Autonomous Vehicles for Small Towns: Exploring Perception, Mobility, and Safety

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16. Abstract

As of 2021, there were 18,696 small towns in the US with a population of less than 50,000. These communities typically have a low population density, few public transport services, and limited accessibility to daily services. This can pose significant challenges for residents trying to fulfill essential travel needs and access healthcare. Autonomous vehicles (AVs) have the potential to provide a convenient and safe way to get around without requiring human drivers, making them a promising transportation solution for these small towns. AV technology can become a first-line mobility option for people who are unable to drive, such as older adults and those with disabilities, while also reducing the cost of transportation for both individuals with special needs and municipalities. The report includes our research findings on 1) how residents in small towns perceive AV, including both positive and negative aspects; 2) the impacts of ENDEAVRide—a novel "Transport + Telemedicine 2-in-1" microtransit service delivered on a self-driving van in central Texas—on older adults' travel and quality of life; and 3) the potential safety implications of AVs in small towns. This report will help municipal leaders, transportation professionals, and researchers gain a better understanding of how AV deployment can serve small towns.

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Introduction

As of 2021, there were 18,696 small towns in the US with a population of less than 50,000; they are home to about 80 million (*1*). These communities typically have a low population density, few public transport services, and limited accessibility to daily services (*2-4*). This can pose significant challenges for residents trying to fulfill essential travel needs and access healthcare. Studies have also demonstrated that small and rural areas account for a disproportionally high rate (53 percent) of road fatalities (*5; 6*). However, since the COVID-19 pandemic, there is a considerable spike in populations moving out of metro areas, leading to a noticeable population growth in small and rural communities (*7*). Such communities are attractive because of lower living costs, relaxed lifestyles, scenic beauty, and lower crime rates (*7*). Population increase in these small communities has also led to economic revitalization (*7*). This trend highlights the importance of small towns as future activity centers, thus necessitating critical transportation planning interventions to improve existing transportation services and infrastructure.

Autonomous vehicles (AVs) have the potential to provide a convenient and safe means to get around without requiring human drivers, making them a promising transportation solution for these small towns. AV technology can become a first-line mobility option for people who are unable to drive, such as older adults or people with disabilities, while also reducing the cost of transportation for both individuals with special needs and municipalities. As with most technologically advanced equipment/devices, current AV research has been carried out primarily in dense, urban contexts, overlooking the perspectives of people from small and rural communities. As a result, such communities have often fallen off the radar of public sector investment and for-profit competitors in the AV technology space (*6*).

The report aims to address such a gap by presenting our research findings on (1) how residents in small towns perceive AVs, including both positive and negative aspects; (2) the impacts of ENDEAVRide—a novel microtransit service delivered on an autonomous van in central Texas—on older adults' travel and quality of life; and (3) the potential safety implications of AVs in small towns. This report will help municipal leaders, transportation professionals, and researchers gain a better understanding of how AV deployment can serve small towns.

Background

Public Perceptions of AVs

In recent years, numerous U.S. cities, such as Phoenix, San Francisco, Austin, and Los Angeles, have introduced driverless ride hailing services to public roads. The public responses are mixed. Users have appreciated the safety, privacy, better driving performance, ease of use, and comfort provided by these vehicles. At the same time, vehicle communication challenges, sensor and software glitches, unpredictable traffic patterns, and pedestrian and cyclist interactions have been the biggest challenges for smooth operation of such vehicles.

Previous studies have summarized numerous societal impacts of AVs, including enabling older people and people with disability to live more independently, reducing car ownership and traffic congestion, increasing trip duration, inducing trips of various purposes, increasing fuel efficiency, and reducing the need for parking spaces, among others (*8-10*). These potential impacts affect both the realms of urban and transportation planning, necessitating extensive research. However, the impacts of AVs are challenging to predict and remain understudied (*11*).

Researchers have also observed demographic differences in terms of interest in AVs, with males showing a greater inclination towards this technology compared to females (*8; 12*). Highly educated people with high incomes living in densely urbanized areas seem more attracted to AVs than their counterparts (*13*). Younger people show more interest in using AVs than older people (*14; 15*). Yet, inconsistencies have also been reported. For example, some studies found that males and young people were less likely to use AVs (*16*). Other studies reported that age and gender had no significant impact on the decision to ride AVs (*17-19*). Most Americans have heard about AVs and have a favorable opinion about them, both as a transportation alternative and for the accrued benefits (*8; 9*). At the same time, people have also expressed concerns over the safety of these vehicles (*8; 9*). Additionally, the proportion of the population worried (60%) about AVs is higher than those who are enthusiastic (40%) about them (*9*). As for views of when most vehicles on the road will be autonomous, almost two-thirds expect it to be in the next half-century (*9*).

The primary barriers to accepting these vehicles revolve around concerns related to safety, mechanical aspects, software reliability, security, attachment to personal vehicles, driving pleasure, and reluctance to rely completely on vehicle automation (*8; 15; 19-24*). In contrast, perceived benefits of AVs include reduced travel times and less traffic congestion, crash reduction in both quantity and severity, decreased travel costs in terms of parking and fuel, and pleasant driving experiences (*8; 20; 24; 25*). Those studies are based on national or international level samples (*8; 15; 23; 26*) and were conducted in larger cities and metropolitan areas, resulting in a significant knowledge gap regarding perceptions of AVs in small and rural communities. There is a dearth of evidence as to how residents of small and rural communities perceive the potential impacts of AVs. Such communities present ideal testbeds for the deployment of AVs at a small scale, enabling further study of reduced operational risks and demographic associations in detail, both qualitatively and quantitatively. They also provide opportunities for pilot programs involving shared and public transit AVs, which can focus on a small geographical location. Additionally, these communities can be used to forecast market penetration in urban areas based on the utility of AVs in small and rural communities.

Emerging Trend of Public Transit in Small Towns

A recent census report on the older population between 2012 and 2016 shows that 10.6 million older adults are living in small towns, and innovative public transit options are needed for this increasingly older population in the foreseeable future (*27*). However, small towns are often underserved by public transit, so most older adults rely on private vehicles for their daily transportation (*28*). This could be a significant issue once they become older and lose the ability to drive themselves. Therefore, efforts are needed to develop a public transit system that can help older adults maintain/improve their mobility and independence.

It has long been a challenge for small public transportation agencies to provide an effective and sustainable transit system for riders in their service areas. Traditional fixed-route transit (FRT) systems are often not efficient in small towns with their predetermined routes and schedules (*29*). The sparse land use and low population density require more flexibility in the transit service design to work effectively in small towns, especially for older adults and people with disabilities (*30*). Therefore, many small public transit agencies choose to adopt demand-responsive transit (DRT) systems that operate in designated zones instead of on fixed routes to increase service coverage in less populated areas. Also, with no predetermined schedules, DRT can provide higher flexibility to public transit agencies. Although DRT ($64.03/trip) is more costly on the per-trip level compared to FRT ($10.36/trip), it is less expensive on the per-service-hour level ($101.30 vs. $160.33), and offers individual riders a door-to-door service that increases their mobility and improves their perception of the public transit service (*31*).

Traditional DRT service requires dispatchers to take requests from riders 24–48 hours before the scheduled trip time and involves negotiating trip details with riders to coordinate multiple passengers with a single connected trip or a checkpoint where multiple passengers can board at the same location. This model has been researched extensively through simulation studies and empirical studies to demonstrate its potential benefits in improving system productivity, lowering financial expenses, promoting equitable access, and reducing greenhouse gas emissions in low-density areas (*32-36*).

More recently, with the advances in information and communication technology, DRT systems can provide real-time communication between the drivers and the riders and the corresponding routing information with computer-aided dispatcher systems and routing algorithms (*29*). Riders can request a ride through phone calls or mobile applications and receive the transportation service promptly. This new DRT model is often named on-demand transit or microtransit. Although previous studies have investigated the benefit of on-demand transit through multiple lenses, limited research has been conducted to investigate how on-demand transit can impact the accessibility for older adults and people with disabilities. This research helps fill in this knowledge gap by asking the question what is the perception of on-demand transit service with AV technology for older adults and people with disabilities?

Enhancing Traffic Safety in Small Towns

Researchers and practitioners have studied traffic risk for decades. Historical crash data (e.g., traffic crash reports) recorded by law enforcement agencies are the primary data source in existing road safety studies. Many studies have been conducted to explore the spatiotemporal distributions

(*37; 38*), uncover the leading factors (*39; 40*), and forecast the likelihood of objective traffic risks (*41; 42*) using crash data. However, compared to the extensive studies on objective traffic risks, studies on subjective traffic risks, such as traffic risk perceptions, are relatively few. Researchers have gradually acknowledged the importance of traffic risk perceptions. For example, traffic risk perception can directly impact road behaviors and consequently impact safety outcomes (*43; 44*). The perception of risk also weighs heavily on neighborhood satisfaction, which is positively correlated with traffic safety (*45*). The connection between physical activity and perceived risk has also received much attention in the literature, albeit with inconclusive results. Therefore, understanding the human mechanisms of how traffic risk is conceived of and realized can have significant implications for road safety planning and enhancement (*46-48*).

As traffic safety is highly correlated with streetscape among other built-environment features, we carried out a systematic literature review to guide relevant safety analysis. We utilized three databases that were the most pertinent to our review, Scopus, Web of Science, and Transport Research International Documentation, and reviewed 63 studies. The majority of the reviewed papers focused on driver-involved crashes (n = 29, 46%), followed by pedestrian-involved crashes (n = 22, 35%). Additionally, cyclists and motorcyclists were also considered in the reviewed studies as ordinary individuals involved in crashes. Statistical results from some studies indicated that both streetscape factors and roadway factors were the main relevant factors associated with traffic crashes (n = 16, 25%).

Although some efforts have been made in the past to compare the relationship between subjective traffic risks (e.g., perceived risk locations) and objective traffic risks (e.g., crashes), several important questions still need to be answered. Most prior studies were conducted in highly populated areas (e.g., urban areas or university campuses), and indicated that rural and underserved communities were more vulnerable and thus more likely to observe crashes (*49; 50*). This could be attributed to differences in road design (*51*), built environments (*52; 53*), and drivers' driving attitudes and risk perception (*54*) between rural and urban areas. However, to date, there is a dearth of investigations on perceived traffic risk in underserved communities.

These unanswered questions motivate us to further traffic safety studies in small and rural communities within the context of AV deployment. Building on earlier studies of this general topic (*48; 55; 56*), we collectively address three objectives in this study: (a) to describe perceived risk from persons residing in six small towns located in Central Texas; (b) to empirically and spatially explore how perceived and observed traffic safety risks are associated with each other; and (c) to estimate the binary spatial relationship (matched or unmatched) between perceived and observed traffic risk locations using a logistic regression model accounting for perceived, personal/household, and neighborhood factors.

Method

Our interdisciplinary team aimed to answer the following convergence research questions:

1. [PERCEPTION] How do residents in small towns perceive the safety and societal impacts of AVs?
2. [MOBILITY] How does ENDEAVRide—a novel microtransit service delivered via an autonomous van—impact older adults' travel and quality of life?
3. [SAFETY] How can traffic safety be enhanced in small towns with the adoption of AVs?

In order to answer the above questions, our team carried out the following major activities.

Baseline Survey

Study Setting and Implementation

Few research studies provide insights regarding the perception of AVs in small and rural communities, resulting in a considerable literature gap. The survey data sought to fill in this gap by revealing how residents from such areas perceive the societal impacts of AVs. It also helped in providing insights on how sociodemographic factors influence how residents perceive such AVs' impacts in these areas.

During August 2021–April 2022, we carried out an online survey in our targeted small towns in Central Texas: Belton, Caldwell, Copperas Cove, Gatesville, Harker Heights, Huntsville, Kempner, Madisonville, Nolanville, Oglesby, and Valley Mills. About half (48%) of the households in the study area earned less than $50,000 annually, and about 25% of the residents had a bachelor's degree or higher (*57*). These communities represented a range of typical small cities/counties settings, with the total population ranging from 15,512 to 41,664 and the population density between 80 and 2,205 people per square mile (*58*). They were somewhat isolated from large metropolitan areas but within an hour's drive of major cities (e.g., Killeen, Austin, and Waco). Belton, Copperas Cove, Coryell County, Harker Heights, Kempner, and Nolanville were served by limited public transportation through the Hill Country Transit District, and the buses operated on an hourly basis from 7 a.m. to 6 p.m. with three fixed routes and a rural service (*59*).

To be eligible, participants needed to be 18 years of age or older, and only one participant was allowed per household in order to gather diversified responses. Our baseline survey aimed to gather data about demographics, intent to use AVs, travel behaviors, and perceived traffic safety risk locations/factors.

We distributed the survey recruitment flyers using the United States Postal Service Every Door Direct Mail service and utilized web-based platforms, Maptionnaire and Qualtrics. We also made the hardcopy available upon request. Participants were compensated with a $10 Amazon e-gift card upon completing the survey. The study was approved by the Institutional Review Board of Texas A&M University. In total, 2,839 participants attempted to complete the survey. However, only 1,153 responses were included in the final analysis for this study after excluding incomplete, invalid, and duplicated response, and those that were completed in an unreasonably short amount of time.

Analytical Approach

We designed AV-perception questions, based on Schoettle and Sivak (*8*), the Pew Research Center (*9*), and our own research experiences. The survey questionnaire consisted of five parts: Part A, Driverless Vehicles; Part B, Telemedicine; Part C, Neighborhood; Part D, Daily Transportation; and Part E, Demographics. There was a total of 65 questions, which consisted of a Likert scale, multiple choice, and open-ended questions. This analysis was based on a subset of questions from Part A and Part E. We captured participants' general perceptions towards AVs through five multi-point, Likert-scale questions (see Table 1).

To capture AVs' societal impacts, we developed questions to measure a range of different impacts. These questions used 5-point Likert scales to record the responses, which were later coded into a 3-point scale as explained in the succeeding section. Addressing the most common impacts of AVs as found in the literature (*8; 9; 60*), they allowed for a comparison of AV impacts as perceived by the residents of small town communities in this study versus those at the national level or in large metropolitan areas. The comparison would offer important insights to guide policy and decision-making for AV planning.

We utilized two approaches to analyzing the responses. To investigate the responses related to the general perceptions of AVs, we used summary statistics and compared our results with those presented by Schoettle and Sivak (*8*) and the Pew Research Center (*9*). The same approach was used by both of these studies to describe and visualize the general perceptions regarding AVs.

To analyze the questions on AVs' community impacts, we utilized the Matt-Whitney U test and Kruskal-Wallis H test to explore the differences in opinions of people from different sociodemographic backgrounds (i.e., age, gender, marital status, education level, household income, and employment status). These tests were used based on the ordinal nature and number of groups within data. Furthermore, we estimated a series of ordered logit regression models to examine the effects of these sociodemographic variables on each of the AV impact variables.

Trip Log Analysis

Trip log data were collected from one of the survey communities, the city of Nolanville. We analyzed ENDEAVRide trip data from August 2021 to March 2022, using trip logs maintained by the operators. The logs record essential trip information such as origin, destination, purpose, and date. In order to visualize the trip metrics while protecting users' privacy, we created a grid system of 500 ft by 500 ft over the city. Figure 1 in Appendix A shows such a system in which trip origin blocks are highlighted. Table 2 shows the trip data summary for these blocks.

Natural Experiment and Focus Group

Our team used natural experiment and focus group approaches to investigate the impacts of ENDEAVRide on users' travel.

Recruitment

Our research focused on older adults and people with disabilities; hence the eligibility criteria were (a) people with disabilities or (b) age 60 or older. To recruit participants, our team explored the following channels:

1. Mailing brochures to residents in targeted communities using Every Door Direct Mail service provided by United States Postal Service. The targeted communities were selected based on discussion with the city staff including the city manager and assistant manager.
2. Word of mouth. City staff communicated with local residents whom they knew might need the demand-responsive service for transportation to medical appointments, grocery shopping, and other errands.
3. Displaying brochures at local venues, including multiple churches, food trucks, and fire department buildings (serving as a food pantry during the study period).
4. Putting door hangers in targeted communities. Over 500 door hangers were distributed over the course of three weeks. The targeted communities were also chosen based on discussion with city staff.
5. Posting service information on the city's official websites and Facebook page.
6. Distributing online surveys via QR codes on brochures and door hangers and communicating with survey respondents.
7. Contacting the director of the local Disabled Veteran association and promoting the service.

Analytical Approach

Data Collection

We followed a pre-post, natural-experiment approach to evaluate the intervention (i.e., the ENDEAVRide)'s impact on users. We tracked each participant's travel for 2 weeks before the intervention and then for 2 months during the intervention. We then calculated and compared their accessibility to essential services between these two periods to assess the impact of this on-demand transit service on accessibility for older adults and people with disabilities in rural areas.

We used Google Timeline to track participants' travel. Each participant could either choose to carry a cellphone with Google Timeline already installed and our project account logged in or give us permission to log in a project account on their personal cellphone. Our team reviewed the travel history weekly and edited the history with the participants if any potential errors were identified. After the clean travel history was collected, we used an open-source package, infostop (*61*), to identify stops in the trajectory data and manually matched the stops to specific points of interest (POIs) on Google Maps.

Participants were expected to attend at least one focus group meeting in person or virtually during the experiment period. Three separate focus group meetings were held in July 2021, November 2021, and April 2022. Each meeting took 90 minutes and included two sections regarding autonomous on-demand transit and telemedicine. Our team designed the script and used it for all three meetings. One of the essential questions was, "Do you see yourself using an on-demand driverless taxi service (like calling up a taxi or Uber) to get around?" One of the team members was designated as a moderator to facilitate the discussion. All focus group meetings were voice recorded, with participants' permission, for later transcription and qualitative analysis.

Cumulative Accessibility Measure

To compute the accessibility of participants, our team used the following equation originally proposed by Hansen (*62*) and widely used in other published studies. Each element in the equation was explained following the language from Levinson and King (*63*):

$$A_i = \sum_j O_j f(C_{ij})$$

where:
A_i: accessibility score for participant i.
O_j: the number of opportunities available at destination j
C_{ij}: cost of travel from i to j (travel distance)
$f(C_{ij})$: impedance function

The impedance function was defined as below, taking a value of 1 if the travel distance is less than a threshold $t = 20$ miles and zero otherwise.

$$f(C_{ij}) = 1 \; if \; C_{ij} \le t, else \; f(C_{ij}) = 0$$

Content Analysis

Our team first transcribed all recordings of the focus group meetings using an online transcribing service and later reviewed the transcripts to correct errors. We then used the cleaned transcripts to extract the themes, concerns, and preferences revealed during the discussion of the designed question.

Interviews

We also recruited 10 ENDEAVRide users who were 60 years or older for individual interviews, to gain more insights on their perceptions and experiences with AVs. Each interview session lasted 20–25 minutes and consisted of two parts. The recorded audio data were imported into NVivo software (*64*) for transcription and analysis. We listened to the recordings and followed Colaizzi's method for phenomenology (*65*) and analyzed the data in seven steps:

1. Familiarization: The researchers thoroughly reviewed the gathered data to acquaint themselves with all the information provided by the participants.
2. Identifying significant statements: The data were carefully examined word by word to identify and extract crucial statements that were relevant to the research question.

3. Formulating meanings: The researchers assigned codes to recurring ideas while consciously setting aside any preconceived assumptions about the phenomenon.
4. Clustering themes: The coded ideas were grouped together to discover meaningful common concepts and create a prototype of the theme. It was important to remain open to new insights and not let existing ideas or literature-based theoretical knowledge influence this process.
5. Developing an exhaustive description: Each topic generated in the previous step was meticulously described in detail. Original statements from the participants were extracted and incorporated into the description.
6. Producing the fundamental structure: Similar topics and descriptions were compared to identify and extract shared ideas. A concise and condensed phrase, known as the topic, was then constructed.
7. Seeking verification of the fundamental structure: The resulting topic structure was shared with the participants for verification, ensuring that their experiences had been accurately captured. If any bias was detected, the researcher must revisit the process from the beginning and reanalyze step by step.

Safety Analysis

Dashboard Design

To collect and analyze transportation safety data for underserved small towns, we developed a human-centered interactive dashboard. We started by collecting video and audio data related to road conditions in Nolanville, Texas. We processed and analyzed the data using geospatial artificial intelligence algorithms. Then, we mapped the results onto a digital dashboard for intuitive visualization.

Comparing Perceived and Objective Safety Risks

This research aimed to empirically and spatially explore perceived and observed associations and patterns; and to estimate the binary spatial relationship (matched or unmatched) between perceived and observed traffic risk locations. In order to carry out traffic safety analysis in our targeted small towns, we first used the aforementioned baseline survey to collect local residents' perceived risk locations, perceived risk factors, and personal information. Next, crash data and road inventory data were used to calculate the zonal crash rates for tessellated uniform grids, which were used as the objective risk observations to compare with the perceived risk locations. Then, we labeled each perceived risk location as "matched" or "unmatched" based on whether it spatially overlaps with any high crash risk grids determined by the crash rates. Meanwhile, we collected and generated a list of features to characterize each perceived risk location from four perspectives: perception-relevant factors, respondent's personal factors, roadway-relevant factors, and built environment and location efficiency factors. Last, we performed statistical tests to assess what factors significantly impact the binary spatial relations ("matched" and "unmatched") between perceived risk locations and observed risk grids and used logistic regression to model this relation. Different approaches were applied to reduce the number of irrelevant and intercorrelated explanatory variables. Our study workflow is illustrated in Figure 2 in Appendix A.

Perceived Safety Risks

During the baseline survey, participants used Maptionnaire (see Figure 3 in Appendix A) to map their perceived risk locations. They would then further specify the types of location (e.g., a POI, an intersection, a road, or a neighborhood) and the perceived risk factors through associated questions, such as poor road surface, high speed limit, aggressive drivers, heavy traffic, poor lighting, poor quality surrounding environment, or too many pedestrians and/or bicyclists.

To comprehensively explore the potential factors impacting the "spatial match" between perceived and observed risk locations, we compiled a list of variables to characterize each collected perception record from four perspectives: individual perception, personal attributes, roadway factors, and neighborhood context and composition features.

Zonal Observed Crash Rate Derivation

Although respondents' perceived risk locations were mapped as points, they could represent four types of locations with different vector types (e.g., point: POI, intersection; line: road; polygon: neighborhood). Meanwhile, since these locations were manually pinpointed, positioning errors could be introduced, making it difficult to pinpoint them precisely on the map, especially for the point and line locations. To effectively accommodate the positioning errors and compare with different types of perceived risk locations, we divided each city into equal-sized tessellated grids and calculated the zonal crash rate for each grid to represent the observed crash risk, which was spatially compared with the perceived risk locations. A crucial step in traffic safety studies is to select and generate appropriate safety performance measures. Crash rate is one of the most used safety measures, which quantifies crash risk by normalizing the crash counts based on traffic exposure (*66*). According to the definition provided by the Federal Highway Administration, the crash rate for a roadway is represented by the number of crashes for every 100 million vehicle miles traveled (VMT), which was calculated through the following equation:

$$\boldsymbol{R_{seg}} = \frac{\boldsymbol{C_{seg} * 100{,}000{,}000}}{\boldsymbol{365 * N * V * L}}$$

where R_{seg} represents the segment-level crash rate; C_{seg} is the count of crashes that occurred on the segment; N represents the number of years; V indicates the traffic volume (annual average daily traffic) of the segment; and L indicates the segment length (in miles).

In this study, we adapted this solution to calculate the zonal crash rate—normalizing the crash counts by the aggregated traffic exposure within each grid using the following two equations (*50*):

$$\boldsymbol{R_{grid}} = \frac{\boldsymbol{C_{grid} * 100{,}000{,}000}}{\boldsymbol{E_{grid}}}$$

$$\boldsymbol{E_{grid}} = \sum_{j=1}^{r}\sum_{i=1}^{n} \boldsymbol{L_i * V_{ij} * 365}$$

where R_{grid} indicates the zonal crash rate of a hexagonal gird; C_{grid} is the number of crashes within the grid during the study period; E_{grid} is the aggregated grid-level traffic exposure; n represents the number of segments within the grid; i is the i-th segment; r represents time span of the crash data (in years), set as 5 in this study; j is the j-th year, L_i is the length of i-th segment (in miles), and V_{ij} indicates the traffic volume of the i-th segment at the j-th year. In accordance with past research, we selected the top 20% of grids ranked by their crash rates to represent the observed risk locations in each of the study cities.

Statistical Tests, Model Development, and Result Evaluation

We employed several exploratory data analysis techniques to understand statistical and geographical traffic risk trends. Traditional descriptive analysis was first applied to participant perceived risks as they related to location and environmental characteristics. We also created geovisualizations using geographic information system (GIS) software to showcase spatial relationships between observed risk zones (i.e., hexagonal grids) and perceived traffic risk locales. In addition, a chi-squared test of independence and unpaired two-sample Wilcoxon test (a.k.a. Wilcoxon rank sum test or Mann-Whitney test) were also applied to assess whether each categorical and numerical explanatory variable was associated with the binary response variable (i.e., "matched" and "unmatched"). The chi-squared test of independence is commonly used to assess whether two categorical variables are likely to be related. The Wilcoxon test is designed to assess differences between two independent groups when the dependent variables are continuous but not normally distributed.

We created a binary logistic regression model to investigate the impacts of several variables from four key categories on the probability of a traffic risk match between perceived risk and objectively measured high-risk traffic zones. Logistic regression has been widely adopted to estimate the likelihood of an event occurring based on one or a group of selected explanatory variables, especially for modeling a binary outcome. To improve the stability and performance of the logistic regression model, we normalized numerical variables measured at different scales to the range of 0 to 1. A forward stepwise regression was utilized to exclude insignificant variables from the model and produce an optimal model using the Akaike information criterion, which is valid measure of model fit. We also ensured that multicollinearity among the explanatory variables was minimal by applying a variance inflation factor threshold of ≤ 10. In this study, we used a threshold of 0.5 to divide the modelling results into two groups, indicating the "matched" (coded as 1) and "unmatched" (coded as 0) locations to ensure that our results are generalizable.

Results

Perception

Overall Perceptions of AVs

As shown in Figure 4 in Appendix A, the majority (60%) of our study participants (*n* = 1,153) have "a little" knowledge of AVs as compared to 37% knowing "a lot" and about 3% knowing "nothing at all." About 31% of respondents who have heard at least a little about the development of AVs reported hearing or seeing both positive and negative remarks. As shown in Figure 5 in Appendix A, about 42% have seen or heard positive reports, whereas about 27% have heard or seen mostly negative reports about AV developments.

Enthusiasm and worry coexist among participants. About 76% of the respondents are somewhat (48%) or very (28%) enthusiastic about it. About 65% of the sample is somewhat (52%) or very (13%) worried about AV development. As for the projected timeline about the road occupancy of AVs, the majority (82%) feel that most of the vehicles on the road will be autonomous in the next 50 years. Twenty-six percent of respondents expect it to happen in the next 10 years. About 15% of respondents expect the scenario to happen 50–100 years from now, and only 1% feel it will never materialize.

Perceived Community Impacts of Autonomous Vehicles

Public attitudes vary with regards to perceived community impacts of AVs as measured by the 20 Likert-scale statements. The Cronbach's alpha, $\alpha = 0.86$, showed acceptable reliability (*67*) and justified the retention of most items. Elimination of any item would result in a slight decrease in the alpha score.

As seen in Figure 6 in Appendix A, the survey confirmed the belief in numerous benefits brought by AVs. The majority of respondents (67.25%) believe that the onset of AVs will make older people and people with disabilities more independent and mobile. Additionally, the majority (51.18%) believe that AVs will help reduce air pollution, and 49.56% believe that these vehicles will be more fuel-efficient. About 50% and 57% of respondents believe that AVs will reduce traffic congestion and traffic accidents, respectively. Concerning land use, 43.54% believe that parking lots will no longer be needed. Regarding autonomous bus services, half of the respondents believe that they would be comfortable riding such buses. On the other hand, 64.19% think that the driver industry will experience job loss as technology replaces drivers. The majority of respondents believe that the average number of trips will increase (55.47%) and that the trips will be longer (54.03%). Consequently, 50.13% of the respondents believe that people would walk less due to AVs. Respondents have also shown overwhelming support for the strategies to facilitate the operation of AVs; 71.47% of respondents are in favor of dedicated road lanes for these vehicles, and 69.56% are in favor of having a "safety" driver. Over 90% support the idea of having a human assistant onboard the vehicle who can assist people with disabilities.

Mobility

Community Level

Figure 7 in Appendix A illustrates the origin-destination patterns of the ENDEAVRide trips provided to the residents of Nolanville. Most destinations are located in Harker Heights and Killeen, neighboring towns with retail and service stores that satisfy the essential needs. Some of the longest trips brought participants to the Veterans Affairs Hospital in Temple.

Table 3 (see Appendix B) summarizes the ENDEAVRide's trip purposes during the study period. Trips to access health care services, such as dialysis and visits to pharmacies/clinics/labs, account for 71% of all the trips, followed by grocery stores (11%) and other retail (5%).

Individual Level: Quantitative Analysis

Twenty-one participants enrolled in our 2.5-month travel data collection via Google Maps. Table 4 in Appendix B summarizes per-person weekly trip counts by destination during the pre-intervention (2 weeks) and intervention (2 months) periods.

Using the cumulative accessibility measure, we found that participants' average accessibility score during the 2-week pre-intervention period was 21. During the 2-month during-intervention period, their average accessibility score was 22.74, which is 8.3% higher than the pre-intervention period.

Individual Level: Focus Group Regarding Autonomous Vehicles in General

Among the 21 study participants, 17 joined our focus group session to offer their insights on the DRT service with the autonomous driving technology. Participants had experience in riding the van equipped with the autonomous driving technology. The themes, concerns, and insights generated from the focus group discussions are summarized below.

- **Familiarity with smartphone technology:** Participants in all three focus group meetings expressed concerns about the smartphone application. They were worried about whether ordering the service through smartphone applications is too complex and may cause errors in the pick-up and drop-off process.
- **Phones without internet access:** Participants also raised concerns about not having a smartphone. Their phones were only substitutes for their previous landline and could only make phone calls or send texts without internet access.
- **Accommodating people with disabilities:** Participants with disabilities raised concerns about whether a driverless vehicle could pick up someone with disabilities from their house. For instance, without assistance from a dedicated driver, it is difficult for people walking with canes, walkers, or wheelchairs to board the vehicles. Other participants also added that getting off the vehicles without assistance at the hospital would also be challenging.
- **Safety concerns:** Participants also expressed concerns about an AV not being able to respond to emergencies, such as reckless drivers on the road and interactions with trains or on-and-off ramps. Participants showed concerns about how the responsibility of driverless vehicles is defined in legal systems and whether riders are protected by the law

in the event of an accident. Only a few participants demonstrated enthusiastic acceptance of driverless on-demand transit. Some were willing to try it if human control could be assumed at any time.

Individual Level: Interviews Regarding Autonomous Public Transportation

Expectations

Attendant. Many participants mentioned that they would want an attendant in the autonomous bus. They expressed the need for assistance with mobility issues, such as preventing falls and providing support for individuals with wheelchairs or limited mobility. They also emphasized the importance of passenger safety, including seat belt usage and training the attendant in emergency services. Additionally, participants highlighted the significance of the attendant being familiar with the community and able to provide information on routes, schedules, and directions. Overall, the attendant should ensure passenger safety, offer assistance with mobility, and provide information about the community.

Reliability. The importance of reliable and timely public transportation services, particularly for older adults, was emphasized by the participants. They shared stories of individuals having to wait for hours after medical appointments, exposing themselves to illness and inconvenience. The need for reliability, convenience, and a timely schedule was highlighted, as it would prevent unnecessary waiting times and improve the overall experience. Participants suggested that a more dependable service would attract a wider range of users, including both older adults and younger individuals. By addressing these concerns and providing a reliable transportation option, more people would be inclined to utilize the service.

App. The mobile application for the self-driving public bus will provide real-time information on the bus's location and fixed route, offering convenience and peace of mind to older adults. Participants expressed enthusiasm for the app, considering it a valuable tool for planning their travel and reducing anxiety while waiting for the bus. The ability to track the bus's location and estimated arrival time was a significant selling point, allowing individuals to better manage their time and activities. Participants recognized the widespread use of apps in their daily life and expressed their willingness to embrace this technology for accessing transportation information. Despite some participants having limited experience with mobile applications, they expressed willingness to learn and utilize the app for its benefits.

Concerns

Safety is a top concern, especially for older adults considering self-driving buses. They expressed worries about passenger and pedestrian safety, as well as potential accidents involving other vehicles. Some participants questioned the lack of supervision in driverless buses, raising doubts about passenger safety. Some highlighted the potential danger to pedestrians in case of a steering failure or loss of control. They expressed concern about accidents and the impact on bystanders.

Several participants expressed concerns about the maturity of AV technology, emphasizing the need for extensive testing and worries about human errors in their development. They were skeptical about computers' ability to respond to threats as rapidly as humans and suggested incorporating emergency buttons for passengers to report potential dangers. While acknowledging the risk of computer malfunctions, they also mentioned technological advancements that can benefit individuals with disabilities.

Participants mentioned the interaction between autonomous buses and other vehicles on the highway, highlighting the challenge of assigning blame in case of accidents involving multiple vehicles. They worried about the presence of reckless drivers on the road, preferred traditional means of transportation, and expressed concerns about the co-existence between autonomous buses and other vehicles.

Overall, participants expressed concerns about safety, trust in technology, and the interaction between autonomous buses and other vehicles on the road.

Safety

Human-Centered Interactive Dashboard for Safety Data Collection and Analysis

Our dashboard (see Figure 8 in Appendix A) includes a trajectory display, selection tools, route length visualization, time nodes, and a bar graph combining time and road segments.

The Nolanville map (center) showcases the trajectory of our video recordings, represented by a purple line. Clicking on a specific trajectory segment opens a pop-up window displaying the corresponding narrative for that particular segment. Located in the top-left corner of the dashboard, the selection tool empowers users to choose one or multiple trajectories. This tool enables customization of the displayed data based on the specific trajectories of interest, allowing users to focus on the most relevant information for their analysis or exploration. The Route Length Display, situated at the top-right of the dashboard, dynamically calculates and presents the total length of the current route displayed on the screen. As users navigate through the map, the route length is automatically recalculated, providing real-time updates and ensuring accurate information regarding the length of the selected route. Time nodes, located at the bottom-right of the dashboard, allow users to access information based on the recording time. By selecting a corresponding road segment on the dashboard, users can retrieve relevant information that corresponds to the time of recording. Incorporating the time element with the road segments, a bar graph located in the right-middle of the dashboard visualizes the relationship between time and the attributes of the road network. Notably, it depicts the amount of green space captured in the video within the current view. In summary, the Human-Centered Interactive Dashboard streamlines Safety Data Collection and Analysis by providing a user-friendly interface, real-time data access, and customizable visualization options. It consolidates data from multiple sources, allowing interactive exploration and collaboration among stakeholders. The presented clear and actionable insights empower decision-makers to implement targeted safety measures and address potential risks proactively, resulting in improved safety outcomes. Moreover, data validation checks ensure the accuracy and integrity of the data throughout the process.

Perceived vs. Objective Safety Risks

Respondents were most concerned about risk near intersections, which was reported by 43.3% of the respondents. Road segments and POIs received a similar number of responses, making up 25.4% and 21.7% of the total sample. In Figure 9 (see Appendix A), high-risk locations determined by the participants are overlayed with the elevated crash risk zones. Huntsville received the most responses, with 123 locations reported by participants, making up 30.2% of the total, followed by Nolanville (87, 21.7%), Harker Heights (86, 21.2%), Copperas Cove (67, 16.5%), Caldwell (31, 7.5%), and Madisonville (12, 2.9%). A total of 411 perceived risky locations were reported by 290 participants, mapped as red points in Figure 9.

Table 5 (see Appendix B) presents the descriptive statistics for crash rates in the six small towns. Among these towns, Caldwell stands out as having the most significant safety concerns, boasting the highest maximum crash rate of 50,783.3 and the highest mean crash rate of 948.4. In contrast, Harker Heights displays the lowest driving risks, with a maximum crash rate of 2,806.1 and a mean crash rate of 183.9. The remaining four cities exhibit similar crash risks, with mean crash rates ranging from 201.7 to 319.6.

Additionally, the smaller towns in terms of area, such as Caldwell, Nolanville, and Madisonville, exhibit a more pronounced dispersion in their zonal crash rates. Specifically, their standard deviation (SD) is considerably higher, ranging from 754.9 in Madisonville to 5,915.0 in Caldwell. This is in contrast to the relatively larger cities, including Huntsville (SD: 593.7), Copperas Cove (SD: 550.2), and Harker Heights (SD: 264.1). The top 20% of grids in the ranking of their crash rates were selected to represent the observed risk locations in each of the study cities, shown as pink hexagons in Figure 9 (see Appendix A).

Figure 10 (see Appendix A) clearly illustrates that perceived risk locations do not always spatially match up with observed risk locations, and are likely dependent on local conditions. Figure 10 in Appendix A shows the overall and city-level matched and unmatched percentages between perceived and observed risk locations. The overall percentage of matched locations is 56.2% (Matched = 228, Unmatched = 178), which aligns with existing findings that identifying crash sites based on perception is difficult (*68*). Among the six selected cities, Huntsville received the highest percentage (82.1%) of matched locations, and Nolanville received the lowest percentage of matched locations (31.0%). It implies that the spatial relations between perceived and observed risk locations are not spatially consistent, which could be impacted by regional sociodemographic and built environmental factors.

Table 6 in Appendix B presents the odds ratios (ORs) and coefficients derived from the binary logistic model, distinguishing between "matched" and "unmatched" perceived risk locations. Several explanatory variables from each category were found to be statistically significant ($p < 0.05$). Perceived high traffic volume ($p = 0.037$) and perceived location type, specifically intersections ($p = 0.002$), emerged as important factors, albeit with different directional influences. Perceived traffic volume decreased the odds (OR = 0.52) of a successful match between perceived and observed risk locations, whereas the odds (OR = 3.28) increased when perceived locations were intersections. Regarding personal characteristics, being involved in a recent traffic crash reduced the odds of a successful match ($p = 0.038$, OR = 0.40), while the odds of a match improved with an increase in the number of household cars ($p = 0.031$, OR = 5.09).

The model outcomes also provided evidence that roadway and neighborhood factors influenced traffic risk match rates. Among the roadway factors, traffic exposure showed statistical significance ($p < 0.001$). With each one-unit increase in a person's traffic exposure, the odds of a successful match decreased by 0.08. Although only marginally significant ($p < 0.10$, OR = 3.19), road density had a positive impact on successful match rates. The neighborhood factor of employment and household entropy displayed strong positive influence with statistical significance ($p < 0.001$), as each unit increase increased the odds of a successful match by a factor of 49.88. Gross population density also exhibited a positive and significant effect ($p < 0.001$), with the match odds increasing by a factor of 1.62 for each unit increase. Walkability ($p = 0.032$, OR = 0.06), proportion of low-wage workers ($p = 0.005$, OR = 0.02), and proportion of two-plus car households ($p = 0.005$, OR = 0.05) had statistically significant, albeit negative, effects on the spatial alignment between observed and perceived risk locations.

Discussion

Our Results from Small Towns vs. Nationwide Studies

We observed several significant differences between our results and nationwide studies regarding the perceptions of AVs. First, the level of enthusiasm for AVs among rural residents of Texas seems much higher than their national counterparts, i.e., 76% vs. 40% (*9*). This could be due to the predominant, automobile-centric nature of small cities in Texas. Having very limited public transportation services, participants in our study area would find themselves more dependent on automobiles than those from the national sample (*69*). Correspondingly, our participants were more enthusiastic about automobile-related technological advancements. At the same time, our participants are slightly more worried about AVs than others in previous studies, i.e., 65% vs. 53% (*9*). This result shows that the idea of a future with AVs as a transportation option has already trickled down from large metropolitan areas to small and rural communities. It is also indicative of the awareness of people from small and rural communities of driverless technologies and beckons to a future where people from such areas will have their transportation needs fulfilled by AVs.

Furthermore, participants of 65+ years are the most enthusiastic and less worried about AVs. This finding warrants attention as the existing literature shows that older people are less enthusiastic and express wariness about the development of technology, including AVs (*9; 14; 15; 70*); for example, a recent Pew Research Center study revealed that 53% of people 50 years and older view AVs as not good for society and argue that these vehicles would increase traffic fatalities and injuries (*70*). Positive responses in our study can be attributed to the potential benefit of AVs to empower small-town older residents (*71*) with more independence. This is one of the major findings of this study and can have policy implications for the deployment of AVs in small towns.

Older people are often limited regarding travel options; if they cannot drive, they are dependent on others for their travel needs or on public transit. In the case of small and rural communities, the population is usually scarce and spread out, activity points are few and far between, and public transit service is mostly neither available nor viable. As such, older residents in these communities are often dependent on others for their travel needs. AVs present a unique and futuristic option to help these people to be more mobile and independent in their daily lives, which is reflected in their enthusiasm for AVs.

AV-enabled Microtransit for Small Towns

The results presented in this report demonstrate positive impacts of the ENDEAVRide pilot program on improving accessibility for older adults and people with disabilities. Currently, the City of Nolanville, in collaboration with ENDEAVR Institute and the Hill Country Transit District, is maintaining the service. Our pilot program has shown the viability of such a service model for small and rural towns, effectively meeting the local travel demand. However, it should be noted that the lack of transit stations at destinations poses a challenge, as Nolanville only has one FRT station located next to the train track, making it less accessible and less preferred by residents. Moreover, one notable success story from our services involves a participant who landed a new job after being transported to multiple job interviews, which were previously inaccessible to her. During the focus group meetings and individual interviews, significant concerns were raised regarding the safety and operation of driverless on-demand transit. These findings align with previous research on the perception of driverless vehicles. However, our results contribute to the field by specifically addressing the responses of older adults and people with disabilities towards driverless vehicle services integrated with smartphone applications.

Safety Implications

To ensure that the future deployment of small-town AV programs lead to desirable safety outcomes, we need to keep in mind the significant factors affecting traffic safety and the match between perceived and objective safety measures. Roadway intersections had high match rates, consistent with previous studies. However, heavy traffic volume reduced successful matches. Respondents in rural communities did not perceive increased VMT as hazardous, despite actual crashes. Exposure to traffic incidents decreased successful matches, indicating higher risk-taking among those involved in accidents due to the transportation environment.

While planning for the deployment of AV programs for small-town America, policy makers need to develop targeted safety education programs for residents to enhance their ability to recognize hazardous scenarios. The number of household cars was significantly related to match rates, reflecting the association between car accessibility, driving experience, and detecting dangerous transportation environments. High-income neighborhoods lacked dangerous traffic scenarios, leading to misaligned risk perception. Interventions should prioritize low-income neighborhoods with fewer cars, such as implementing Complete Streets Policies to reduce accidents and improve public health. Neighborhood vitality factors like employment, household entropy, and population density increased traffic risk match rates, indicating heightened risk awareness. Planners should model these neighborhoods to reduce accidents in areas with confusing risk levels. Low-wage employment neighborhoods showed misalignment in traffic risk, suggesting economically disadvantaged commercial districts with sparse population density. Interventions could include site-specific road safety messages for employers and through-travelers.

Conclusions and Recommendations

This report has documented evidence about how AVs are perceived in small-town America and their implications for mobility and safety. Overall, study participants agreed with AVs' stated impacts such as increased independence for older people and individuals with disabilities, potential job loss for those who drive professionally, and the need for safety drivers onboard. This positive reception is significant as it reflects views from disadvantaged populations with limited transportation options. Surprisingly, older people in the study communities showed enthusiasm for AVs, contrary to previous research. These insights shed light on AV acceptance in small and rural communities and emphasize the need for further research, policy innovations, and engineering solutions to effectively implement AVs in these areas. AVs have the potential to enhance mobility, accessibility, affordability, and public transit in these communities, while also promoting equity and reducing traffic congestion.

To better understand AVs' safety implications, we developed GIS-based instruments to measure and compare perceived traffic safety risk locations with observed traffic risks in Texas small towns. We found that perceived risk locations do not always align with high crash rates, suggesting unreported traffic events in certain regions. Personal factors such as having a valid driving license and recent crash involvement influenced individuals' sensitivity to perceived crash-intensive areas. Additionally, the built environment factors, including density, diversity, walkability, and location efficiency, influenced the alignment between perceived and observed risk locations. Our binary logistic regression model could determine whether a perceived risk location matches the observed risk locations with high accuracy, demonstrating the potential of perception data for road safety assessments. Our human-centered transportation dashboard for small towns, developed using heterogeneous datasets and AI techniques, offers enhanced road information, navigation tools, and visualizations, empowering transportation managers to make informed decisions. It showcases the potential of AI and video data in developing interactive transportation dashboards for small towns and paves the way for future research in this field. It holds promise for optimizing traffic management, reducing accidents, and improving transportation efficiency, contributing to safer and more efficient transportation systems in small towns.

Small and rural communities, including suburbs, have experienced an increase in population as more people adapt to flexible and remote work arrangements. This trend has led individuals to seek refuge from the busy urban environment, opting for quieter and more affordable small communities. Innovative programs like ENDEAVRide could contribute to sustaining the small-town renaissance. This pilot program was supported mainly by local funding, volunteers, and private donations. Its significant impacts on participants' travel and accessibility to essential services are encouraging evidence that emerging technologies such as AVs could lead to affordable mobility solutions for small towns. The program's positive impacts on and acceptance by residents are built upon strong partnerships among local stakeholders, nonprofits, and the industry.

Additional Products

Education and Workforce Development Products

This project has supported three doctoral students' dissertation research and two master's students' Professional Paper research.

Technology Transfer Products

Our webinar, titled *Autonomous Vehicles for Small Towns: System, Service, and Safety from Research to Practice* is available at https://youtu.be/UleRRjK_vIc. This project fosters the adoption of open-source technologies for self-driving and telemedicine. These technologies can potentially be sustained over the long term by a community of developers and users.

In this YouTube Channel, we publish videos that document various aspects of our initiatives, mainly featuring our volunteers:

https://www.youtube.com/channel/UC5UWZZWpCxK1AJqoXinbHFA.

This LinkedIn Page promotes awareness of using technologies to serve small, rural communities: https://www.linkedin.com/company/endeavr-institute/.

This is the website: www.endeavr.city.

Data Products

Data from our survey and safety analysis will be made available at Safe-D Dataverse.

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Appendix A: Figures

Figure 1. Map. 500-ft by 500-ft grid system.

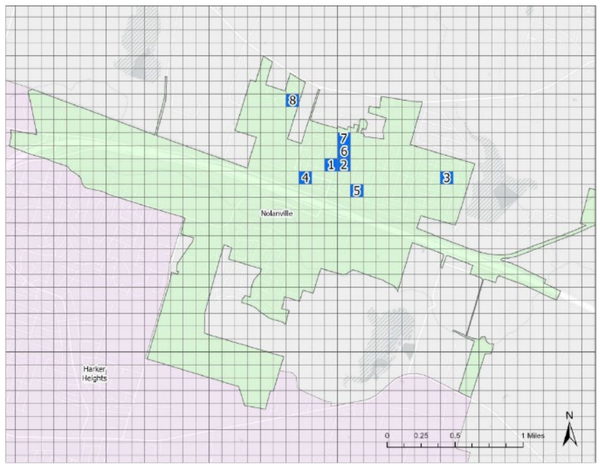


Figure 2. Diagram. Traffic safety risk analysis.

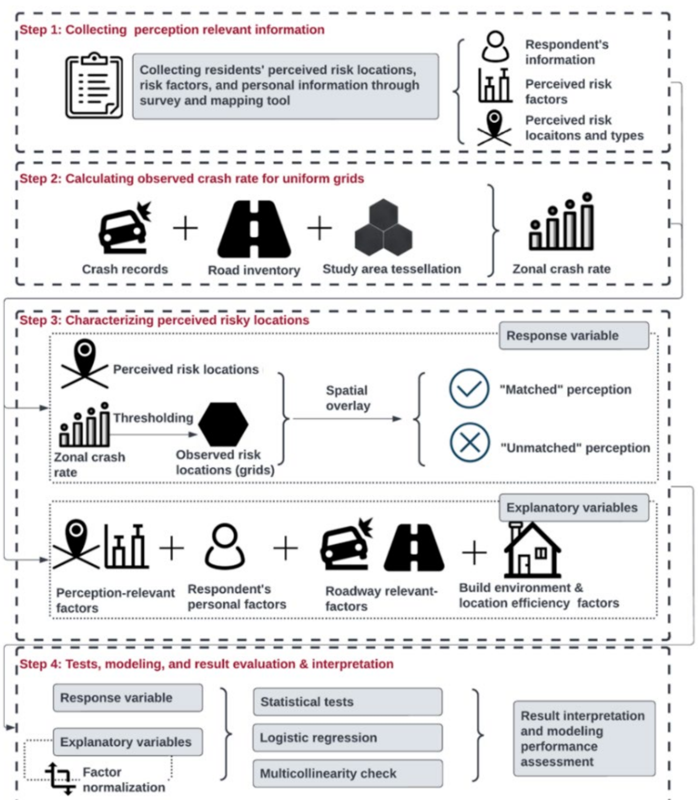


Figure 3. Screen capture. Participants report traffic safety risks using Maptionnaire.

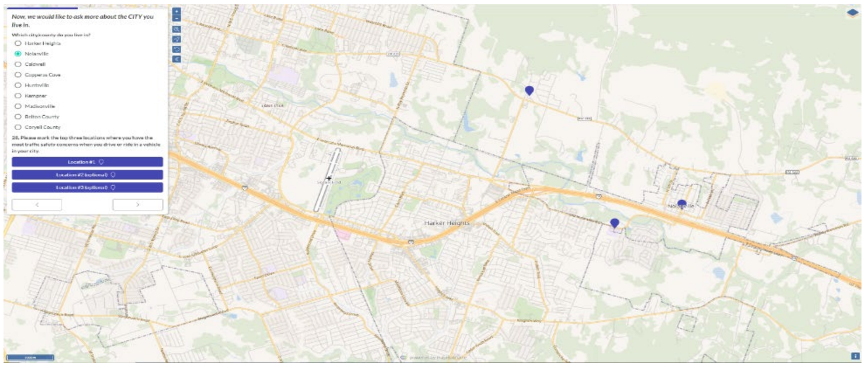


Figure 4. Chart. Overall knowledge of AVs.

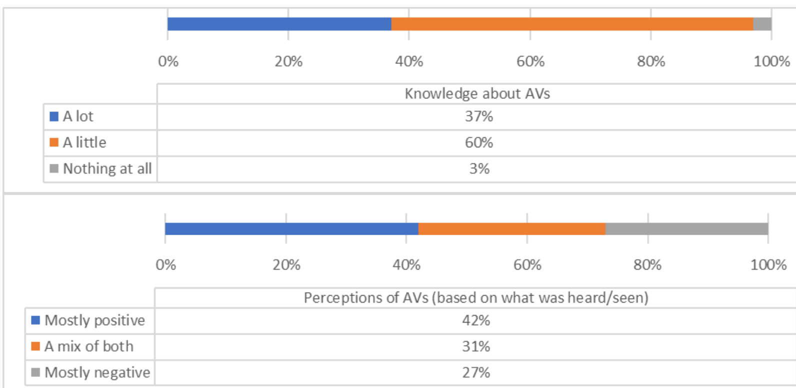


Figure 5. Chart. Enthusiasm and worry about the development of AVs.

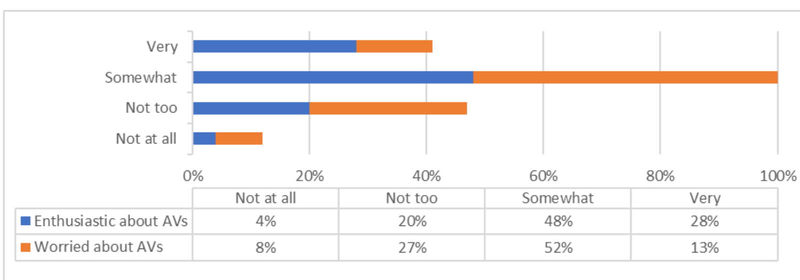


Figure 6. Chart. Perceived societal impacts of AVs.

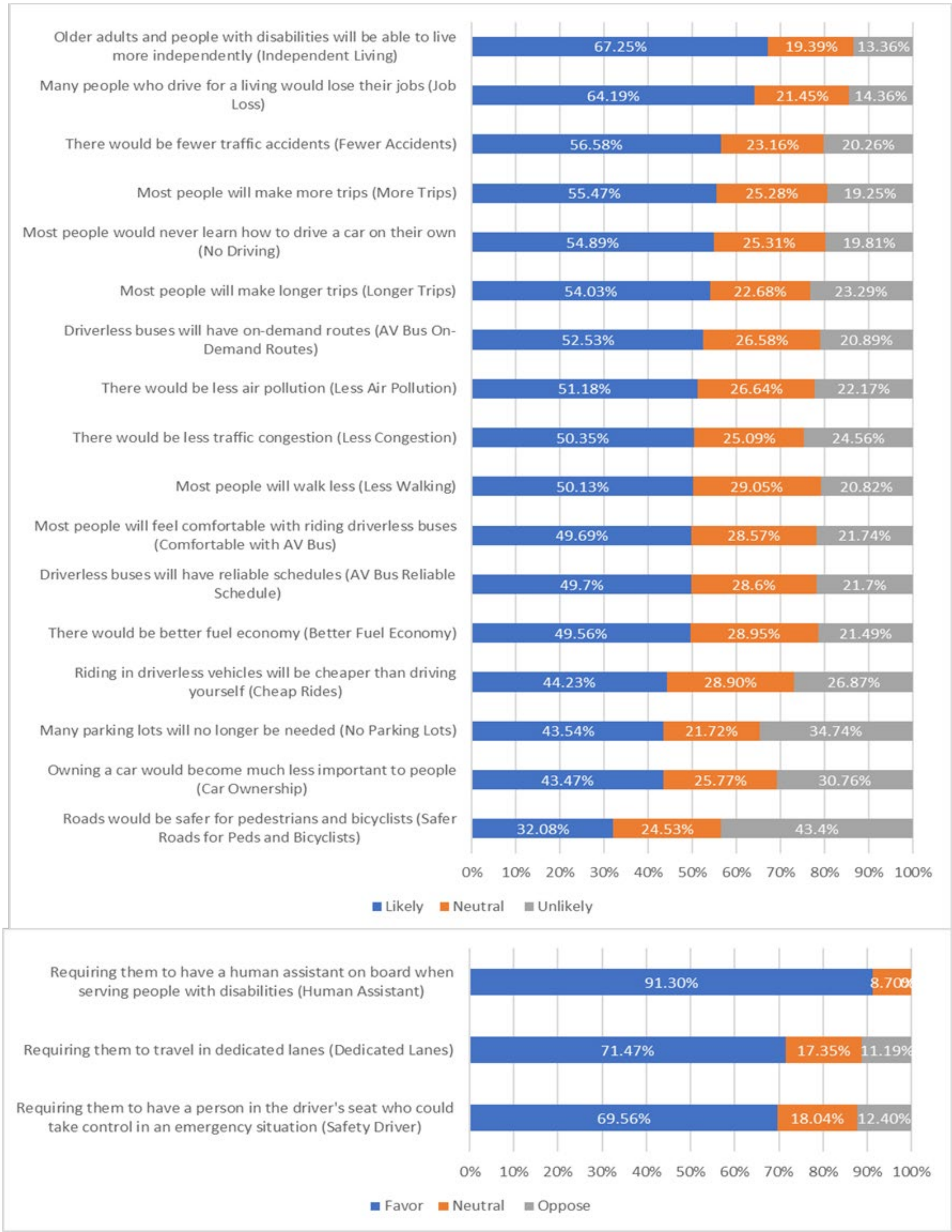


Figure 7. Map. Original-destination pattern of ENDEAVRide trips.

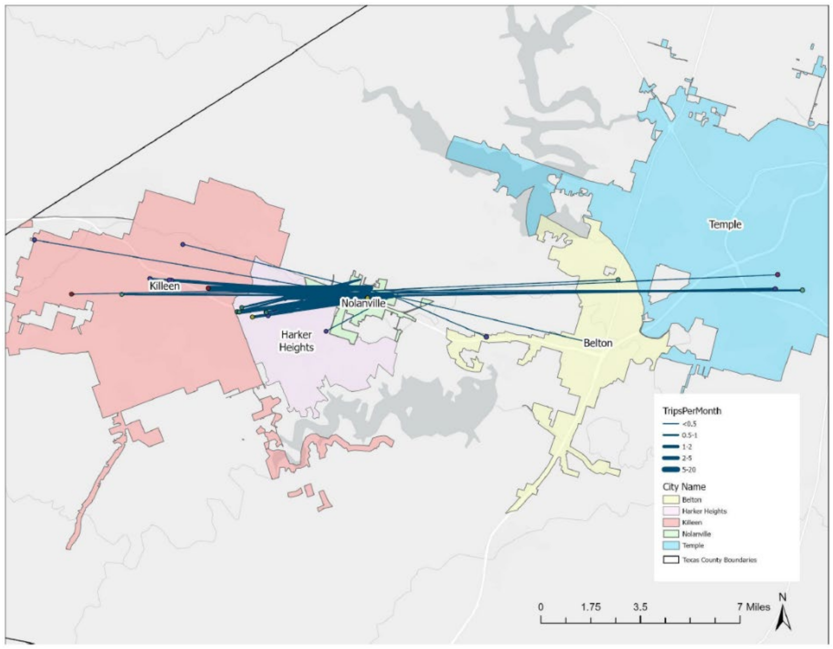


Figure 8. Screen capture. Human-centered interactive dashboard for safety data collection and analysis.

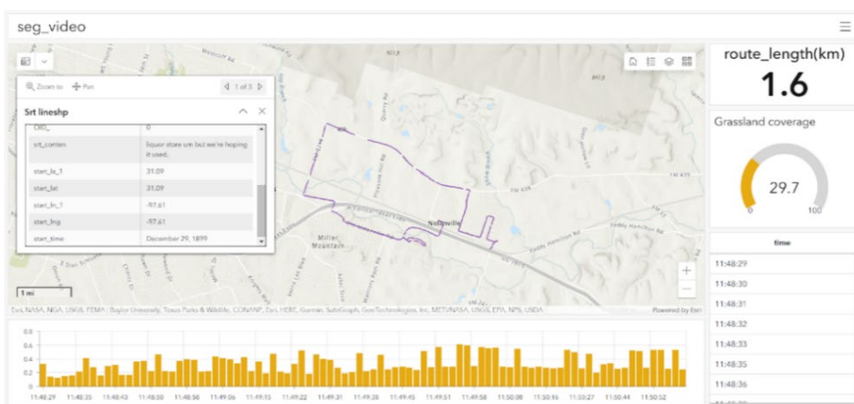


Figure 9. Map. Perceived vs. objective safety risk locations.

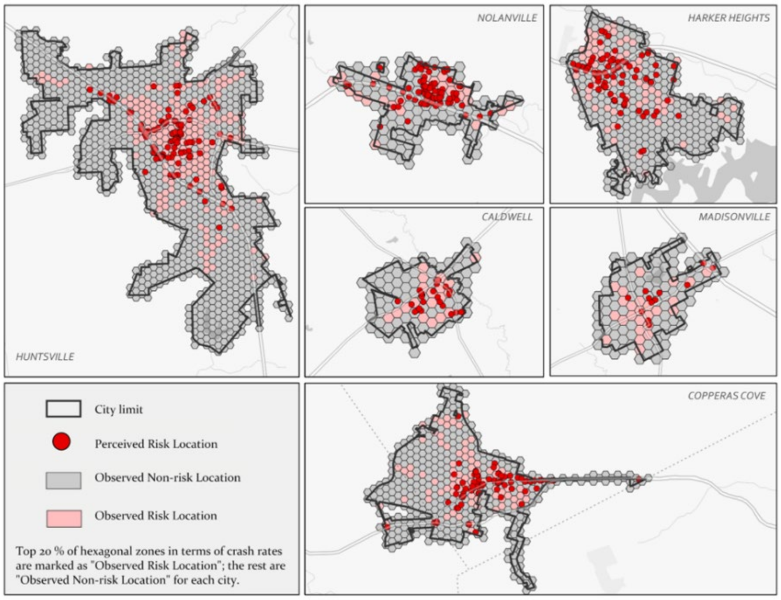
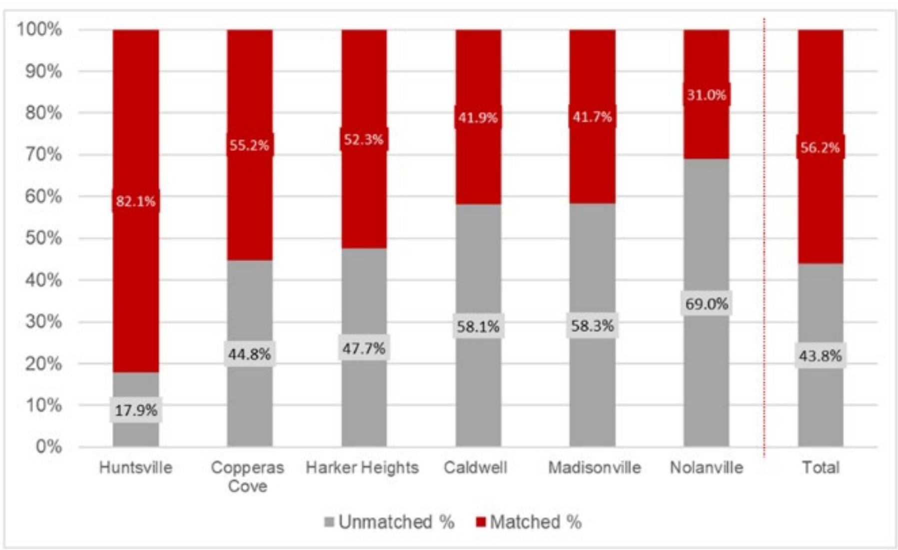


Figure 10. Chart. Matched and unmatched safety risk locations.



Appendix B: Tables

Table 1. General Perceptions Questions about AVs

Question	Response Scale
How much have you seen or heard about Autonomous Vehicles – that is, cars, trucks, and buses that can operate on their own without a human driver?	Nothing at all, a little, a lot
Has what you've seen or heard about Autonomous Vehicles been mostly positive, mostly negative, or a mix of both?	Mostly negative, a mix of both, mostly positive
How enthusiastic are you, if at all, about the development of Autonomous Vehicles?	Not at all, not too, somewhat, very
How worried are you, if at all, about the development of Autonomous Vehicles?	Not at all, not too, somewhat, very
How long, if ever, do you think it will take for most of the vehicles on the road to be driverless, rather than driven by humans?	Less than 10 years, 10 to less than 50 years, 50 to less than 100 years, 100 years or more, it will never happen

Table 2. Summary of Trip Data

Block #	Total Trips	Trips Per Month
Block 1	4	1.25
Block 2	20	3.21
Block 3	78	12.51
Block 4	128	20.53
Block 5	8	1.28
Block 6	14	2.25
Block 7	98	15.72
Block 8	16	2.57
Total	**366**	**59.32**

Table 3. Average ENDEAVRide Trip Count by Purpose

Destination	Trips Per Month
Health Care	41.6948
Grocery Store	6.4004
Retail	3.2087
Services	2.2462
Other	1.2835

Table 3. Average Weekly Trip Counts Per Person by Destination

Destinations	Pre-Intervention Weekly Trip Count	During-Intervention Weekly Trip Count	Change
Church	2.30	2.90	+0.60
Hospital & Clinic	0.30	0.48	+0.18
Work	1.40	1.80	+0.40
Grocery Store	2.70	3.35	+0.65
Restaurant & Bar	5.50	6.55	+1.05
Shopping Center	0.40	0.43	+0.03
Residential Community	1.70	2.10	+0.40
Gas	2.90	3.60	+0.70
Autoshop	0.10	0.08	-0.02
Park	0.40	0.38	-0.02
Unidentified	3.20	2.88	-0.32

Table 4. Descriptive Statistics of Crash Rates in Six Small Towns

City name	Maximum	Minimum	Mean	SD
Caldwell	50,783.3	0.0	948.4	5,915.0
Copperas Cove	4.671.7	0.0	319.6	550.2
Harker Heights	2,806.1	0.0	183.9	264.1
Huntsville	10,301.1	0.0	201.7	593.7
Madisonville	6,773.8	0.0	276.5	754.9
Nolanville	8,329.7	0.0	282.6	1,093.7

Table 5. Logistic regression results for predicting travel risk perception.

Explanatory variables	(β)	OR (95% CI)	p-value
Perception relevant factors			
Perceived heavy traffic volume			
Ture (reference = False)	**-0.65**	**0.52 (0.28-0.96)**	**0.037***
Perceived location type			
Intersection (reference = POI)	**1.19**	**3.28 (1.56-6.91)**	**0.002****
Road (reference = POI)	-0.23	0.8 (0.36-1.79)	0.583
Neighborhood (reference = POI)	-0.64	0.53 (0.19-1.50)	0.230
Respondent's personal attributes			
With a valid driving license			
Yes (reference = No)	-0.75	0.47 (0.18-1.22)	0.123
Involved in crash in past two years			
Yes (reference = No)	**-0.92**	**0.4 (0.17-0.95)**	**0.038***
Retired			
Yes (reference = No)	-0.56	0.57 (0.27-1.19)	0.136
Total household income			
Under $50k (reference = Unwilling to response)	-0.16	0.86 (0.3-2.43)	0.770
$50k-$100k (reference = Unwilling to response)	-0.89	0.41 (0.14-1.18)	0.097
Over $100k (reference = Unwilling to response)	-0.71	0.49 (0.17-1.45)	0.198
Number of cars within your household	**1.62**	**5.09 (1.16-22.38)**	**0.031***
Roadway factors			
Road density (mile/square mile)	1.16	3.19 (0.89-11.44)	0.074
Traffic exposure	**-2.48**	**0.08 (0.02-0.31)**	**0.000*****
Built environment and location efficiency factors			
SLC score	-1.24	0.29 (0.04-1.98)	0.206
National walkability index	**-2.90**	**0.06 (0-0.78)**	**0.032***
Percent of low wage workers	**-3.87**	**0.02 (0-0.31)**	**0.005****
Gross population density	**0.48**	**1.62 (1.31-2.00)**	**0.000*****
Employment and household entropy	**3.91**	**49.88 (5.08-489.68)**	**0.000*****
Percent of two-plus-car households	**-3.08**	**0.05 (0.01-0.40)**	**0.005****
Number of training samples (N) =325; Response variable 0: unmatched risk locations (N=150) & 1: matched risk locations (N=175) β = Estimated coefficients; OR = odds ratio, 95% confidence intervals (CI) in parentheses * p<0.05, ** p<0.01, *** p<0.001			