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Accelerating Adoption of Disruptive Technologies: Impact of COVID-19 on Intentions to Use On-Demand Autonomous Vehicle Mobility Services

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Abstract

One of the most notable global transportation trends is the accelerated pace of development in vehicle automation technologies. Uncertainty surrounds the future of automated mobility as there is no clear consensus on potential adoption patterns, ownership versus shared use status, and travel impacts. Adding to this uncertainty is the impact of the COVID-19 pandemic which has triggered profound changes in mobility behaviors as well as accelerated the adoption of new technologies at an unprecedented rate. Accordingly, this study examines the impact of the COVID-19 pandemic on people's intention to adopt the emerging technology of autonomous vehicles (AVs). Using data from a survey disseminated in June 2020 to 700 respondents in the United States, a difference-in-difference regression is performed to analyze the shift in willingness to use AVs as part of an on-demand mobility service before and during the pandemic. The results reveal that the COVID-19 pandemic had a positive and highly significant impact on the intention to use AVs. This shift is present regardless of tech-savviness, gender, or urban/rural household location. Results indicate that individuals who are younger, politically left-leaning, and frequent users of on-demand modes of travel are expected to be more likely to use AVs once offered. Understanding the systematic segment and attribute variation determining the increase in consideration of AVs is important for policy making, as these effects provide a guide to predicting adoption of AVs—once available—and to identify segments of the population likely to be more resistant to adopting AVs.

Keywords

data and data science, national and state transportation data and information systems, general, planning and analysis, sustainability and resilience, transportation and society, transportation and public health, transportation choices and behaviors

Autonomous vehicles (AVs) are vehicles capable of operating and performing necessary functions without human intervention (*1*). With full vehicle autonomy potentially a close reality (*2*), while acknowledging predictions that the technology may not be available until decades from now (*3–5*), it is increasingly important to understand AV adoption (*6*). It is hypothesized that AVs, like many of the ground-breaking technologies before it, will have significant benefits to society and the economy—as well as potential drawbacks (*6–8*). The ease of use of AVs and the expected benefits, however, do not necessarily ensure prompt large-scale adoption of the technology (*9*, *10*). Given the novelty of this technology, its potential safety implications, and mistrust in untested technologies, mass adoption may be slow and take years.

Adding to the uncertainty of future adoption patterns is the ongoing global COVID-19 pandemic, triggering massive changes in behavior. The pandemic has disrupted behavior in almost every facet of society and everyday life, from business to education, healthcare, and retail services (*11–13*). Most of these disruptions have been in the form of shifting activities from

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involving in-person interactions to reducing or removing these interactions altogether, such as shifting to telework or e-learning or ordering groceries online instead of visiting the grocery store. At the same time, the pandemic has been an accelerator of technological adoption. This paper hypothesizes that this acceleration in technology adoption is not only limited to current technologies, but could alter sentiments toward and consideration of future technologies, specifically AVs in this study. Additionally, concern about virus transmission could serve as a catalyst for increased preference for AVs, especially among users of on-demand modes of transport, by providing a transportation alternative that does not require a driver or any human interaction. An important unanswered question is whether or not the increased AV consideration triggered will remain in the post-COVID era, inviting important research on how future rates of AV adoption are shaped by the pandemic.

Therefore, the objective of this study is to assess the impact of the COVID-19 pandemic on intentions to adopt AVs, specifically as an on-demand mobility service. This study focuses on the *SAE Levels of Driving Automation*, where level 0 is no driving automation, level 1 is driver assistance, level 2 is partial driving automation, level 3 is conditional driving automation, level 4 is high driving automation, and level 5 is full driving automation (*1*). SAE levels 4 and 5 would be considered highly to fully autonomous and require no human intervention, whereas level 3 refers to conditional autonomy. This objective falls under two overarching goals. The first is to gain understanding of adoption of novel transportation technologies by analyzing the hypothetical willingness to use future automated modes of transport. The second goal is to deepen the understanding of the impact of major life disruptions on technology adoption. Here, this is analyzed by studying the role of the COVID-19 pandemic and related experiences on AV adoption. Along with Li and Liu (*14*), this is among the first works to investigate the impact of a global health pandemic on perceptions of automated transport. This study is the first, however, to do it in a U.S. context. This paper also extends the overall AV literature through observations and conclusions that may extend beyond the confines of the pandemic. Moreover, the paper also contributes insight on the shifts in technology adoption behaviors resulting from major life disruptions.

The remainder of this paper is organized as follows. The following section presents a brief literature review on technology adoption during COVID-19 and on adoption of AVs. Next, the data collection process is described and preliminary insights are provided. The fourth and fifth sections present the modeling results and discussion. Finally, the paper is concluded with remarks on limitations and future research.

Literature

In March 2020, the World Health Organization declared the spread of COVID-19 a global pandemic (*15*). Being multiple times more contagious than seasonal influenza and having more severe symptoms and higher fatality rates (*16*, *17*), governments and cities around the world started mandating shelter-in-place orders as well as social distancing. These orders have had significant effects on lives and communities around the world, heavily restricting mobility (*18*) and economic activities (*19*) during the peaks of the pandemic.

These restrictions, as well as wariness toward the virus, resulted in rapid shifts in behaviors throughout multiple facets of everyday life, such as work, education, travel, and leisure. As a result of these new constraints and changes in consumer demand, technological innovations have emerged and been broadly adopted, including video-conferencing tools for telework, virtual performances in entertainment, grocery delivery services, telehealth, and e-learning (*20–23*). For example, the COVID-19 pandemic forced many companies and employees to adapt to a remote work environment (*24*) and spurred a sharp increase in the use of technologies enabling virtual communication such as Zoom, Microsoft Teams, and Slack (*25*). The same is true in education as students and teachers of all ages transitioned to remote classrooms, thus adopting digital tools used to provide a mix of synchronous and asynchronous instruction including emails, video-conferencing, and learning management systems (*12*). In the healthcare sector, the pandemic led to the development and adoption of technology solutions providing safety through physical distance for patients and healthcare providers alike, including telehealth visits as well as robotics to perform tasks such as taking a patient's temperature or disinfecting rooms (*11*, *26*, *27*).

Fearfulness around contracting the virus as well as social distancing guidelines caused a drastic shift in mobility patterns during the pandemic (*18*), which brought about the constriction of activities requiring in-person interactions with non-household members and an increase in use of no-contact options. Consequently, consumers became familiar with and willing to adopt no-contact deliveries and curbside pick-up (*20*, *28*, *29*), as well as autonomous delivery vehicles for groceries, specifically sidewalk robots and mobile parcel lockers, as they were perceived to be safer because of the lack of a driver in the vehicle (*30*). Similarly, consumers preferred mobility modes that were perceived as having the lowest risk of exposure, namely a personal vehicle, walking, and biking as opposed to modes that were perceived as the riskiest: public transportation, taxi, and ridehailing (*18*, *31*, *32*).

A future possible no-contact alternative to these shared vehicle transportation options which were perceived to be more risky during the pandemic, particularly for individuals who do not own a personal vehicle, is the emerging technology of AVs, especially as part of an on-demand mobility service model. The public interest in AVs predates the potential benefits related to curtailing disease transmission. Despite many questions with regard to drawbacks of the technology (such as increased vehicle-miles traveled) as well as barriers to implementation and mass-market adoption (*6*, *7*), AVs are posited to have benefits ranging from safety to fuel-efficiency, congestion mitigation, and access to mobility for underserved and excluded groups (*7*, *8*). Nonetheless, the benefits of AVs will not be realized until the technology is adopted at sufficient scale (*33*).

The obstacles to prompt market penetration are highlighted throughout the literature of adoption of AVs, summarized in recent review articles including those by Alawadhi et al. (*34*) and Pigeon et al. (*35*). Studies have shown that trust in the technology is one of the most important factors affecting AV adoption (*36*, *37*). In a U.S. survey, 82% of respondents consider safety as the most important factor affecting their perception and adoption of AVs, while only 6% are more concerned with cost (*9*). Other factors include the context in which the AV use would take place, demographics (*38*), social influence (*39*) and perceived usefulness (*37*).

Recent work most closely related to the present study is that of Li and Liu (*14*). Using a sample of 1,087 Chinese participants across two cross-sectional stated-preference survey experiments, Li and Liu examined the influence of the COVID-19 pandemic on preferences toward autonomous taxis. In their first experiment, Li and Liu focused on the impact of the pandemic on the decision to use autonomous taxi as opposed to other modes. They found that, even when holding safety equal between traditional and autonomous taxis, a shift toward autonomous taxi is observed, making it a more popular choice than the conventional option. Respondents were allowed to choose from four modes: conventional taxi, autonomous taxi, public transport, and shared bike. More interestingly, when accounting for the improved safety offered by AVs, the increase was much larger, resulting in the choice of autonomous taxis surpassing even public transport. The second experiment assessed the shift in perception toward autonomous taxi compared with conventional taxi, revealing increased willingness to use autonomous taxi associated with the pandemic, as well as decreased fear and anxiety toward the mode.

In summary, a key takeaway from the literature is that the COVID-19 pandemic has precipitated the adoption of many new technologies. Although AVs are not yet fully operational, past studies have identified factors that contribute to AV adoption, of which one of the most important is risk perception. This study contributes insight about the role of the pandemic for AV adoption, whereas it has been hypothesized that COVID-19 concerns could increase interest or trust in AVs (*40*) and thus accelerate willingness to adopt them.

Survey Design and Data Collection

The data for this study were collected using a web survey designed on Qualtrics and disseminated through the Prolific respondent platform and completed by 700 respondents in the contiguous United States in early June 2020. Although online sampling can result in self-selection or coverage bias, specifically related to internet access (*41*), recent evidence indicates that online samples are more diverse and often comparable in quality to traditional survey samples (*42–44*).

Survey Design

The main purpose of the survey is to collect information and data on the shift in likelihood of adopting AVs as a result of the COVID-19 pandemic. The authors hypothesize that wariness toward in-person interactions is a catalyst for increased consideration of automated modes of travel that minimize exposure to other people. To capture this shift in likelihood, a difference-in-difference stated-preference experiment is designed. Given the role of in-person interactions—or lack thereof—during the COVID-19 pandemic, the experiment is anchored on on-demand modes of travel (ridehailing, such as Uber and Lyft, and taxi), where at least one unfamiliar person (the driver) is present in the vehicle. Using on-demand modes as benchmarks in the experiment is also more generalizable and relatable to respondents regardless of car-ownership status. Using on-demand modes removes deliberations specific to owning an AV and would allow for a more focused assessment of the sentiment toward the technology regardless of the complexities related to ownership, specifically financially. That is not to say that on-demand services do not entail their own set of challenging deliberations; however, they provide a lower barrier-to-entry than ownership and should be perceived by respondents as easier to access.

Before the experiment, the respondents were first presented with a simple definition of AVs, accompanied with the image shown in Figure 1: "Autonomous Vehicle: A vehicle in which human drivers are never required to take control to safely operate the vehicle. An autonomous vehicle can carry passengers [...] without requiring a driver." Terminology such as "ridehailing" was also explained to respondents before the experiment to ensure clarity and consistency.

Respondents were then asked the following two questions, on a hypothetical on-demand AV service, which form the basis of the difference-in-difference analysis:

1. "Assume that you need to make a trip for an essential purpose **DURING** the outbreak. How likely are you to request a ridehailing service that uses automated cars and has no driver or other passengers in the vehicle?"
2. "Assume that you needed to make a trip for an essential purpose **BEFORE** the outbreak. How likely would you have been to request a ridehailing service that uses automated cars and has no driver or other passengers in the vehicle?"

The responses are measured on a five-point Likert scale ranging from "very unlikely" (1), through "neither likely nor unlikely" (3), to "very likely" (5). A five-point scale was used in place of a seven-point option to prevent respondent fatigue (*46*) given that the experiment was part of a larger survey.

Using on-demand services as control modes, respondents were also asked the following on a similar five-point Likert scale,

3. "Assume that you need to make a trip for an essential purpose **DURING** the outbreak. How likely are you to request a typical ridehailing service (such as Uber or Lyft) or taxi service?"
4. "Assume that you needed to make a trip for an essential purpose **BEFORE** the outbreak. How likely were you to request a typical ridehailing service (such as Uber or Lyft) or taxi service?"

Figure 1. Image of an automated vehicle (Waymo) provided to respondents in the survey (*45*) (CC BY-SA 4.0).

For the purposes of this experiment, both ridehailing and taxi are suitable control modes (*47*) and are used in conjunction to keep the experiment as relatable as possible to most respondents, specifically across different age groups.

Assuming a counterfactual that the only significant difference between conventional and AV on-demand services is the lack of a human driver, it is possible to accurately measure the effect of COVID-19 on the intention to use on-demand AVs while controlling for unobserved mode-specific attributes. It is important to point out that these questions emphasize trips made for essential purposes, as this distinction is likely to influence responses and have an effect on the model presented in later sections of the paper. The survey does not specify what essential purpose trips are, leaving this up to respondents to define according to their lifestyles and state guidelines at the time of the survey (*48*).

In addition to the latter experiment, the survey consists of three other sections relevant to this study. The first section asked respondents about COVID-19 factors, covering their status as essential worker, the extent to which the pandemic affected their lives, whether someone in their household has been laid-off, quarantined, or hospitalized in this period, and the duration that their household has been under stay-at-home order, if at all.

The next section collected information on the respondents' latent attitudes toward technology. Respondents were presented with indicator statements such as, "Technology is changing society for the better" and "I am excited to learn about new technologies in the market," then asked to rate these statements on a five-point Likert scale ranging from "strongly disagree" (1), through "neither agree nor disagree" (3), to "strongly agree" (5).

Finally, respondents were presented with questions related to their socioeconomic status and demographics, such as gender, age, ethnicity, employment status, education, household size, and income.

Sample Description and Statistics

To ensure data quality, a respondent screening was applied in Prolific (prolific.co) to only include participants with a high acceptance score (*49*). Furthermore, careful examination of response quality in the final sample was carried out. Out of 700 responses, one response was removed for missing critical data, was response is removed for being outside the contiguous United States (Hawaii), and seven responses were removed for being low-quality (straightlining, extreme hastiness, etc.), resulting in 691 usable data points. Looking at the usable data, responses have been collected from 46 out of 48 states within the contiguous United States as well as

Table 1. Sample Statistics

Statistics†	Sample (responses)	Sample (%)	U.S. population/other sources* (%)
State			
California	110	15.9	12.0
Texas	55	7.9	8.3
New York	52	7.5	6.2
Florida	46	6.6	6.7
Gender			
Male	346	50.1	48.7
Female	331	47.9	51.3
Non-binary	14	2.0	—
Age			
18–24 years	207	30.0	12.2
25–34 years	229	33.1	17.9
35–44 years	136	19.7	16.3
45–54 years	56	8.1	16.7
55–64 years	39	5.6	16.6
65 years or older	24	3.5	20.2
Political leaning			
Democrat	406	60.0	56.1
Republican	98	14.5	41.5
Independent/no preference	155	22.9	1.3
Other (progressive, liberal, libertarian, ...)	18	2.6	1.1
Income			
<$25,000	112	16.6	14.4
$25,000–$49,999	156	23.1	19.6
$50,000–$99,999	254	37.7	32.0
$100,000–$149,999	97	14.4	17.3
⩾$150,000	55	8.2	16.7

†Non-responses per category: state = 0, gender = 14, age = 0, political leaning = 14, income = 17.
*Sources: U.S. Census (*50*): state, gender, age, and income; Pew Research 2018 Sample (*51*): political leaning.

Washington, D.C. The number of responses from the four most represented states and other sample statistics are shown in Table 1. The two unrepresented states, Vermont and Wyoming, are the least populated states, with 0.2% of the adult population each.

Looking at the age distribution, the sample leans toward adults under the age of 45, with mean and median age of 33.4 and 30 years, respectively, resulting in a sample leaning toward younger adults. Politically, the sample is Democrat leaning. Excluding respondents who preferred not to answer and other responses, 60.0% of the sample lean Democrat, 14.5% lean Republican, and 22.9% consider their political views as independent or have no preference. While data have been collected in a slightly different manner, according to samples surveyed by Pew Research in 2020 (*51*), these percentages were 56.1%, 41.5%, and 1.3% respectively. This bias toward left-leaning partisanship is not, however, attributed to the higher response rates from states that tend to vote Democrat in recent elections, an observation confirmed by simulating elections using the sample distribution and election data (*52*). Instead, this bias is likely the result of self-selection in non-random online surveys (*53–55*). Finally, the average and median income for the sample are $72,100 and $62,500 annually, compared with $88,600 and $62,800 in the 2019 five-year American Community Survey (*56*). Accounting for household size, the average and median annual household income for the sample were approximately $29,300 and $21,900 annually per household member, respectively. Additional modeling summary statistics are provided in Table A1 in the appendix (see Supplemental Materials online).

As for the response patterns of the likelihood of using typical on-demand services before and during the COVID pandemic, the average response score shifts from 2.81 (closest to the scale midpoint of "neither likely nor unlikely") to 2.18 (closest to "unlikely") respectively. In other words, on average, a decrease in the stated likelihood to use on-demand modes is observed during the pandemic (Mann–Whitney–Wilcoxon test: $p < 0.001$). As shown in Figure 2, 42.1% of respondents claim a decrease in their likelihood of using on-demand services because of COVID. The largest share of respondents (48.5%) remain at pre-COVID levels. This result can be compared with the analysis in Batool et al. (*57*) who found that the transportation and accommodation sectors are the sharing economy sectors most negatively affected by the pandemic.

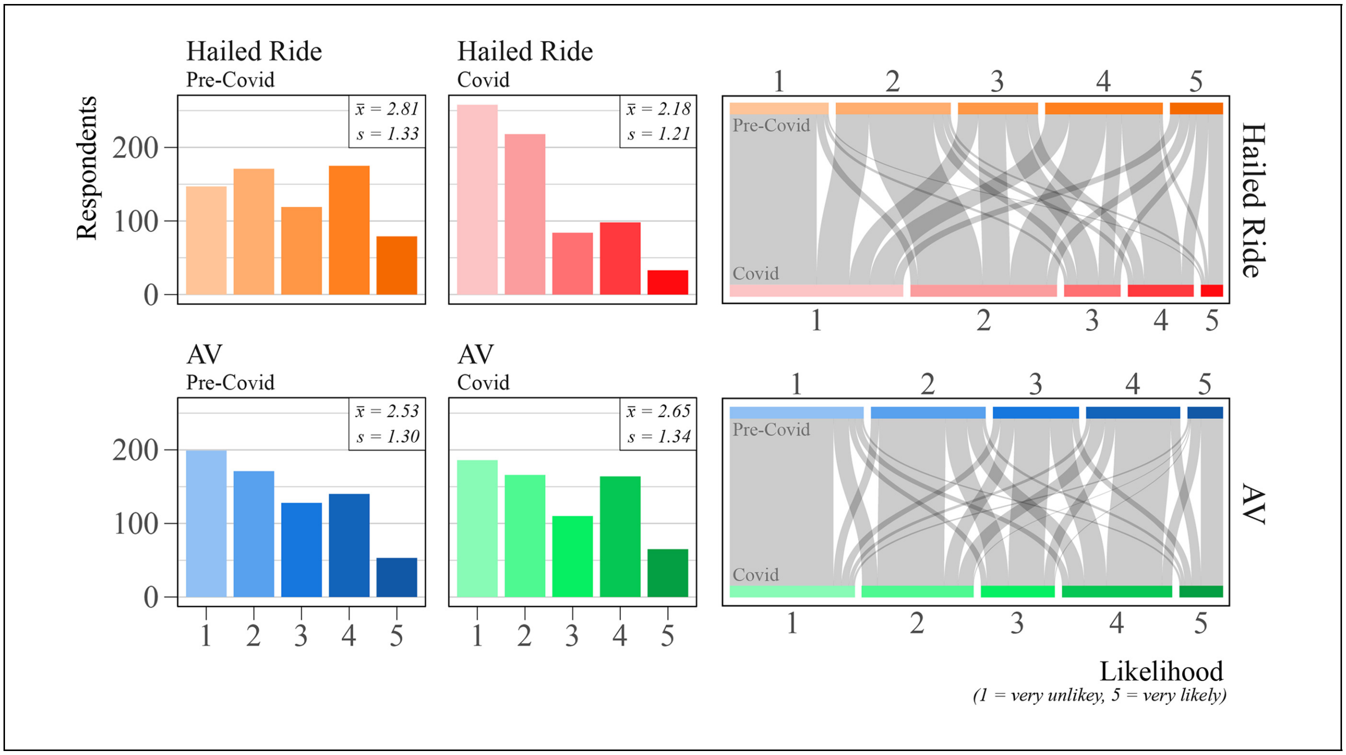

Figure 2. Response distributions (left) and flow diagrams (right) for likelihood of using conventional ("Hailed Ride") and autonomous (AV) on-demand services before and during the COVID-19 pandemic.

Table 2. Mean and Standard Deviation for Attitudinal Construct Indicators

Indicator: Attitude toward technology	Mean	Standard deviation
Technology is changing society for the better.	3.89	0.78
I am excited to learn about new technologies in the market.	4.16	0.82
I pay more to get more technologically advanced products.	3.33	1.06
I use the internet daily for chatting and entertainment.	4.56	0.70

Note: Scores from five-point Likert scale: 1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree.

For the hypothetical AV ridehailing service, the average response score increases from 2.53 (between "unlikely" and "neither likely or unlikely") to 2.65 (closer to "neither likely or unlikely"). Nonetheless, this difference is not statistically significant, with a Mann-Whitney-Wilcoxon Test p-value of 0.125. This can be observed visually in Figure 2 through the small shifts in likelihood of using the hypothetical AV service as a result of COVID. Indeed, 61.1% of respondents believe that their likelihood of using this service would remain unaffected by COVID-19. Yet, 23.4% claim an increase in likelihood of using AV ridehailing as a result of the pandemic, versus 15.5% claiming a decrease in likelihood.

Statistics for the attitudinal indicators are provided in Table 2.

Effect of COVID-19 on Willingness to Use AVs

Difference-in-difference regression allows for capturing the impact of a treatment or intervention on a target group with respect to a control group through systematic comparison of observed outcomes (cf. Batool et al. [*57*]). The goal of a difference-in-difference regression is to estimate the isolated treatment effect of a natural non-experimental intervention while eliminating unobserved biases that may be present between groups. Without other covariates, a generic difference-in-difference regression is formulated as,

$$y_{imt} = \beta_0 + \beta_1 Target_{im} + \beta_2 Treated_{it} + \beta_3 (Target_{im} \times Treated_{it}) + \epsilon_{imt} \quad (1)$$

where y_{imt} is an observed outcome for individual i in group m given treatment t. $Target_{im}$ is a dummy variable equal to 1 if the outcome corresponds to the target group and 0 otherwise. $Treated_{it}$ is a dummy variable equal to 1 if the outcome corresponds to an observation that has received the treatment and 0 otherwise. $(Target_{im} \times Treated_{it})$ is a binary term equal to the product of the latter two dummy variables, and ε_{imt} is the error term. Here, the *treatment effect* is calculated via the estimated parameter β_3.

In the same vein, a difference-in-difference regression model is estimated to calculate the shift in intention to use *AV services* (target group) as a result of the *COVID-19 pandemic* (treatment) while controlling for unobserved mode-specific attributes. Assuming the only key difference between conventional and automated on-demand services is the lack of a driver, *traditional on-demand services* (ridehailing and taxi) are used as a control group in this model. This assumption entails that *Parallel Trends* holds true (i.e., in the absence of treatment, the difference in likelihood of using traditional and AV on-demand services remains constant across time). Accordingly, the difference-in-difference model is initially formulated as follows,

$$\begin{aligned} LL_{imt} = {} & \beta_0 + \beta_1 (Mode = AV)_{im} \\ & + \beta_2 (Time = COVID)_{it} \\ & + \beta_3 ((Mode = AV)_{im} \times (Time = COVID)_{it}) \\ & + \epsilon_{imt} \end{aligned} \tag{2}$$

where LL_{imt} is the observed likelihood of individual i using mode m at time t. $(Mode = AV)_{im}$ is a dummy variable equal to 1 if the mode is AV and 0 otherwise. $(Time = COVID)_{it}$ is a dummy variable equal to 1 if time is *during the COVID pandemic* and 0 otherwise, and ε_{imt} is the error term.

Including covariates such as gender, age, and income, the formulation is extended as,

$$\begin{aligned} LL_{imt} = {} & \beta_0 + \beta_1 (Mode = AV)_{im} \\ & + \beta_2 (Time = COVID)_{it} \\ & + \beta_3 ((Mode = AV)_{im} \times (Time = COVID)_{it}) \\ & + \sum_k \beta_k X_{ki} + \epsilon_{imt} \end{aligned} \tag{3}$$

where each β_k denotes a coefficient for socioeconomic and choice attributes and X_{ki} is a set of respondent-specific covariates. For a more detailed treatment of difference-in-difference models, the reader is referred to Wing et al. (*58*).

Given that LL_{imt} is an ordinal measure, the difference-in-difference regression is estimated using an ordered logit regression model to appropriately account for the ranked nature of the dependent variable. In this form, instead of directly estimating LL_{imt}, the dependent variable is a continuous latent variable LL^*_{imt} defined through a censoring approach as follows,

$$LL_{imt} = \begin{cases} 1 & if \quad -\infty < LL^*_{imt} \leqslant \mu_1 \\ 2 & if \quad \mu_1 < LL^*_{imt} \leqslant \mu_2 \\ 3 & if \quad \mu_2 < LL^*_{imt} \leqslant \mu_3 \\ 4 & if \quad \mu_3 < LL^*_{imt} \leqslant \mu_4 \\ 5 & if \quad \mu_4 < LL^*_{imt} \leqslant \infty \end{cases} \tag{4}$$

where μ_1 to μ_4 are threshold parameters to be estimated. Note that, as a result, β coefficients are no longer interpreted as linear coefficients, but as log odds. For information on ordered regression modeling, the reader is referred to Greene and Hensher (*59*). The results are presented in Table 3 using robust standard errors clustered at the respondent level, a summary of model variable statistics is shown in the Table A1 in the appendix (see Supplemental Materials online).

Impact of the Pandemic on Consideration of AVs

The difference-in-difference coefficients are presented in Table 3. Looking at the coefficient for the mode (*mode = AV*), the model indicates that there is a general propensity among respondents away from AVs compared with traditional vehicles before the COVID-19 pandemic ($\beta = -0.441$, $p < 0.001$). Similarly, the time coefficient (*time = COVID*) indicates a decrease in consideration of on-demand services associated with COVID ($\beta = -0.978$, $p < 0.001$).

The parameter of interest here, capturing the impact of the COVID-19 pandemic on potential use of on-demand AVs, is the difference-in-difference (*treatment effect*). This effect is estimated to have a positive and highly significant effect ($\beta = +1.149$, $p < 0.001$), indicating a positive and significant impact of the COVID-19 pandemic on the intention to use AVs. Transformed to a linear term, the magnitude of this impact is equal to $+0.952$, roughly a full level on the likelihood scale used in this study. In other words, the impact of the pandemic on AV consideration is roughly the same as transitioning from being "neither likely nor unlikely" to use an AV for making an essential trip to being "likely" to do so. More interestingly though, returning to Figure 2, this finding is representative of the potential resilience of AV services in the context of a global health pandemic; intentions to use this mode remain relatively unchanged whereas conventional on-demand services instead experience a significant drop.

Control Covariates

As shown in Table 3, the difference-in-difference model is estimated along several other covariates. Although

Table 3. Ordered Difference-in-Difference Regression for Shift in Likelihood of Autonomous Vehicle Use Related to COVID-19

Model statistics: Number of Observations: 691 Adj. McFadden ρ^2: 0.064
Log-likelihood at zero: −4,245.17 AIC: 7,954.52
Final log-likelihood: −3,960.26 BIC: 8,055.23

Parameter	Coefficient	*t*-Value	*p*-Value
Difference-in-difference coefficients			
Mode = AV	−0.441***	−6.24	0.000
Mode is on-demand AV			
Time = COVID	−0.978***	−13.01	0.000
Time is during COVID pandemic			
Treatment effect	**1.149*****	**13.69**	**0.000**
Effect of COVID on intention to use on-demand AV			
Socioeconomic and demographics			
Male	0.187*	1.71	0.087
Gender is male			
Urban	0.212*	1.72	0.086
Urban household			
(Age −45) × (Age ⩾ 45)	−0.047***	−3.96	0.000
Age of respondent (in years); linear coefficient only for respondents 45 years or older			
AsianPacific	0.343***	2.76	0.006
Ethnicity is Asian or Pacific Islander			
Typical modes of travel			
PrivateMode	−0.457***	−2.98	0.003
Typical pre-pandemic mode of travel is private car or motorcycle			
On-demand	1.073***	8.26	0.000
Typical pre-pandemic mode of travel is taxi or ridehailing			
Political views			
Left-leaning	−0.397***	−3.32	0.001
Political view is left-leaning			
PolViewmissing	−0.115	−0.263	0.793
Political view is not reported			
Latent variable			
Tech-savviness	0.413***	5.93	0.000
Attitude toward technology			
Impact of COVID			
Quarantined	0.277**	2.12	0.034
One or more household members have been quarantined because of COVID-19			
Ordinal thresholds			
μ_1	−1.798***	−12.21	0.000
μ_2	−0.523***	−3.63	0.000
μ_3	0.281*	1.95	0.051
μ_4	1.985***	13.01	0.000

Note: With robust *t* and *p*-values; Treatment effect highlighted in bold.
***Significant at 0.01 level; **significant at 0.05 level; *significant at 0.10 level.

difference-in-difference models control for unobserved mode-specific attributes, the selected covariates control for user-specific attributes, specifically: gender, residential location, age, ethnicity, typical mode of travel, political views, tech-savviness, and major impacts of COVID on the respondent. The interpretation of the respective coefficients for these covariates, nonetheless, is somewhat ambiguous. Given that the dependent variable is a measure of likelihood without regard to mode or time, the latter coefficients measure the effect of a covariate on consideration of both conventional and AV on-demand modes, for both pre-COVID and during COVID. As a simplification, these coefficients can be considered as a general measure of the effect of these covariates on acceptability of on-demand mobility services, without accounting for autonomy or the pandemic. Given this built-in ambiguity in interpretation, this discussion is focused on a few select coefficients below, followed by a deeper analysis assessing the treatment effects on AV consideration by user-specific attributes.

Age. Preliminary inspections of the relationship between age and the dependent variable reveal a non-linear relationship, as shown in Figure 3. Accordingly, the covariate for age is included in the model as a piecewise

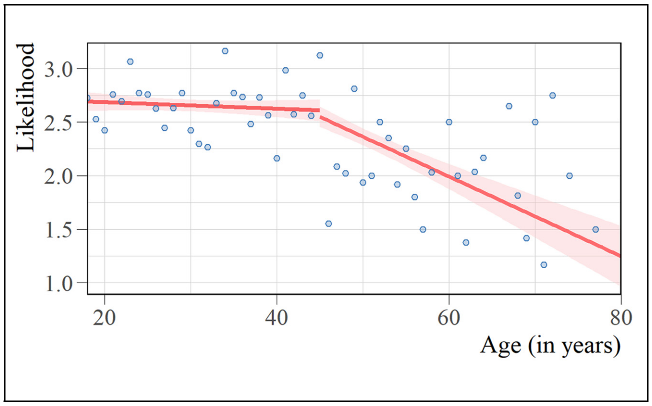

Figure 3. Piecewise relationship between consideration likelihood and age.

function, equal to zero below 45 years of age and increasing linearly above the age of 45. In other words, given a negative coefficient for this piecewise age function, respondents over 45 are increasingly less likely to consider on-demand modes of travel for essential purpose trips compared with younger individuals ($\beta = -0.047$, $p < 0.001$).

Typical Modes of Travel. The model also controls for respondents' self-reported (revealed) typical modes of pre-pandemic travel, which is likely to be a source of endogeneity in the experiment, especially for those who consider on-demand ride services as a typical mode of travel. Indeed, the coefficient for typical use of on-demand services ($\beta = +1.073$, $p < 0.001$) is positive and significant, controlling for the heightened preference toward on-demand modes by habitual users of these services. On the other hand, the model also finds evidence for a reduced preference among typical users of private vehicles ($\beta = -0.457$, $p = 0.003$).

Tech-Savviness and Attitudinal Constructs. Similar to the effect of being a typical user of on-demand ride services, it is hypothesized that having positive attitudes toward technology would result in higher consideration of on-demand services, whether traditional or autonomous, and higher consideration of new technologies, including autonomous cars. Accordingly, the latent construct tech-savviness is estimated using exploratory and confirmatory factor analyses as shown in Table 4. The construct is significantly measured by the four indicator statements ($p < 0.001$) in Table 4 with acceptable to good reliability according to the fit indices (RMSEA < 0.08, CFI > 0.95, TLI > 0.95) (*60–62*).

Estimated threshold parameters are omitted for brevity given that threshold parameters do not have a direct interpretation. Factor scores are calculated using the Empirical Bayes Modal method for each individual to be used serially in the regression model.

In line with the hypothesis, tech-savviness has a positive and significant coefficient ($\beta = +0.413$, $p < 0.001$), indicating an increased likelihood of using on-demand services for essential trips for respondents who are considered to be tech-savvy.

Threshold Parameters. Similar to the threshold parameters in the confirmatory factor analysis in Table 4, the threshold parameters in Table 3 are—for the most part—considered nuisance parameters with limited value for interpretation but rather necessary for estimation (*59*). Nonetheless, the thresholds are all significant, indicating clear separation between likelihood levels in the dependent variable.

Segmentation Analysis

The preceding section presented the difference-in-difference model results, showing that the COVID-19 pandemic had a significant effect on intentions to use on-demand AV services. Nonetheless, the model has an ambiguous interpretation of the effect of individual characteristics, such as gender or age, on the impact of COVID-19 on the future adoption of AVs. To assess these effects in a more direct and intuitive manner, a segmentation approach is used, whereby the main model is applied separately to different segments. The treatment effects from these segmented models are illustrated in Figure 4, controlling for the same covariates presented in Table 3. Results are presented with the 95% confidence intervals to facilitate comparison of effects.

As defined in the previous sections, the *treatment effect* illustrates the change in likelihood of using AVs as a result of the COVID-19 pandemic. Looking at Figure 4, the increase in intention as a result of the COVID-19 pandemic is positive and significant for most segments, with the exception of respondents aged 45 or above. For some features there is little distinction, suggesting that regardless of differences in tech-savviness, gender, or urban/rural household location, individuals are more likely to adopt AVs in the future. Instead, for several factors like age, typical travel mode, and political views, there are structural differences within the categories.

Looking at age, the treatment effect of COVID on AV consideration is declining with increasing age. While the magnitude of the treatment effect is 1.62 for respondents aged 18 to 24, it declines to 0.83 for respondents aged 35 to 44, and becomes insignificant for respondents older than 45. These results reveal that the increased propensity to adopt new technologies observed among younger individuals, a phenomenon which has been reported in several studies (*63*), remains true for AVs. This result is also

Table 4. Confirmatory Factor Analysis Model for Latent Attitudes

Robust Model Statistics: Chi-squared test statistic: 86.099 Comparative Fit Index (CFI): 0.972
Degrees of Freedom: 19 Tucker-Lewis Index (TLI): 0.958
Root Mean Square Error of Approximation (RMSEA): 0.072

Indicator: Tech-Savviness	Estimate	z-Value	p-Value
Technology is changing society for the better.	0.740***	27.28	0.000
I am excited to learn about new technologies in the market.	0.916***	43.81	0.000
I pay more to get more technologically advanced products.	0.694***	26.32	0.000
I use the internet daily for chatting and entertainment.	0.502***	12.29	0.000

Note: Ordinal threshold effects are estimated but omitted from the table for concision.
***Significant at 0.01 level.

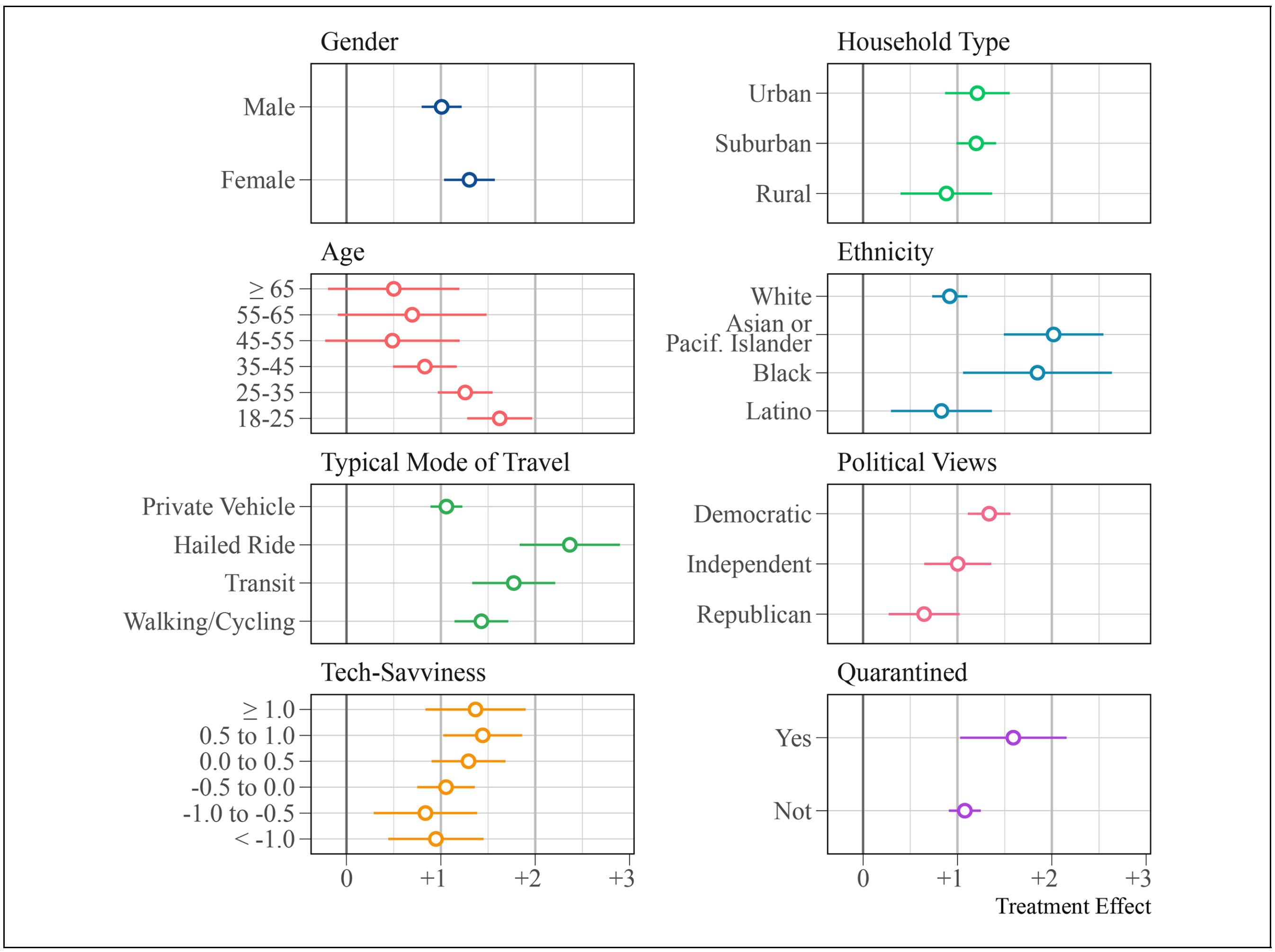

Figure 4. Treatment effects of individual characteristics on the intention to use autonomous on-demand services as a result of COVID-19 (with 95% confidence intervals).

consistent with pre-pandemic findings by Lavieri et al. (*64*).

Considering ethnicity and race, Asian and Pacific Islander respondents have a significantly greater increase in likelihood of using AVs because of the pandemic compared with White, Hispanic, or Latino respondents. Black respondents also experience a similar boost in AV consideration but have less prominent separation, with only 0.10 level of significance compared with White respondents. Niño et al. (*65*) found that ethnic minorities were more likely to be fearful of COVID-19 and to perceive it as a threat, which could explain why Asian, Pacific Islander and Black respondents are more likely to consider AV as a safer mode of transport because of its no-contact advantage.

Considering the typical pre-pandemic travel mode of respondents, results show that drivers would experience a significant increase in consideration of AVs associated with the pandemic. That effect is however less than half that found among respondents who typically travel by on-demand ride services. Transit and active mode users (walking or cycling) fall in between these positions. This suggests that more shared transportation experiences lead to a higher positive shift in AV consideration. This trend is consistent with higher COVID-19 risk perception when using public modes of transport compared with private modes (*31*).

With regard to political views, a declining treatment effect is observed as respondents lean Republican as opposed to leaning Democrat. This effect is in line with observations by Mack et al. (*66*) who found that political moderates and liberals have higher AV adoption intentions than conservatives. The treatment effect could be explained by Republicans being less likely to abide by social distancing guidelines than individuals leaning Democrat (*67*) and therefore feeling less of a need for AVs. Segmentation models for other political views, such as Libertarian or Liberal, are not estimated given the few observations for those segments in the sample.

The differences in treatment effects for other attributes, mainly gender, household location type, quarantine experience, and tech-savviness, are insignificant. In the case of gender, some previous studies indicate that male gender is positively correlated with AV adoption (*38*, *64*, *68*) but this effect has also been observed to be insignificant (*38*, *68*). Tech-savviness displays a general positive correlation with AV consideration, but there is no significant difference in the magnitude of treatment effects across different levels of tech-savviness. This observation is at odds with the hypothesis that more tech-savvy individuals would have a greater shift in consideration of AVs because of the pandemic, but is consistent with the work of Koul and Eydgahi who studied the effect of technophobia (the reverse of tech-savviness) on AV adoption, finding that it was insignificant in the model although there was a weak, negative correlation (*69*). Conversely, Lavieri et al. (*64*) found that tech-savviness increased propensity to adopt AVs. Finally, individuals who have had to quarantine during the pandemic are noticeably more likely to consider AVs in the future on average, yet this effect is also insignificant, even at a significance level of 0.10.

Conclusion

Given the push of the COVID-19 pandemic toward the use of digitization and numerous technologies to ameliorate the impacts of restricted mobility and social distancing, this study analyzes the impact of COVID-19 on consideration and future adoption of new technologies. Specifically, this paper assesses the change in consideration and perception of AVs associated with the pandemic.

Using data from a U.S. sample of 691 respondents, this study finds that the COVID-19 pandemic has a significant positive effect on the intention to use AVs in the future. Indeed, as hypothesized, autonomous on-demand services offer greater resilience to a novel health emergency than conventional shared modes. Additionally, this study finds that younger, left-leaning, and frequent users of shared modes of travel show higher intention to use AVs once offered. Other variables have a more nuanced impact. Ethnicity is associated with different degrees of shifting intentions, with Black, Asian, and Pacific Islander respondents having a more pronounced positive shift compared withWhite and Latino respondents. Contrary to what is commonly hypothesized, the extent to which one is tech-savvy has a limited effect on the shift in consideration associated with the pandemic. Similarly, women and men experience a similar pandemic-induced increase in consideration of AV use.

Understanding the effect of the COVID-19 pandemic on the intention to use autonomous technologies is important for policy making. While the disruptions caused by the pandemic have generally been negative for shared vehicle use, the innovative setting of on-demand AV services appears to promise higher intentions of future use. This suggests that in a future with increasing penetration of AVs, overall mobility and economic activities may be relatively robust against demand disruptions caused by ongoing and evolving health pandemics. Moreover, the estimated segmentation effects from this work illuminate the effect of various socioeconomic and demographic attributes on the changes in consideration of AVs. This modeling provides a guide to future adoption of AVs by identifying segments of the population likely to be more resistant to it. These findings are important, especially given the potential benefits of AVs to marginalized segments of the population, such as seniors who are both more vulnerable to adverse effects of the pandemic, and hypothesized to benefit more from the increased accessibility AVs would provide. At the same time, as suggested in this work, older respondents are more reluctant to adopt AVs.

Limitations and Future Work

This study is not without limitations. Given that AVs are not yet available for adoption, respondents may face some difficulty in anchoring their potential experience with the mode. Nonetheless, this study is designed to minimize this issue. Specifically, respondents are presented with questions about a shared AV service, which is not dissimilar to ridehailing or taxi services, albeit without a driver. By reducing the difference to solely the presence of a driver, this study aims to minimize any anchoring issues of the pandemic on this consideration process. Additionally, this study uses convenience online sampling recruitment, resulting in a sample that is more representative of left-leaning, lower-income, and younger respondents. These sociodemographic features are, however, controlled for in the models presented in this study, in an attempt to reduce potential biases. Another limitation relates to the use of cross-sectional data to measure change in consideration over time. Ideally, this study would have used longitudinal data collected at two points in time, before the pandemic and during it. This data could have informed whether varying levels of COVID-related infections or hospitalizations relate to different levels of openness toward AV use. Nonetheless, given the unpredictable nature of the pandemic, acquiring data in such a longitudinal manner is challenging. While this study acknowledges the biases inherent in asking respondents to recall their past consideration of using a mode, the data still offers valuable insight into the impact of the pandemic on this consideration process.

Further research is needed to understand more fully the role of the pandemic in shaping future adoption of transportation innovations like automated driving. A first important avenue of future research is to account better for the dynamic nature of the decision-making surrounding the use of new mobility options in the COVID-19 era. At least three areas of behavior require careful data collection, experiment design, and modeling: (i) daily travel decisions have seen major shifts with increased use of (private) cars and active modes as well as decreased use of transit; (ii) risk perceptions and protective behaviors are shaped by vaccine penetration, restrictive policies, and case rates which are all undergoing constant change; (iii) the view of AV driving technology itself is shaped by personal and media-diffused experiences, technological maturation, and changing business models (such as sharing versus ownership). Future research should aim to capture better the dynamics both within and across these areas. Future AV adoption will contend with general daily travel trends (durability of pro-car attitudes), the ongoing impact of pandemic risk behavior (objective changes and subjective risks), and the state of AV development (acceleration in development and deployment fostering new demand).

Second, these results suggest a general positive pandemic-era shift seen in the latent construct measuring tech-savviness. As the pandemic persists and morphs, further research is invited on how AV adoption is shaped by COVID-19 in the long run. Promising areas include identifying latent factors related to future work-from-home and remote office policies that are likely to alter home-location and daily travel patterns. Attitudes and aspirations around future work should play an increasing role in future models of mobility innovation adoption. A second promising area is to identify latent factors related to pandemic risk. In particular, the authors suspect that AV adoption might be driven both by enthusiasm (closely related to the tech-savviness concept) and fear (avoiding viral exposure). Further work is needed to capture better the mix of push and pull factors driving adoption of AVs in addition to preferences toward different use models (shared fleet versus private ownership).

Third, this work highlights a new aspect to investigate further, namely, the impact of political beliefs on willingness to adopt new technologies. Although this work finds that respondents who lean Democrat have a greater consideration of AVs associated with the pandemic, further research is needed to know whether this observation is the result of COVID-specific political attitudes (e.g., regard for social distancing guidelines) or whether this effect will persist beyond the presence of COVID mitigation measures. This question is particularly important as increasing political polarization may lead to a divide between segments of the population according to willingness to adopt new technological developments, including AVs.

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The authors confirm contribution to this paper as follows: study conception and design: M. Said, A. Stathopoulos; data collection: M. Said, A. Stathopoulos; analysis and interpretation: M. Said, E. R. Zajdela, A. Stathopoulos; draft manuscript preparation: M. Said, E. R. Zajdela, A. Stathopoulos. All authors reviewed the results and approved the final version of the manuscript.

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Supplemental Material

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