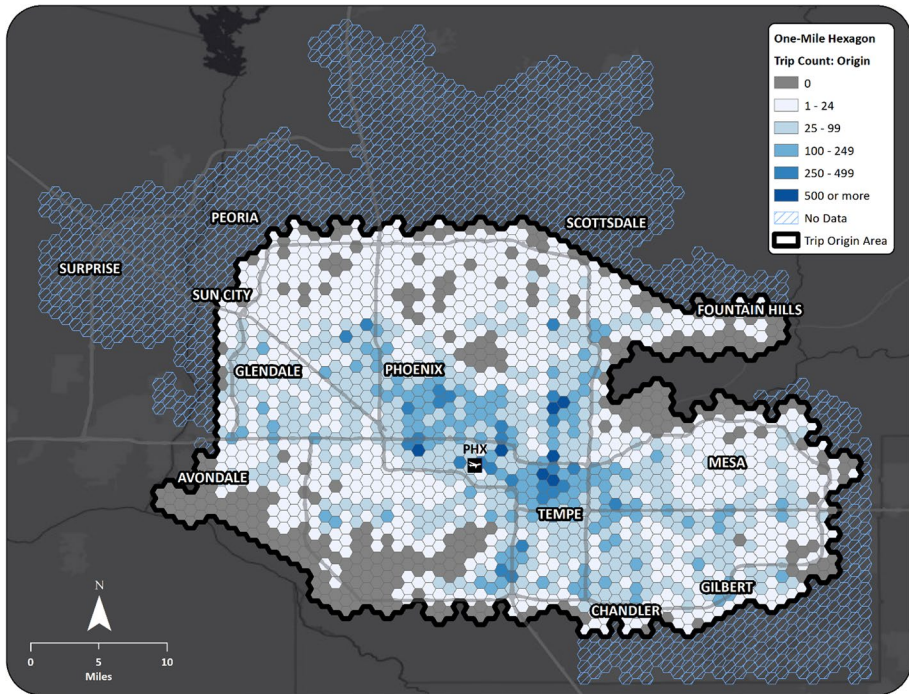
$$w_{ij} = \exp\left[-1/2(d_{ij}/h)^2\right] \quad (4)$$

where,  $w_{ij}$  is the weight value of the observation at hexagon  $j$  for estimating a hexagon  $i$  coefficient,  $d_{ij}$  is the distance between the hexagons  $i$  and  $j$ , and  $h$  is a bandwidth or smoothing parameter that lessens the steepness of a kernel by adding more adjacent hexagons in its local calibration as its value increases. The fixed bandwidth for the final GWR model was obtained by a computationally demanding technique in which many regression equations are estimated with various fixed bandwidths chosen by a leave-one-out cross-validation process until an optimal  $h$  value is determined (Bivand et al. 2008). An assessment of the performance of the one-mile hexagon GWR model and its ordinary least squares (OLS) counterpart is possible by comparing Akaike Information Criterion corrected (AICc) calculations (Lu et al. 2014).

## Results

### Spatial factors associated with ridehailing trip frequency

Figure 2 shows the count of ridehailing trips in the study sample that originate in the area enclosed by AZ-101 to the north and AZ-202 to the south. As expected, most trips start in the most central portions of the Phoenix metro region, where residential and employment activity is relatively high. Particularly, a swath of high frequency ridehailing pick-ups extends from midtown Phoenix southeastward toward the northern part of Tempe; an area that traverses Phoenix's city center, Sky Harbor International Airport, and Arizona State University's main campus. Other clusters of high ridehailing trip production are located in South Scottsdale and its Old Town neighborhood as well as downtown Chandler, located south of Tempe. Fewer trips in this study sample were observed in the southwest section of the trip origin area, which encompasses South Mountain Park and Preserve and the urban villages of Ahwatukee and Laveen, and the northernmost part of the origin area. The former spatial pattern is likely due to the rural nature of the southwestern area, while the latter is more likely to be related to data set incompleteness. In all, spatial clustering of trip origin activity aggregated to this one-mile hexagon system was confirmed by calculating a global Moran's index of spatial autocorrelation ( $I=0.56$ ,  $p < 0.001$ ).



**Fig. 2** Ridehailing trip generation frequency within inner core neighborhoods of the Phoenix metro region

To help understand the neighborhood-level factors attributed to this described spatial pattern, Table 3 shows the SLX model estimates of ridehailing pick-up frequency as a function of socioeconomic context and built environment variables measured at a one-mile spatial extent. The significant spatial lag parameter for trip generation frequency in neighboring hexagons confirms that the spatial clustering of trip origins remains evident after controlling for other zone characteristics. Looking at socioeconomic context variables in the final model, an increase in the zonal share of adults in the 18–34- and 45–64-year-old cohorts was found to be associated with higher ridehailing pick-up frequencies, with a similar positive relationship also observed between this modeled outcome and the share of individuals in a one-mile hexagon who identified as Black/African American or resided in a zero-car household. In contrast, those hexagons with a greater share of individuals younger than 18 years and residents who identified as male or Asian were associated with fewer generated ridehailing trips. A similarly negative relationship was modeled when looking at the neighborhood-level share of adults who were unemployed or households earning less than \$35,000 annually and the frequency of ridehailing trips generated in a hexagon. As for built environment measures that were statistically significant, one-mile hexagons characterized by higher population densities, a more traditional gridiron street network design, and a greater representation of primary or secondary streets were all found to be connected to more ridehailing trips being generated in a given zone.

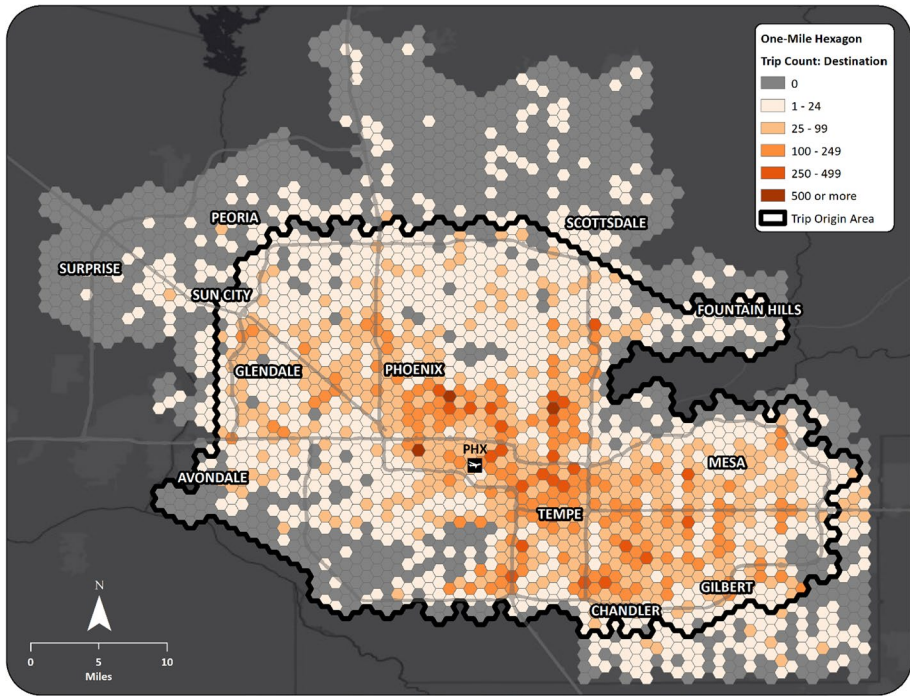
Turning to trip destinations, Fig. 3 shows the spatial pattern of neighborhoods in the region based on the frequency of sampled ridehailing trips that terminated within

**Table 3** Spatial lag of X (SLX) negative binomial model estimates of ridehailing trip frequency at origin

Variable	$\beta$	SE	<i>p</i> -value
Intercept	-0.34	0.48	<0.001
Spatial lag: Trip generation frequency	0.01	<0.01	<0.001
<i>Socioeconomic Context</i>			
Sex: Male	-4.52	0.82	<0.001
Age: Less than 18 years old	-2.46	0.55	<0.001
Age: 18–34 years old	5.33	0.52	<0.001
Age: 35–44 years old	-0.98	0.12	0.420
Age: 45–64 years old	2.98	0.79	<0.001
Race/ethnicity: Black/African American	3.06	0.68	<0.001
Race/ethnicity: Asian	-3.77	0.82	<0.001
Household income: Less than \$35,000	-1.34	0.34	<0.001
Work status: Adult unemployment	-10.73	2.18	<0.001
Car ownership: 0	8.37	1.36	<0.001
<i>Built environment</i>			
Persons per acre	0.11	0.01	<0.001
Intersections per acre	1.10	0.07	<0.001
Beta index	2.46	0.30	<0.001
Share of primary roads	1.83	0.16	<0.001
Share of secondary roads	1.93	0.20	<0.001
<i>Model summary</i>			
Number of hexagons			1794
Theta (SE)			0.67 (0.02)
Log-likelihood			-6956
Akaike information criterion			13,949

a one-mile hexagon, having originated inside the Phoenix metro region's inner core. While this map similarly shows higher levels of ridehailing trip activity in the central portion of the study area, a wider dispersion of hexagons with trip destinations can be observed. Specifically, hexagons in North Scottsdale and East Mesa, where a higher concentration of predominately residential neighborhoods exist, have a disproportionate number of drop-offs compared to pick-ups. Outside of the origin area, several hexagons were found to have more than 25 ridehailing drop-offs, with those zones nearing Apache Junction to the east of Mesa and Phoenix-Mesa Gateway Airport in the region's southeast corner having higher frequencies. Akin to the trip origin patterns, a global Moran's *I* calculation confirmed the presence of spatial clustering of trip destinations aggregated to the one-mile hexagon system ( $I=0.52$ ,  $p<0.001$ ).

Table 4 reveals estimation results of the SLX model examining the spatial predictors of ridehailing drop-off frequency across the region. In contrast to the trip generation model findings, the spatial spillover of trip destination frequency into neighboring zones was not found to be significant after controlling for the socioeconomic context and built environment metrics specified in the base NB model. Zonal socioeconomic predictors in this trip destination model that were also statistically significant in the trip



**Fig. 3** Neighborhood-level ridehailing trip attraction frequency within the Phoenix metro region

generation model included the share of male residents and individuals in the 18–34- and 45–64-year-old cohorts compared to the referent group of adults aged 65 years or older, with each factor having the same directional relationship with ridehailing drop-off activity as with pick-up frequency. However, hexagons with a higher percentage of individuals under 18 years of age were found to have a higher frequency of ridehailing trip destinations, while the opposite association was found between trip attractions and zones with higher shares of adults in the 35–44-year-old cohort. Other socioeconomic context variables with a significant, positive relationship with ridehailing trip destination frequency included the share of households with annual incomes between \$35,000 and \$74,999 and renter-occupied housing units, while a significant, negative relationship with the outcome variable was found for the share of households with two vehicles and adults with a high school education. An increased percentage of families living below the federal poverty line was found to have a positive relationship with ridehailing drop-off activity when measured at the one-mile hexagon geography. While this model finding may suggest that lower-income families are utilizing ridehailing services as an alternative to more affordable mobility options, a more plausible explanation may be that ridehailing trips tended to terminate in zones with higher concentrations of out-of-home activities and more heterogenous residential populations. Supporting this last point, the five built environment measures that were significant in the ridehailing trip generation model were also significant and positively linked with ridehailing trip

**Table 4** Spatial lag of X (SLX) negative binomial model estimates of ridehailing trip frequency at destination

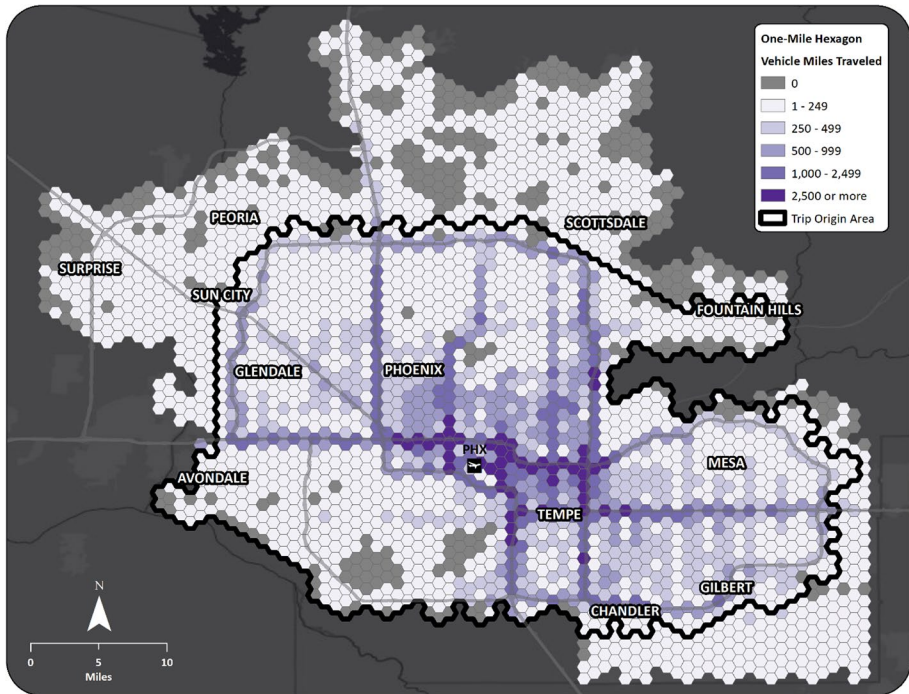
Variable	$\beta$	SE	<i>p</i> -value
Intercept	-1.90	0.51	<0.001
Spatial lag: Trip attraction frequency	<0.01	<0.01	0.496
<i>Socioeconomic context</i>			
Sex: Male	-4.42	0.90	<0.001
Age: Less than 18 years old	1.92	0.66	<0.001
Age: 18–34 years old	5.00	0.59	0.013
Age: 35–44 years old	-3.21	1.29	<0.001
Age: 45–64 years old	2.77	0.70	<0.001
Education: High school or less	-3.77	0.38	<0.001
Household Income: \$35,000–\$74,999	2.51	0.61	<0.001
Poverty status: Families below poverty line	2.18	0.62	<0.001
Tenure: Renters	1.55	0.32	<0.001
Car ownership: 2	-1.56	0.41	<0.001
<i>Built environment</i>			
Persons per acre	0.20	0.01	<0.001
Intersections per acre	1.25	0.08	<0.001
Beta index	3.44	0.32	<0.001
Share of primary roads	1.57	0.17	<0.001
Share of secondary roads	2.22	0.20	<0.001
<i>Model summary</i>			
Number of hexagons			2673
Theta (SE)			0.41 (0.01)
Log-likelihood			-8189
Akaike information criterion			16,416

destination counts (persons per acre, intersections per acre, beta index, and share of primary or secondary roads).

### Spatial factors associated with ridehailing vehicle miles traveled

To assess ridehailing travel patterns between trip origins and destinations, the distance of all observed ridehailing traces were clipped to hexagons, with total VMT observed in each zone summed. Figure 4 shows the enumeration and variation of ridehailing VMT across one-mile hexagons during the study's timeframe. Unsurprisingly, in this map, hexagons with the highest volumes of ridehailing VMT can typically be found along major roadways and within the origin area bounded by the semi-belt of AZ-101 in the north and AZ-202 in the south. Hexagons located between Arizona State Highway 60 (AZ-60), which bisects Tempe and Mesa from Chandler and Gilbert, and the boundary of Interstate 10 and AZ-202 to its north, traversing the center of the study area and encompassing central Phoenix and Sky Harbor International Airport, were each observed to have VMT levels in the highest category. Another stretch of hexagons with the highest volumes of ridehailing VMT extended north–south from North





**Fig. 4** Neighborhood-level ridehailing vehicle miles traveled (VMT) within the Phoenix metro region

Scottsdale to South Chandler along AZ-101, while an additional stretch of higher VMT levels observed in the portion of Interstate-17 extending north from downtown Phoenix.

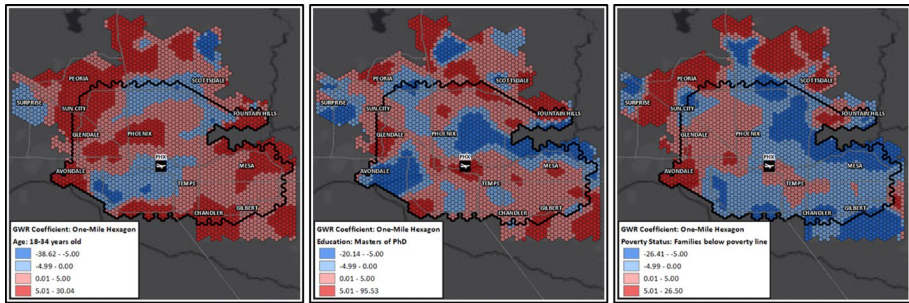
After log-transforming VMT calculations made at the one-mile spatial extent, this third ridehailing outcome was modeled as a function of socioeconomic context and built environment characteristics. Table 5 shows outcomes of the GWR model estimation of ridehailing VMT, summarizing the local estimates for significant socioeconomic context and built environment predictors. All independent variables in the final model specification exhibited spatial autocorrelation. For all independent variables except secondary road shares, at least one cluster of hexagons exhibited a minimum or maximum local coefficient that differed in its direction of association to its global estimate. While this finding emphasizes the intuitive and consistent correlation between minor arterial roadway access and higher ridehailing vehicle exposure, the variation of other predictors was quantified by measuring the interquartile range (IQR) to help highlight how the spatial distribution of these modeled effects can differ across a larger study area. Comparing the localized estimates of the GWR model to the global estimates of the OLS model, the median local coefficient values of each significant built environment predictor had the same directional relationship to its global mean estimate. Regarding socioeconomic context, the local median and global mean coefficients for predictors reflecting the share of adults 18 to 34 years old (IQR = 5.92) and adults older than 25 years with an advanced college degree (IQR = 7.15) were positively associated with ridehailing VMT, as was the percentage of the foreign-born population within a hexagon. However, the coefficient estimates for foreign-born population displayed the largest

**Table 5** Geographically weighted regression model estimates of ridehailing vehicle miles traveled (log-transformed)

Variable	Min	Q <sub>1</sub>	Median	Q <sub>3</sub>	Max	Global
Intercept	-52.24	-2.28	0.05	3.30	26.09	-1.17
<i>Socioeconomic context</i>						
Age: 18–34 years old	-38.62	0.52	3.51	6.44	30.04	4.89
Education: Masters of PhD	-20.14	-3.19	0.96	3.96	23.35	4.05
Immigrant status: Population foreign-born	-25.06	-1.82	2.25	7.21	64.38	1.07
Household Income: \$150,000 or more	-13.04	-3.87	-1.16	1.96	9.40	-0.70
Poverty status: Families below poverty line	-26.41	-4.93	-0.93	3.82	26.50	0.82
Internet access: Household subscriptions	-23.62	-3.77	-0.36	2.83	51.23	-1.23
Car ownership: 3 or more	-9.49	-2.34	-0.64	1.35	21.11	-0.41
<i>Built environment</i>						
Persons per acre	-1.39	0.03	0.09	0.18	0.85	0.18
Jobs per acre	-0.43	0.03	0.14	0.33	5.46	0.07
Share of mid-wage workplaces	-11.65	-1.44	0.51	2.73	17.40	1.88
Share of high-wage workplaces	-17.05	-1.51	0.05	1.23	12.39	0.94
Intersections per acre	-0.52	0.49	0.81	1.26	2.34	1.06
Beta index	-0.91	0.81	1.47	2.87	7.59	1.79
Share of primary roads	-0.28	1.16	1.61	2.31	6.48	1.81
Share of secondary roads	0.04	0.57	0.88	1.15	1.76	0.67
Half-mile light rail transit shed	-43.09	-4.04	-1.39	0.02	7.32	-1.01
<i>Model summary</i>						
Number of hexagons						2673
Akaike information criterion corrected (OLS model)						8955
Akaike information criterion corrected						8442
Quasi-global <i>R</i> -squared						0.850

variation (IQR = 9.03), with changes in the effect's sign indicating the existence of clusters where a negative association with ridehailing VMT was found. In turn, zones with a greater share of households in the highest annual income cohort (IQR = 6.60) and those owning three or more vehicles (IQR = 3.69) were more likely to experience less ridehailing VMT near their homes than their counterparts, with these two factors having the weakest spatial variation of all social context predictors. Zonal measures of household Internet access (IQR = 6.60) and family poverty-level status (IQR = 8.75) were also negatively associated with ridehailing VMT; however, a positive global estimate of ridehailing VMT was found for the zonal measure of families living below the poverty line. Differences in the association of local and global estimates for this latter socioeconomic factor, where the local median is less than the global mean, and it having the second highest measure of variation may signify that neighborhood clusters with a very high share of lower-income families are exposed to a disproportionately higher share of ridehailing VMT.

Figure 5 shows the local estimates for neighborhood-level variables often reported in the literature as being significant person-level predictors of ridehailing activity: age, education, and income (or poverty status). Inspecting these three maps, local differences across the Phoenix metro region in the GWR modeled associations between ridehailing VMT and



**Fig. 5** Local parameters for one-mile hexagon-level age, education, and household poverty status in geographically weighted regression (GWR) model of vehicle miles traveled (VMT)

these three attributes were found. In examining the relationship between the zonal shares of young adults and ridehailing VMT, a positive link (visualized in warmer hues) was found across most of the region (expected given the positive value of the first quartile estimate shown in Table 5) including one-mile hexagons near Grand Canyon University in western Phoenix and Arizona State University in northern Tempe. In contrast, neighborhoods near South Mountain and south of Interstate 10, which encompass South Mountain Community College, were found to have a negative link (visualized in cooler hues). Across most of the region, a positive association with ridehailing VMT can also be found for neighborhoods with a higher percentage of adults with an advanced college degree; however, a cluster of one-mile hexagons in the northwest that encompasses Surprise and the expansive retirement community of Sun City West in addition to a stretch of zones in Old Town Scottsdale to the east of midtown Phoenix are shown to have a negative connection to observed ridehailing VMT. Turning to the map of lower-income family shares and ridehailing VMT, a majority of zones were found to have a negative modeled association (signified by the negative median estimate shown in Table 5), with most of these zones appearing in the eastern half of the study area. However, positive local estimates that align with the positive global mean estimate were found in the neighborhoods including and west of Phoenix's central city and midtown areas, which also includes zones with higher trip end activity. Inside the origin area, a cluster of zones with the highest local estimates can be found in northern Avondale and the minority-majority City of Tolleson to its east as well as a stretch of zones in central Scottsdale intersecting East Shea Boulevard.

## Conclusions

Ridehailing service growth before the Covid-19 pandemic raised important concerns about disproportionate access to this new mobility option for residents of under-resourced neighborhoods (Abdelwahab et al. 2021) as well as the detrimental air quality and public health impacts of living where ridehailing demand and vehicle emissions exposure increased (Barnes et al. 2020). These topics were explored in this study by estimating socioeconomic context and built environment factors associated with aggregated ridehailing trip pick-ups and drop-offs as well as zonal VMT calculations. An examination of these three ridehailing travel outcomes and accounting for the spatial spillover effects of ridehailing trip end

frequency and VMT offers evidence into the spatial equity implications of increased ridehailing activities in the Phoenix metro region.

Overall, this study's analysis of macro-level predictors of trip end activity confirmed past research findings, while also suggesting that spatial inequities in ridehailing service adoption likely exist. Zones with a disproportionate share of lower-income households and unemployed adults, who are likely to have limited resources to cover higher transportation costs associated with frequent ridehailing service or private car use, were most likely to see lower ridehailing trip generation activity. Aligned with past ridehailing studies, trip generation model results found that zones with larger shares of young adults and zero-car households were associated with higher pick-up frequencies. However, in contrast, a positive association existed between ridehailing pick-up frequency and the zonal share of residents who identified as Black/African American. This unexpected finding has been shared elsewhere (Clewlow and Mishra 2017) and may reflect residential and employment location clustering rather than passenger composition given that central and southwestern hexagons near AZ-60 have greater Black/African American representation and are denser housing and job districts. In analyzing ridehailing trip attraction, one-mile hexagons with a higher share of younger adults, more renter-occupied units, and higher population densities were positively linked to drop-off frequencies, while zones with a higher percentage of adults without a college education had a negative association with this ridehailing outcome. Yet, zones with a higher share of families living in poverty tended to have higher frequencies in ridehailing drop-offs. Without trip-level knowledge about the ridehailing passenger, there is difficulty in knowing whether ridehailing services are offering this population a competitive travel option or that zones with higher shares of lower-income residential populations often located near city centers are generally more attractive ridehailing travel destinations. While unexpected variations in the trip frequency models existed, the study findings of lower ridehailing trip generation rates for neighborhoods with higher shares of lower-income households and unemployed adults highlights a need for public policies that rebuild and help to bolster accessible and affordable bus services in under-resourced neighborhoods detrimentally impacted by ridehailing service introduction and the Covid-19 pandemic. For all individuals who adopt ridehailing services, which includes adults whose families live below the poverty line, public-private efforts to make ridehailing services more affordable via the reimplementation (or introduction) of pooling services and programs that shift ridehailing travel away from being a primarily single-party mobility option should remain a priority.

In this study's latter half, the estimation of a GWR model of ridehailing VMT as a function of zonal socioeconomic and built environment attributes offered new evidence on an understudied travel outcome with exposure-related consequences. Importantly, the estimation of local coefficients and mapping of select spatial equity-related model predictors permitted a more nuanced investigation into the spatial variation of these modeled relationships across the Phoenix region. Using route-level information, global estimates from an OLS analysis, like the trip generation model results, found that those zones with a higher percentage of households living below the federal poverty level were also more likely to experience higher volumes of ridehailing VMT. However, GWR model estimates, which had a negative local median and relatively higher IQR value, point to spatial variations in the relationship between this spatial equity predictor and ridehailing VMT. This model finding, when combined with the aforementioned trip generation model results regarding lower-income households and unemployed adults, suggests that under-resourced households generally have more limited access to less-affordable ridehailing services and that some under-resourced neighborhoods are disproportionately exposed to the adverse

impacts of higher vehicle emissions as well as added roadway traffic that is slowing more affordable travel alternatives such as buses. By mapping localized GWR model estimates, the spatial variation in well-documented socioeconomic determinants of ridehailing activity were revealed, with central Phoenix neighborhoods—where spatial clusters of ridehailing activity at and between trip ends were observed—displaying increases in ridehailing VMT associated with higher shares of younger adults and families living below the poverty level. A dichotomy in findings that when also seen with local variations in the relationship between higher educational attainment and ridehailing VMT perhaps further illustrates the presence of spatial inequities in who benefited most by the growth of ridehailing availability prior to the Covid-19 pandemic. Planners and policymakers must remain steadfast in supporting programs that promote ridesharing and subsidize ridehailing fares for lower-income travelers that better approximate public transit fares. This is especially true in the Phoenix metro region which has seen the introduction of autonomous ridehailing services that operate in a limited area including parts of Chandler, Gilbert, Mesa, and Tempe (Waymo 2022). While autonomous technologies remain in their infancy and have yet to become a viable competitor to established services, results from a demonstration project in the region revealed these services to have higher ratings than driver-based ridehailing services for cost, comfort, convenience, and travel and wait times (Stopher et al. 2021). Mobility as a Service (MaaS), which bundles available mobility services including ridehailing and public transit under a common digital architecture that gives consumers the flexibility to subscribe to modes that best fit their travel needs (Matyas and Kamargianni 2019), may offer a more immediate opportunity to promote a lower-cost and efficient travel alternative to car ownership if safeguards are employed by public officials to ensure greater social inclusion (Pangbourne et al. 2020).

Beyond its contributions to practice and the evidence base, limitations in this study's methodology should be addressed through future research. Regarding the ridehailing travel data set, an analysis of route-level information for drivers representing both Uber and Lyft was a study asset; however, the observed trips only represent a marginal share of all ridehailing trips undertaken during this timeframe and likely exhibit bias related to driver participation in the third-party app. Second, these sample data reflect ridehailing trips that originated in the innermost portion of the region; therefore, patterns and estimates related to ridehailing drop-offs and VMT outside of the origin area likely under-represent the true magnitude of ridehailing travel in the study's timeframe. Third, the analyzed ridehailing data set, which is effective in accounting for annual variation in travel missing from most ridehailing studies to-date, does not capture month-to-month trip variations; although, October is considered a stable period for understanding travel patterns and behaviors. Fourth, while this study's implementation of spatial modeling techniques helped to control for variations in the spatial distribution of ridehailing trip activity, future research should assess alternative specifications or methods such as a Spatial Durbin Model (e.g., Soria and Stathopoulos 2021) to account for spatial patterns in chosen trip frequency predictors. Finally, this study of neighborhood-level socioeconomic context factors somewhat assumes significant predictors of ridehailing activity are reflective of individuals who adopt these services. This contextual fallacy (Fowler et al. 2020) can only be resolved by analyzing person-level data that have usually been collected by intercept surveys which have other biases and often produce smaller sample sizes to investigate. While these limitations warrant future consideration, this study has identified how ridehailing services prior to the Covid-19 pandemic impacted urban neighborhoods in divergent and disproportionate ways. Given the likelihood that the lasting impacts of the Covid-19 pandemic may worsen near-term inequities in multimodal access, transportation planners, practitioners, and policymakers

must maintain high-quality and affordable mobility options are available and accessible to under-resourced neighborhoods and communities.

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**Authors contributions** SRG: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing—original draft, Writing—review & editing. MPH: Data curation, Formal analysis, Software, Visualization, Writing—original draft.

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## Declarations

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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