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An alternative to slow transit, drunk driving, and walking in bad weather: An exploratory study of ridesourcing mode choice and demand

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ABSTRACT

Companies providing ridesourcing, or the use of mobile phone apps to request rides from drivers of privately-owned vehicles, have expanded rapidly in many cities in recent years. To shed light on this phenomenon, this paper reports an exploratory study of ridesourcing trip patterns and mode choice in Washtenaw County, Michigan, USA, which obtained a convenience sample of 167 respondents (reporting 192 trips) via geographically targeted online and offline ads. Consistent with previous empirical studies, ridesharing users are younger and a greater percentage are female than the the general public, and most trips occur in a small number of high density block groups. When asked what other options were available for ridesourcing trips, respondents reported transit (63%), private vehicles (32%), walking (32%) and bicycling (18%). Specific reasons for choosing ridesourcing instead of these options included the frequency of transit, alcohol use for driving, and weather and distance for walking and biking. A multivariate analysis found variables related to greater ridesourcing use for a block group included job density, jobs-housing balance, bar and restaurant density, and presence of households without vehicles. The paper demonstrates the potential of survey data to generate greater geographic insights into ridesourcing use, as well as the potential for extending established travel-behavior research approaches to ridesourcing.

1. Introduction

One of the most dramatic changes to urban transportation in recent years has been the rise in app-based transportation providers such as Uber, Lyft, DiDi Chuxing, Ola Cabs, and Grab. Sometimes called real-time ridesharing or transportation network companies (TNCs), these companies typically connect customers seeking transportation with drivers of personally owned vehicles via a mobile phone app. After Rayle et al. (2016), we have used the more precise term *ridesourcing* for these services because rides are purchased and not always shared among multiple riders. Fewer than 10 years since the founding of market leader Uber in 2009, ridesourcing companies have undergone rapid growth in many cities worldwide, and several market research firms estimated that by 2018 roughly one-third of Americans had used these services (Molla, 2018). An analysis of the 2017 U.S. National Household Transportation Survey found that 9.8% ± 0.4 of respondents had used ridesourcing at least once that year. Despite this rapid growth, this analysis also found that traditional taxis and ridesourcing encompass only 0.50% ± 0.08 of all trips in the U.S. (Conway et al., 2018).

The advent of this new mode of urban transportation has resulted in the urgent need for research, especially that which investigates the geographic nature of this mode of travel and draws on detailed information from travelers. To help meet this need, we report on results of an exploratory survey of ridesourcing riders in Washtenaw County, Michigan, which includes the cities of Ann Arbor and Ypsilanti. Although the study is limited by the use of a convenience sample with unknown representativeness of the respondents, we used respondents' linked demographic and travel information to analyze their mode selection decision-making and the geography of their trips. The findings show that ridesourcing riders are younger and include a higher proportion of women than the population at large. In analyzing which other modes were available to users taking ridesourcing trips, we found that transit was the main mode available, suggesting that this is the mode most trips have shifted from since the introduction of ridesourcing. A geographic analysis of the trips shows that most occur in a relatively small number of high-density neighborhoods, although the data suggest important differences between trips originating in denser, urban areas and those originating in suburban areas.

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2. Background

The rapid adoption of ridesourcing by urban travelers has important consequences for urban transportation systems. Often more convenient and less expensive than traditional taxis, these services have grown quickly in popularity. Ridesourcing users tend to be well-educated, higher-income, and employed, and they usually reside in high-density areas (Conway et al., 2018; Dias et al., 2017). Other researchers have documented distinct barriers for ridesourcing adoption by low-income users, such as digital access and literacy (Dillahunt et al., 2017). Furthermore, there is a growing perception that the benefits of ridesourcing have been accompanied by undesirable public side-effects, such as a decline in public transit ridership and an increase in driving and traffic congestion in some cities (San Francisco County Transportation Authority, 2017). A recent national survey found that ridesourcing users reported a decrease in public transit use and that approximately one-half of trips would have been made by walking, biking, or transit, or avoided altogether (Clewlow and Mishra, 2017). As a result of these findings, we examined ridesourcing from the perspective of the sustainable mobility paradigm, which replaces the traditional focus on individual cost-minimization and system optimization, with an interest in the social factors influencing travel and transportation system sustainability (Banister, 2008; Sultana et al., 2017).

Research on ridesourcing as a new transportation mode can shed light on the role it plays in urban transportation systems to more deeply understand the spatial nature of ridesourcing travel. In addition, research on ridesourcing today might shed light on future urban transportation issues. This is because ridesourcing companies could be the first site of mass deployment of automated vehicles. Because automation could further reduce the cost of ridesourcing trips and therefore increase adoption, understanding ridesourcing today might inform what could emerge as an ever more widely used transportation mode tomorrow—automated ridesourcing.

A growing body of research has resulted in a deeper understanding of ridesourcing, but two topics have been relatively neglected: the types and locations of specific travel destinations for ridesourcing trips, and the specific motivations for choosing ridesourcing over other transportation modes. These questions are difficult to answer because of researchers' limited access to ridesourcing company data and difficulty collecting information from users. Two recent reports by public agencies characterize the extent of ridesourcing in urban centers. Through analysis of data obtained via creative data collection from Uber and Lyft's public-facing application programming interfaces (APIs), the San Francisco County Transportation Authority (SFCTA) mapped ridesourcing pickup hotspots, showing high usage in San Francisco's downtown area. However, because the study relied on system-level data it did not analyze specific trips or riders (San Francisco County Transportation Authority, 2017). A study conducted by Boston's Metropolitan Area Planning Commission utilized in-vehicle rider intercept surveys to provide insight into rider demographics and trip characteristics, showing that many ridesourcing trips were chosen as substitutes for public transit (42%) or walking and biking (12%) (Gehrke et al., 2018). However, the researchers did not collect detailed origin and destination data and therefore only mapped the density of trips beginning or ending at riders' homes, summarized by ZIP codes. These two studies focused on U.S. metropolitan regions with the first- and third-highest per capita use of ridesourcing services, so it is unclear how their findings might translate to other types of cities (Conway et al., 2018).

Academic studies provide greater detail on the issues of trip characteristics and traveler motivations for ridesourcing. Utilizing intercept surveys conducted in known ridesourcing hotspots in San Francisco, Rayle et al. (2016) explored rider demographics, trip details, and mode choice, although it is difficult to know whether the sampling approach introduced a bias in the results. Hoffmann et al. (2016) found that ridesourcing and public transit are both substitutes and complements: although their use in particular areas correlates, they also found ridesourcing use increases after local subway stations close. Yet, this aggregate observational study did not probe individual travelers regarding their decisions. Researchers with access to ridesourcing system data have gained operational insights into issues such as driver behaviors (Dong et al., 2018), trip characteristics (Komanduri et al., 2018), and whether service quality varies by neighborhood characteristics like income and minority population (Hughes and MacKenzie, 2016; Wang and Mu, 2018). To build on those studies, we investigated the research question: *What explains why travelers choose ridesourcing over other travel modes available to them: driving a personal automobile, riding transit, walking, or biking?* To contextualize the representativeness of our sample, we compared the demographics of the survey respondents and the trip destination categories in this study with those obtained by other researchers.

The geographic nature of ridesourcing travel is also not well known. Although there is a growing awareness of the characteristics of places with high ridesourcing demand, we are aware of only one other study that directly examined exact relationships between ridesourcing demand and neighborhood characteristics. Using a dataset released by a ridesourcing operator in Austin, Texas, Lavieri et al. (2018) constructed models to predict ridesourcing trip generation and distribution. Their analysis of demand at the traffic analysis zone level found it was related to proximity to the University of Texas, higher population and employment densities, greater proportions of population ages 18–29, and household income. However, their analysis did not include variables describing land use diversity, urban design, or accessibility, which are typically included in the large body of literature on travel behaviors like mode choice or vehicle miles traveled (e.g., Ewing and Cervero, 2001). Yang et al.'s (2018) study of taxi demand in Washington, D.C., used a similar design to these studies, finding demand related to population and employment density but not mixed-land uses. The current study applied this general design to see whether ridesourcing follows similar patterns, and to build on Lavieri et al.'s (2018) preliminary findings. In doing so, this study sought to answer the second research question: *What are the built environment characteristics that explain ridesourcing trip demand?*

3. Methods

To understand why travelers choose ridesourcing over other travel models, we employed a voluntary survey that was available online via a responsive survey tool suitable for mobile phones or desktop computers. The survey contained sections about the respondents' demographic and household characteristics, as well as trip-level information for up to five recent ridesourcing trips. The questions about destination types and reasons for choosing ridesourcing were based on Rayle et al. (2016), although unlike in that study we used a tailored set of questions about reasons specific to each mode. Because of the limited literature on the issue, the survey also included novel reasons based on the popular discussion and our knowledge of the context, including the need to carry luggage, weather considerations due to Michigan's cold winters, and the availability of a bicycle. We advertised the survey in Washtenaw County, Michigan, in the months of April and May 2018, through several means: (1) geographically targeted Facebook and Google Adwords ads, (2) flyers posted at busy public places, and (3) an advertisement displayed on the interior of 25 city buses for 1 month. Google Adwords resulted in 160 visitors and Facebook resulted in 517 visitors to the survey landing page, but we could not track visitors from the flyers and bus ads.

We obtained a total of 167 valid responses, defined as respondents who reported using a ridesourcing service at least once in the last year on the survey's first question. These respondents provided information for 198 trips with valid information for both the origin and destination. The provided addresses were geocoded using a combination of OpenStreetMap's Nominatim geocoding API and Google geocoding API. During geocoding, 98.5% of the addresses (384 out of 390) were matched, and we excluded the 6 trips with unmatched origins or destinations from the spatial analysis, resulting in a total of 192 trips included in that analysis. We mapped the resulting data using the ArcGIS software and conducted statistical analysis using Stata.

For the demand analysis, the trips were summarized to the 251 census block groups in Washtenaw County using a spatial join function. This analysis made use of the U.S. Environmental Protection Agency (EPA) Smart Location Database (SLD), a nationwide geographic data resource for analyzing travel behavior based on 2010 data (Ramsey and Bell, 2014). It includes variables describing characteristics such as housing density, diversity of land use, neighborhood design, destination accessibility, transit service, employment, and demographics. Most attributes are available for every census block group in the United States. The population of Washtenaw County has increased by an estimated 7.6% since 2010; however, the overall urban form and transit system have remained mostly unchanged. The demand analysis also made use of two additional variables that were constructed to complement those in the SLD because of the distinct nature of ridesourcing travel described by previous research. The first is the density of bars and restaurants for each block group. To create this variable, we searched the D&B Hoovers commercial database for all businesses in Washtenaw County categorized under NAICS code 164 (restaurants and bars). We geocoded the resulting records using the same method described earlier in this section, and we computed the density by calculating the kernel density and then applying zonal statistics to find the mean density for area within each census block group. We also created a dummy variable for block groups included in the area served by the Ann Arbor Downtown Development Authority (DDA), which encompasses Ann Arbor's downtown area. This area contains the highest density of commercial land uses in the study area, and is where most parking is provided by the DDA at a modest hourly rate (about $1.60 USD/h) through parking garages, lots, and on-street metered spaces.

To understand how the built environment factors relate to ridesourcing use, we conducted a multivariate analysis relating ridesourcing demand with these built environment variables. Because we were interested in the overall demand for particular places, we measured demand by summing the total number of trip origins and destinations for each block group, creating a trip count for each block group. In addition to this measure, we divided the trip count by area to create a measure of trip density. Our primary analysis of these outcomes used a linear regression to explore relationships between trip density and our build environment variables. As a secondary analysis, we fit a negative binomial regression between the trip count and the same set of explanatory variables. The major drawback of negative binomial regression is that it does not account for the varying size of block groups, however we decided to use it for exploratory purposes since it is the most appropriate model for count data and may have greater sensitivity to certain relationships than linear regression. Because many block groups had no trips, we considered fitting a zero-inflated model, which models two processes: one set of variables explaining whether trips occur, and another to predict the number (Long and Freese, 2006). Among the 251 block groups, 50.7% are zero-demand zones, forcing the estimation of the non-zero portion of the model to be done using only 111 observations, which is not satisfactory for our multivariate design.

Washtenaw County, Michigan, had an estimated population 364,752 in the 2016 American Community Survey, and is part of the Detroit–Warren–Ann Arbor Combined Statistical Area. Located west of metropolitan Detroit, the two primary cities in the county are Ann Arbor and Ypsilanti, and the county contains many smaller cities, villages, and townships in rural areas (Fig. 1). The largest employer is the University of Michigan, a large public university that operates a major regional hospital complex. Separate from the university, other employers include clusters of information technology and automotive-related firms. The largest industries by employment are health care and social assistance (27.4%), retail trade (12.3%), accommodation and food services (11%), professional, scientific and technical services (9.9%), and manufacturing (9.8%) (U.S. Census Bureau, 2012). Public bus transportation is provided by the Ann Arbor Area Transportation Authority (AAATA) in Ann Arbor and Ypsilanti, with limited service in some surrounding areas. The University of Michigan operates multiple bus routes connecting university properties. Sidewalks are available on almost all streets within the cities of Ann Arbor and Ypsilanti, and many major routes in these cities have bike lanes. However, sidewalks and bicycle lanes or paths are sparse outside these two cities.

Ridesourcing has been available in Washtenaw County since 2014, with Uber entering the market in April and Lyft in May (Allen, 2014). Since then, the AAATA system ridership has increased, reaching record ridership in fiscal year 2017 (Stanton, 2018). Factors related to increasing transit ridership include a service expansion funded by a transit tax approved in May 2014, as well as continued commercial and residential growth in areas served by transit.

4. Results

We present the study results in four parts. First, we compare the demographic profile of ridesourcing users in our sample with that of another ridesourcing study and with Census demographic data. Second, we present trip destination types and spatial distribution. Third, we present data about the respondents' choice to use ridesourcing over other modes. Fourth, we present the results of the analysis of built environment factors, which includes the statistical models quantifying the relationship between ridesourcing demand and built environment variables.

4.1. Rider demographics

The demographics of ridesourcing users who provided them in the survey are presented in Table 1, which also contains similar demographics from Rayle et al. (2016) and the American Community Survey 1-year estimates for Washtenaw County for 2017 (the most recent year available). Note that in the discussion we compare the rider demographics with those of two additional ridesourcing user studies, but they are not reported here because of their use of different aggregate categories that allow only more limited comparisons; specifically Clewlow and Mishra (2017) and Dawes (2016). Overall, respondents had a wide variation of incomes, most were younger than 34 (67%), and most were female (67%). Many respondents (32%) reported having either an associate's degree or an incomplete college education. Respondents' races roughly mirrored the county makeup, although the percentage of white respondents (77%) slightly exceeded the county proportion (74%). Although many respondents reported having no vehicle available to them (27%), the majority had vehicle access.

4.2. Mode choice analysis

Respondents reported that 67% of trips had one passenger, 21% had two, 9% had three passengers, and less than 3% had larger groups. For each trip provided, we asked respondents whether any of four alternative modes of travel was available to them for this trip. For private vehicles, we asked about “available” vehicles that were registered, insured, and drivable. For public transit, bicycle, and walking, we simply asked whether these modes were an “option.” Diverse interpretations of these questions might influence our results. For respondents who indicated that one or more modes were available to them for a particular trip, we prompted the users to tell us precisely why they had chosen ridesourcing instead of any of the other modes available to them. Transit was available for 63% of all ridesourcing trips in the dataset, while walking was available to only 32%. Biking, the least available mode, was only available for 18% of the trips. The survey allowed respondents to provide information for multiple modes.

The ratings for the reasons participants chose ridesourcing over transit are shown in Table 2. The top-rated reason was frequency or

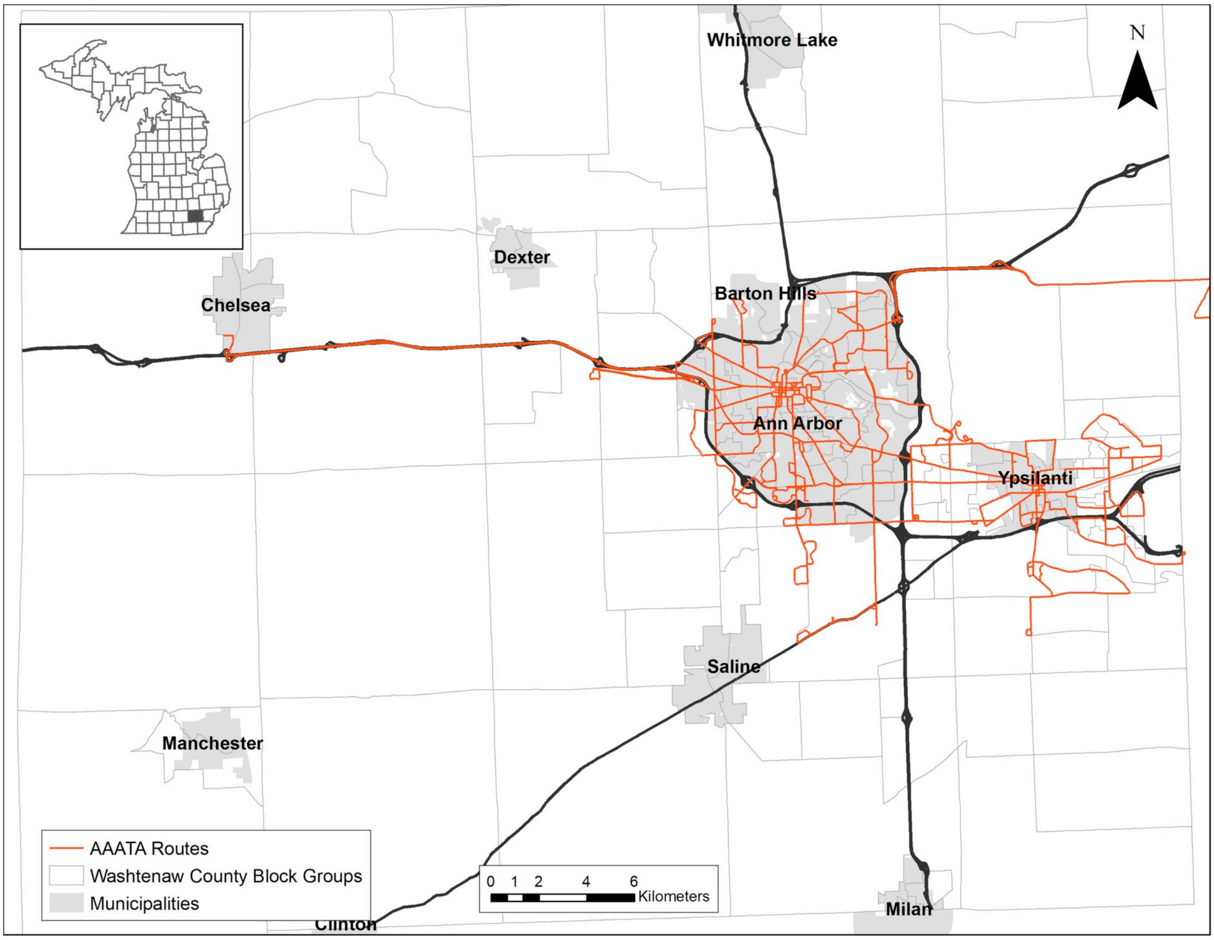

Fig. 1. Study area.

speed of route (4.3), and the second, and third top-rated reasons were to avoid walking, and the weather, although only the frequency or speed of route received a mean rating greater than 4 (very important).

The ratings for the reasons participants chose ridesourcing instead of using a personal automobile, walking, or biking are shown in Table 3. Highly rated reasons for choosing ridesourcing instead of driving a personal vehicle are "alcohol, tiredness, or medication," "parking cost or availability," and "stress." The top-rated reason for both walking and biking is weather.

4.3. Trip origins and destinations

The locations of ridesourcing trips are shown in Fig. 2, which shows the sum of trip origins and destinations for each block group. Many block groups in low-density rural areas and in predominantly residential areas within Ann Arbor and Ypsilanti had no trips in the dataset. All remaining block groups had between one and 10 trips, except for two block groups: one with a shopping mall had 12, and one in downtown Ann Arbor had 45. To facilitate comparison, we divided these counts by the block group area to create a measure of trip density (Fig. 3).

The information provided about destination type is reported in Table 4. The most popular destinations were home (32%), work or school (20%), and social and recreational (18%), with a smaller number of trips for other purposes, like the airport, medical or dental services, or shopping.

4.4. Demand analysis

The set of built environment variables used for the demand analysis are shown in Table 5. Our initial model included variables that had been well-established in the transportation literature for explaining mode choice, falling into the categories of density, land use diversity, design, destination accessibility, and distance to transit (known as the "five Ds") (Ewing and Cervero, 2010), using the EPA Smart Location Database. The additional variables for bar and restaurant density and DDA area are shown in Fig. 4.

Using a regression model, we quantified the relationship between trip density and built environment variables. The units of observation were the census block groups in Washtenaw County. We computed the dependent variable, trip density, by dividing the number of trips with the area of the block group. Although the dependent variable is skewed, because of the continuous nature of the variables and exploratory nature of the study we initially fit a standard multiple linear regression. The independent variables we considered were mainly built environment variables, but they also included other demographic variables. Among the independent variables, 15 of the pairwise correlations were greater than 0.5, with most of these affecting the employment-related variables (see Appendix A). We fit three linear regression models, reported in Table 6. To simplify interpretation, we reported beta coefficients. Model 1 included all variables, Model 2 removed variables without significant coefficients and removed two of the three correlated employment-related variables to avoid multicollinearity, and Model 3 included an alternative employment variable (office jobs). We included auto ownership in Model 2 but not Model 3 because it was correlated with office job density ($r = 0.54$). The signs and magnitudes of the

Table 1
Ridesourcing survey respondent demographics.

Demographic categories	Current study		Rayle et al. (2016)	Washtenaw county ACS 1-year (2017)
	Count	%	%	%
Household income				
Less than $25,000	40	38	n/a	19 ± 0.9
$25,000 – $49,999	24	23	n/a	20 ± 0.8
$50,000 – $99,999	21	20	n/a	28 ± 0.8
$100,000 – $199,999	17	16	n/a	24 ± 0.7
$200,000 or more	3	3	n/a	9 ± 0.4
Age				
18–24	32	33	16	19 ± 0.1
25–34	33	34	57	10 ± 0.1
35–44	15	15	19	8 ± 0.3
45–54	10	10	6	9 ± 0.1
55–64	6	6	1	8 ± 0.3
65–74	2	2	0	5 ± 0.1
75+	0	0	0	5 ± 0.1
Sex				
Female	72	67	40	51 ± 0.1
Male	33	31	60	49 ± 0.1
Other	2	2	n/a	n/a
Vehicle availability				
None	29	27	43	8 ± 0.5
1	47	44	n/a	35 ± 0.8
2	22	21	n/a	39 ± 0.8
3+	9	8	n/a	17 ± 0.6
Educational attainment				
High school or less	7	7	n/a	20 ± 1.3
Some college or associate's degree	34	32	n/a	25 ± 1.4
Bachelor's degree	31	29	54	27 ± 1.1
Graduate or professional school degree	35	33	27	29 ± 1.1
Race and ethnicity				
White	82	77	n/a	74 ± 0.2
Asian	7	7	n/a	9 ± 0.1
Black or African American	10	10	n/a	12 ± 0.3
Two or more or some other race	8	7	n/a	5 ± 0.3

Table 2
Reasons for choosing ridesourcing over transit.

Reason	Mean importance (Std. dev.)	*N*
Frequency or speed of route	4.3 (1.2)	117
Less walking	3.4 (1.5)	116
Weather	3.2 (1.6)	118
Transit service less easy to use	3.1 (1.5)	115
Transit less comfortable and pleasant	2.7 (1.5)	115
Concern about transit reliability	2.4 (1.5)	115
Transit service hours concern	2.2 (1.5)	116
Carrying heavy item	2.1 (1.5)	116
More convenient for travel with a group	1.9 (1.5)	116
Personal safety	1.8 (1.3)	115
Transit knowledge	1.7 (1.4)	113
Less expensive for travel with a group	1.6 (1.3)	117

Scale: Extremely important (5), very important (4), moderately important (3), slightly important (2), not important at all (1).

significant beta coefficients were consistent across all three models except for the coefficients for employment in Model 1, which might be negative because of multicollinearity.

The variables with the strongest relationship with trip demand were bar and restaurant density, and entertainment and office job density. Auto ownership was significant in Model 2, but with a small magnitude. Variables with a negative relationship with ridesourcing demand included population density, jobs–housing balance, and DDA area. Model 3, our final model, explained roughly 73% of the variation in the dependent variable using five variables.

Table 3
Reasons for choosing ridesourcing instead of personal vehicle, walking, or biking.

	Reasons	Mean importance rating (Std. dev.)	*N*
Personal vehicle	Alcohol, tiredness, medication	3.3 (1.4)	64
	Parking cost or availability	3.0 (1.6)	63
	Stress	2.7 (1.3)	63
	Sustainability	1.5 (0.9)	63
	Injury or illness	1.4 (0.6)	66
	Personal vehicle reliability	1.2 (0.4)	63
	Characteristics of vehicle	1.2 (0.5)	62
	Driver's license	1.1 (0.6)	63
Walking	Weather	3.4 (1.6)	59
	Distance	3.2 (1.4)	59
	Infrastructure	1.8 (1.5)	59
Biking	Weather	3.2 (1.4)	32
	Availability of bike	2.8 (1.8)	33
	Infrastructure	2.4 (1.6)	33
	Distance	1.8 (1.2)	33

Scale: Extremely important (5), very important (4), moderately important (3), slightly important (2), not important at all (1).

In our second multivariate analysis we used a negative binomial regression to explore the relationship between the count of ridesourcing trips, computed as the sum of origins and destinations in each block group, with the same set of independent variables. Table 7 shows two models, Model 1, which included all variables, and Model 2, which included all variables that were significant along with several which were significant in the previous OLS models. When comparing Model 2 to the results of the linear regression, DDA area and population density were no longer significant, and intersection density, land-use mix, job accessibility by transit, and distance to nearest transit stop were significant. The table also includes McFadden's pseudo R-squared of these models, 0.109 and 0.105. Although this metric can also vary between 0 and 1 like the more familiar adjusted R-squared for OLS models, it does not describe the explained variation and therefore should not be directly compared with standard R-squared values. The findings here, with relatively high adjusted R-squared for models constructed from grouped data but a McFadden's pseudo R-squared for a corresponding model with a categorical outcome (like negative binomial) with magnitude near 0.1 is typical (Bartlett, 2014).

5. Discussion

We begin with a discussion of the demographics of the survey respondents, and proceed to discuss the results of the study's two research questions. We then conclude with a discussion of the significance for an understanding of the geography of urban travel.

5.1. Rider demographics

By definition, convenience samples do not result in statistically representative samples for a broader population; however, a consideration of the results of this study in light of other works helps contextualize the findings. Although statistical methods exist for making inferences from non-representative samples (such as weighting), they require precise information about the population that does not exist for our population of interest here, ridesourcing users in Washtenaw County. Furthermore, even if precise population information existed, the user population is rapidly changing. Whereas a Pew Research survey found that 15% of Americans in 2015 had used a ridesourcing service, private sector data providers who use credit card data to track spending patterns found that between 32% and 43% of card holders had used a ridesourcing service in 2018 (Molla, 2018). In 2015, the Boston

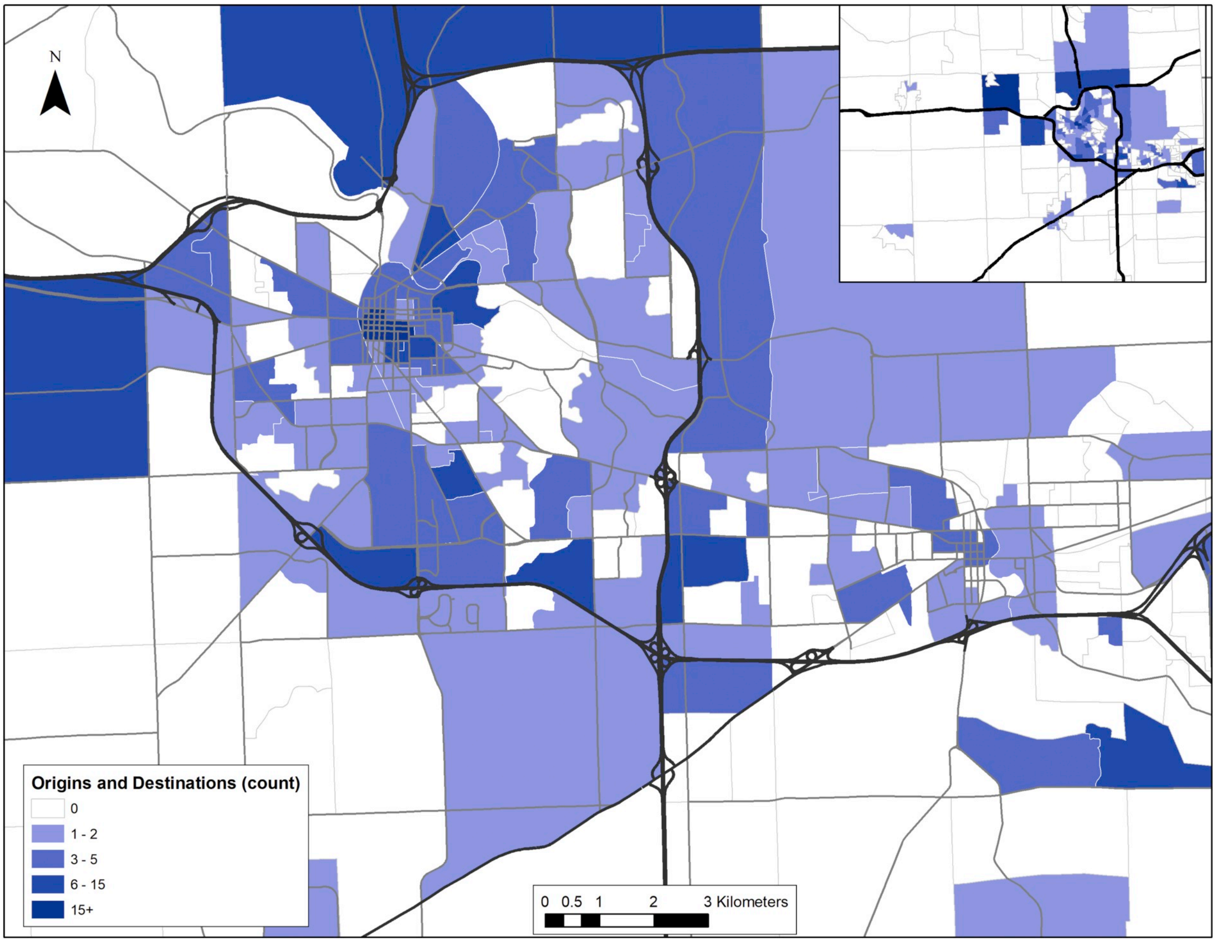

Fig. 2. Map of origins and destinations.

Federal Reserve found that 76.9% of Americans held a credit card (Green et al., 2017). Combining the two statistics shows us that roughly 25% to 33% of Americans have used ridesourcing services at some point. Clewlow and Mishra's national survey (2017) found that 21% of adults had used ride-hailing services, and an additional 9% reported they had used ridesourcing as a passenger and were not account holders themselves.

The detailed demographic profile obtained in this study resembles those found in previous research. Using national survey data, Clewlow and Mishra (2017) and Dawes (2016) found that ridesourcing was used by more women than men, different from the findings in Rayle et al.'s (2016) San Francisco intercept study, where 60% of riders were men. Clewlow and Mishra reported a much less dramatic difference in use between sexes than was seen in both our study and Dawes's study. Similarly, although the response categories differ slightly, most users in all of these studies were young (younger than 34 in Dawes, and Rayle et al.; younger than 49 in Clewlow and Mishra). The main discrepancies between this survey and the results of this study likely reflect the unique characteristics of the geographic area studied here. Our higher proportion of users reporting having "some college" and users in lower-income categories than in either of the other surveys is likely a result of the large population of college students in Washtenaw County.

5.2. Mode choice analysis

Overall, the observed reasons for choosing ridesourcing closely align with the findings of Rayle et al. (2016) from data collected in San Francisco in 2015, the primary previous study that examined this issue in detail. In that study, more than 20% of respondents reported a desire to not drink and drive, which was among the top five reasons riders opted for ridesourcing over driving a personal vehicle. The second top-rated reason for using ridesourcing in this study, to avoid parking inconveniences, also rated highly among the Rayle et al.'s (2016) respondents. The reasons riders chose ridesourcing over transit are similar, with trip time and convenience topping both lists. Overall, the data here seem to support the finding by Dawes (2016) that ridesourcing is used primarily for special-purpose trips, like avoiding driving while intoxicated or traveling to the airport, and not for regular commuting.

Our data suggest that ridesourcing trips can be grouped into two general categories. First, some people use ridesourcing as a substitute for public transit, and to a lesser extent for bicycling and walking. Because the respondents reported transit as an option for some of these trips, we can assume the trip origins and destinations were both somewhat transit-accessible. Although the issue requires further research, the data in Section 4.2 suggest that weather, distance, and transit convenience were factors leading people to choose ridesourcing instead of transit. The data also suggest that the trips where riders choose ridesourcing exclude very short trips in walkable areas. We make this conclusion because distance (presumably, longer trips) was rated as an important factor for choosing ridesourcing over walking.

The second general category of ridesourcing trips is those to or from largely auto-oriented suburban and rural areas, for which transit, bicycling, and walking are generally not options but driving a privately owned vehicle may be. For the trips where ridesourcing users have access to a vehicle, expected alcohol use, parking difficulties, and the stress of driving, are top-rated factors for choosing ridesharing. Analyzing these trips might identify opportunities for public transit service expansion, although the low population densities and infrequent use of ridesourcing might mean

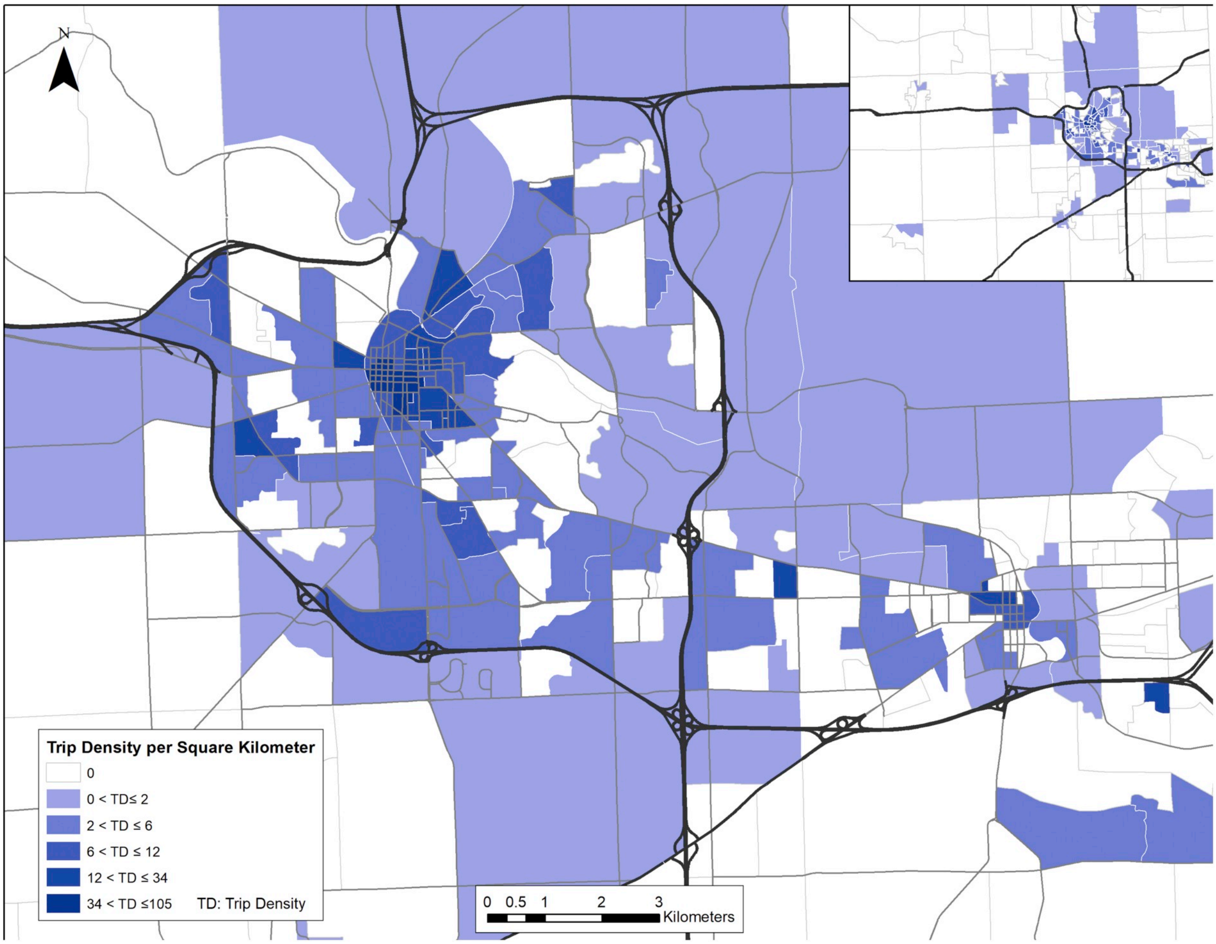

Fig. 3. Ridesourcing trip density.

that traditional scheduled, fixed-route transit service is not viable in these areas. In fact the local transit provider, AAATA, is operating a pilot demand-response service called FlexRide in one of the areas where our data show ridesourcing demand but which are not well served by the fixed-route service. The pilot service area, located in a portion of Ypsilanti Township south of the City of Ypsilanti, includes the two block groups with observed demand on the bottom right of Fig. 3.

It is important to note that this analysis was conducted at the scale of particular trips, and did not extend to the broader question of what explains the adoption of ridesourcing services in general (e.g., installing the applications, signing up, and learning to use the service). Studying the adoption of car-sharing services, Kent et al. (2017) concluded based on a qualitative analysis of interviews that such decisions are driven by disruptions—such as an international move, loss of a job, or a broken down car. However, even when disruptions occur, adoption requires that users be willing to try the mode and have the ability to do so. Future research could probe these issues in the context of ridesourcing to better understand the possibilities and limitations of adoption.

5.3. Trip origins and destinations

Examining the spatial pattern of trips shown in Figs. 2 and 3 provides additional insights to these data. Most trips, 69% of all origins and destinations, began or ended within the City of Ann Arbor, where

Table 4
Origin and destination types.

Type	All		DDA		City of ann arbor		Outside of ann arbor		Totals	Percentage of total
	O	D	O	D	O	D	O	D		
Home	103	61	5	1	67	43	33	18	164	43%
Work or school	21	36	4	6	19	26	5	11	57	15%
Social or recreational	25	34	12	19	20	29	9	5	59	15%
Medical or dental services	6	12	1	0	4	7	3	5	18	5%
Family or personal obligations	4	8	1	0	3	5	0	3	12	3%
Shopping or errands	12	8	1	1	6	6	4	2	20	5%
Airport or train station	6	12	0	0	2	5	1	7	18	5%
Arts and culture	3	7	2	2	3	4	0	3	10	3%
Other	9	14	5	2	10	5	6	7	26	7%
Totals	192	192	31	32	134	131	61	61	384	100%

O: Origins; D: Destinations; DDA: Downtown Development Authority.

Table 5
Demand analysis variables.

Category	Variable	Description	Mean	Std. dev.
Density	Population density	Gross population density (people/acre) on unprotected land	6.98	8.76
	Job density	Gross employment density (jobs/acre) on unprotected land	5.23	33.29
Diversity	Land use mix	5-tier employment entropy (denominator set to observed employment types in the census block group)	0.42	0.34
	Jobs–housing balance	Employment and household entropy	0.41	0.24
Design	Intersection density	Street intersection density (weighted, auto-oriented intersections eliminated)	52.00	41.52
	4-way intersection density	Intersection density in terms of multi-modal intersections having four or more legs per square mile	4.46	8.81
Destination accessibility	Job accessibility by auto	Proportional accessibility to regional destinations - Auto: Employment accessibility expressed as a ratio of total MSA accessibility	0.0039	0.0011
	Job accessibility by transit	Proportional accessibility of regional destinations - Transit: Employment accessibility expressed as a ratio of total MSA accessibility	0.0036	0.0041
Distance to transit	Distance to nearest transit stop	Distance from population weighted centroid to nearest transit stop (meters) within transit service area	378.69	375.00
Other	Bar and restaurant density	Density of businesses categorized under NAICS code 164 (restaurants and bars)	3.47	6.78
	Entertainment job density	Density of entertainment industry jobs	55.00	145.19
	DDA area	Dummy variables for block group in DDA area	0.063	0.24
	No auto households %	Percentage of households with no access to automobiles	44.56	68.81
Outcomes	Trip density	Sum of origins and destinations divided by block group area in square kilometers	2.87	9.18
	Trip count	Sum of origins and destinations within each block group	1.46	3.53

DDA: Downtown Development Authority; MSA: Metropolitan Statistical Area.

transit service and pedestrian and bicycle facilities are generally available. Considering the block groups with high density of origins and destinations outside the two main cities provide insights into these trips. The block groups located to the north and northwest of the city and outside the freeway loops are primarily residential areas with no transit service to the city and with limited commercial destinations of any type, so most riders are traveling to or from residences. The block group immediately to the west of the city contains a cluster of automotive dealerships and repair facilities, as well as a large apartment complex and some other commercial destinations. Therefore, these areas might produce ridesourcing trips among people dropping off or picking up a personal vehicle undergoing repairs, as well as other trips

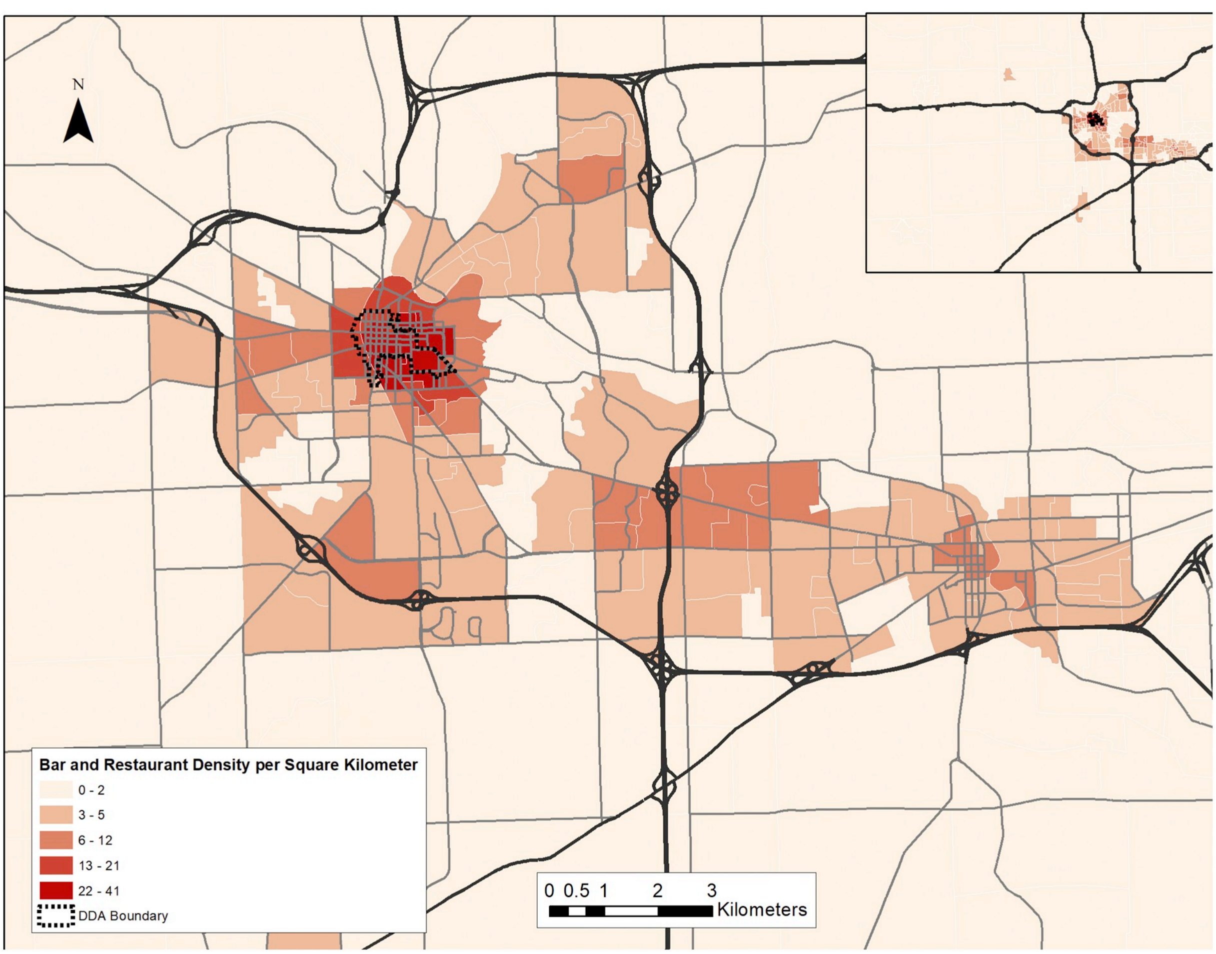

Fig. 4. Bar and restaurant density and Downtown Development Authority area.

Table 6
Multivariate analysis of ridesourcing trip demand.

Category	Variable	OLS Model 1	OLS Model 2	OLS Model 3
Density	Population density	−0.080	−0.189***	−0.152***
	Job density	−0.122**		
	Entertainment jobs density	−0.172**	0.338***	
	Office jobs density	0.700***		0.502***
Diversity	Land use mix	0.418		
	Jobs–housing balance	−0.110**	−0.131**	−0.097***
Design	Intersection density	−0.020		
	% 4-way intersections	0.030		
Destination accessibility	Job accessibility by auto	−0.014		
	Job accessibility by transit	−0.0139		
Distance to transit	Distance to nearest transit stop	0.053		
Ridesourcing-specific variables	Bar and restaurant density	0.664***	0.771***	0.738***
	DDA area	−0.099*	−0.130**	−0.156***
	No auto households %	0.004	0.133***	
	N	251	251	251
	Adj R-squared	0.739	0.658	0.729

Dependent variable: trip density per square kilometer. Beta coefficients reported.
DDA: Downtown Development Authority.
OLS: Ordinary Least Squares.
* P ≤ .10.
** P < .05.
*** P < .01.

to and from the apartment buildings, restaurants, and other businesses. Similarly, the block groups in areas surrounding Ypsilanti are also mostly residential neighborhoods with limited transit service and limited access to commercial amenities, so these trips are generally to and from residences.

5.4. Demand analysis

The demand analysis provides additional nuanced insight into the picture emerging from the data. Overall, the variables with the strongest relationship to ridesourcing demand were office jobs, entertainment jobs, and the density of bars and restaurants (ordinary least squares [OLS] Models 2 and 3 in Table 6). This is consistent with Lavieri et al. (2018), who found ridesourcing demand to be related to residential and retail employment density. Paradoxically, the variable for block groups located within the DDA area was negatively related to ridesourcing demand in the linear regression model, even though these areas generally have expensive and limited parking supply and a high density of destinations. However, these areas are generally very walkable, bikeable, and well-served by the city's transit system, which has a radial organization from two central depots in the downtowns of Ann Arbor and Ypsilanti. The positive coefficient on the variable for percentage of households with no auto ownership (OLS Model 2) supports the idea that ridesourcing is more popular among households without automobiles.

The models present inconsistent results for jobs–housing balance, measured using an entropy measure where higher values were assigned to block groups where both were present. Typically areas with greater jobs–housing balance are thought to be more conducive to non-auto modes. We did not have a strong hypothesis about the relationship we would find. Although previous researchers, such as Rayle et al. (2016), found ridesourcing to be popular in relatively dense areas with a mix of land uses and therefore higher jobs–housing balance, neighborhoods dominated by one or the other might result in greater demand for longer trips well-suited for ridesourcing. The OLS model found a negative relationship between this variable and ridesourcing demand, and the negative binomial regression Model 2 found a positive relationship,

Table 7
Negative binomial regression of ridesourcing trip demand.

Category	Variable	Model 1 coefficients	Model 2 coefficients
Density	Population density	−0.003	
	Job density	0.002	
	Entertainment jobs density	−0.021	
	Office jobs density	−0.008	0.036
Diversity	Land use mix	0.434	0.372
	Jobs–housing balance	1.334**	1.35**
Design	Intersection density	−0.009**	−0.009***
	% 4-way intersections	0.008	
Destination accessibility	Job accessibility by auto	351.308**	405.316***
	Job accessibility by transit	130.266***	129.185***
Distance to transit	Distance to nearest transit stop	−0.001	
Other variables	Bar and restaurant density	0.015	0.006
	DDA area	−0.445	
	No auto households %	0.001	
	N	251	251
	Alpha	1.194***	1.236***
	Pseudo R-squared	0.109	0.105

Dependent variable: count of trip origins and destinations.
DDA: Downtown Development Authority.
** P < .05.
*** P < .01.

so future research is needed to explore the nature of the relationship between jobs–housing balance and ridesourcing demand.

The final negative binomial regression model showed statistically significant relationships with jobs–housing balance, intersection density (negative), and job accessibility by auto and transit, but did not find DDA area and percentage of no auto ownership to be significant. These differences most likely reflect the nature of the different dependent variables and model form but do not lead to major differences in the substantive interpretation. Instead, the results showing greater demand for ridesourcing in areas with high transit accessibility support the survey data indicating that many users use ridesourcing as a substitute for traditional public transit.

Because the linear regression models explain nearly three-quarters of the variation in ridesourcing demand, the results from the multivariate analysis could be converted into a planning tool to predict demand for areas undergoing development, or used to create maps to estimate ridesourcing demand in existing cities or as part of future land-use scenarios. Given the reluctance of ridesourcing companies to share detailed demand data, this could prove useful for transportation planners to understand where to provide facilities such as dedicated drop-off spaces, or where improvements to transit might capture trips currently being taken through ridesourcing.

5.5. Insights on the geography of urban travel

Urban travel has long had a complex geographic nature because city residents can choose from a variety of transportation modes, and these choices are strongly influenced by aspects of the urban built environment and the location of fixed-transit networks. The recent introduction of ridesourcing has raised the question of how it is influencing the use of these existing transportation modes. The results described in this paper provide some insights into this transition. First, in contrast with the statements of some boosters who envision their services as replacements of cars suitable for nearly all forms of urban travel, the survey data show that ridesourcing has been adopted in more specific ways. Although most survey respondents had access to a vehicle, most reported that for the particular trip where they chose ridesourcing, they chose it over public transit. Respondents also indicated that walking was an option for nearly one-third (32%) of trips, suggesting that some trips might have shifted to ridesourcing from this mode. As a result, the data show a striking spatial pattern with the highest densities of demand occurring in the study area's two main urban downtowns, each with a high density of commercial services and high levels of transit service and walkability. Future research could probe more deeply into which neighborhoods have the greatest adoption as a proportion of all travel; further study could also explore the relationship between ridesourcing and other modes.

5.6. Limitations and future research

A major limitation of this study is the use of a convenience sample of riders who volunteered to complete the survey after viewing online and offline public advertisements. The resulting sample was younger and had a higher proportion of women than the overall population (Table 1), but as discussed, the sample resembles rider demographics found in the limited previous empirical research. A biased sample might affect not only the findings derived from the survey data, but also the analysis of trip origins and destinations, and demand, if passengers taking trips to and from particular locations were underrepresented or missing from the survey data. One research strategy for survey-based research that might result in more representative samples is the in-vehicle intercept survey reported in Gehrke et al. (2018). However, even intercept surveys are vulnerable to bias if certain types of respondents are more likely to agree to participate. With greater knowledge of the demographics of the user population, survey data can be weighted to improve accuracy. A new data source that would allow for unbiased analysis of the geographic patterns of demand and use is raw trip data, which might become increasingly available because of regulatory initiatives. In one notable example, in April 2019 Chicago released a dataset of roughly 14 million ridesourcing trips (Greenfield, 2019).

6. Conclusion

Ridesourcing has been one of the most notable transportation innovations in recent years, with the number of users rocketing from zero to roughly one-third of Americans in less than a decade. This had been especially notable in big cities like New York and San Francisco, with large populations of young tech-savvy residents eager to try innovations and with large taxicab fleets and complex multi-modal transportation networks. Yet even in these higher-use areas, the role of ridesourcing within the broader suite of transportation options and the spatial nature of ridesourcing use is unclear because of a lack of data. Furthermore, it is not clear whether adoption patterns in smaller cities and rural areas are similar to more closely studied big city markets.

In this paper we reported the results of an exploratory survey on ridesourcing use in Washtenaw County, Michigan, the location of the cities of Ann Arbor and Ypsilanti. To collect detailed information about ridesourcing use, we recruited survey respondents through a variety of online and offline advertisements, resulting in a convenience sample of 167 users corresponding with 192 trips. Despite being a non-random sample, the respondents' demographics are broadly similar to those obtained from national sample surveys, showing that ridesharing users tend to be younger than the population at large. Our sample differs from other ridesharing survey data in two particular ways: our respondents had lower educational attainment and income. This is likely a result of the prevalence of current college students in the area. However, the sampling approach means the results should be interpreted with care.

Overall, the paper contributes to the young body of literature on ridesourcing by providing information and analysis regarding its geographic context. Respondents reported taking many of their trips using modes other than public transit for reasons of speed and convenience. Among the riders choosing ridesourcing over driving, the top three reasons for this choice were to avoid driving under the influence of alcohol, parking costs, and to avoid the stress of driving. Finally, weather was the top reason for taking transit modes over walking. Areas with the highest demand tended to have high office and entertainment employment and high density of bars and restaurants. Paradoxically, population density in a downtown area with limited parking (but high transit access and walkability) was related to lower ridesourcing demand, perhaps because trips in these areas were taken by other modes.

Overall, the results suggest that for cities like Ann Arbor, ridesourcing fills a niche in the transportation system but has not displaced traditional travel modes for routine travel. Most survey respondents reported using ridesourcing as an alternative to the area's public transit system, or instead of using privately owned cars. Although it seems plausible that low-cost, automated ridesourcing could result in greater mode shift from transit, it might not result in shifts from private auto trips, where ridesourcing was taken only for particular trip types (such as where parking is expensive or alcohol consumption is planned). However, this study suggests that what may be emerging in regions similar to Washtenaw County is a more complex transportation system, where ridesourcing coexists alongside other modes.

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Appendix A. Trip analysis variable correlation matrix

	Ridesourcing trip density	Population density	Job density	Entertainment job density	Office job density	Land use mix	Jobs-housing balance	Intersection density	% 4-way intersections	Job accessibility by auto	Job accessibility by transit	Distance to nearest transit stop	Bar and restaurant density	DDA Area	No auto ownership
Ridesourcing trip density	1														
Population density	0.4626	1													
Job density	0.3095	0.4859	1												
Entertainment job density	0.6316	0.3738	0.5357	1											
Office job density	0.7249	0.3496	0.5487	0.8898	1										
Land use mix	0.113	−0.1123	−0.0313	0.163	0.1333	1									
Jobs-housing balance	0.1336	−0.1204	−0.0174	0.2925	0.195	0.6942	1								
Intersection density	0.263	0.529	0.1309	0.2135	0.181	−0.0898	−0.0453	1							
% 4-way intersections	0.3506	0.3616	0.0663	0.2508	0.2598	0.0435	0.0983	0.4915	1						
Job accessibility by auto	0.2908	0.4936	0.1701	0.2489	0.1924	−0.0981	0.0853	0.5691	0.2941	1					
Job accessibility by transit	0.4766	0.5498	0.2662	0.4411	0.3947	0.0075	0.1364	0.6161	0.3374	0.6263	1				
Distance to nearest transit stop	0.234	0.4431	0.1138	0.1886	0.1421	−0.0964	0.0894	0.5633	0.3052	0.6999	0.5933	1			
Bar and restaurant density	0.7369	0.6961	0.3309	0.5167	0.497	0.1268	0.1842	0.3927	0.3787	0.4474	0.6257	0.3536	1		
DDA Area	0.5724	0.5503	0.3912	0.4712	0.4565	0.1448	0.1363	0.3253	0.1686	0.3155	0.5201	0.2138	0.8088	1	
No auto ownership	0.4846	0.3397	0.1106	0.4989	0.5404	0.0644	0.1429	0.1849	0.2443	0.2445	0.3094	0.2412	0.3993	0.3182	1

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