Autonomous vehicle adoption: use phase environmental implications

Wissam Kontar, Soyoung Ahn and Andrea Hicks

Department of Civil and Environmental Engineering, University of Wisconsin-Madison, 1415 Engineering Drive, Madison, WI 53706, United States of America

* Author to whom any correspondence should be addressed.

E-mail: hicks5@wisc.edu

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Abstract

This paper investigates the environmental trade offs resulting from the adoption of autonomous vehicles (AVs) as a function of modal shifts and use phase. An empirical approach is taken to formulate a mode choice model informed from a stated preference (SP) survey conducted in Madison, Wisconsin. A life cycle analysis based on well-to-wheel model is then conducted to quantify the use phase environmental impacts across different categories. The mode choice analysis reveals the potential users of AVs and its attractiveness as a mode of transportation, ultimately competing with traditional modes available. This translates into modal shifts that are shown to result in an expected increase in environmental impacts across all studied categories: energy consumption (5.93%), greenhouse gas emissions (5.72%), particulate matter (6.80%), sulfur (6.85%) and nitrogen oxides (5.70%). The adoption of electric AVs (E-AVs) is then analyzed as an offsetting strategy to combat the increase in environmental impacts. The analysis reveals that E-AVs are capable of offsetting the foreseen impacts, yet their effectiveness is dependent on the electricity generation mix and adoption rate.

1. Introduction

Autonomous vehicle (AV) technology is rapidly developing with the excitement that it can bring substantial benefits in terms of transportation operations, safety and accessibility [4, 15, 22, 36, 40]. Yet, this excitement could be overshadowing potential environmental impacts. The automation technology itself might not lead to direct environmental impacts. However, its presence could induce significant changes in the transportation demand and supply, which cascades into environmental impacts. For transportation demand, adoption of AVs is likely to alter travel behavior patterns and cause a shift in demand for different existing transportation modes, resulting in changes in use phase environmental impacts. This study presents an analysis into the nature of use phase environmental impacts resulting from the adoption of AVs. Studying these impacts is of key importance to researchers and policy makers in order to exploit the full potential of AVs while understanding any potential environmental implications.

In recent years, AVs have seen tremendous advancement with optimistic predictions expecting fully reliable AVs to be commercially available by 2030 [22]. Two general modes of AVs are prevalent: privately-owned AVs and AV taxis. Researchers foresee that privately-owned AVs will likely cause more congestion, increase vehicle hours traveled and lead to more dispersed urban growth [2, 10, 17, 21, 30]. On the contrary, research suggests that AV taxis are likely to be prevalent [4, 5, 16, 25, 41]. This comes at a time when mobility is witnessing a radical development away from traditional modes of transportation and towards on-demand mobility; providing door-to-door service via web-based platforms. As a result, literature suggest that AVs would lead to a shift away from private car ownership, reducing the number of vehicles within a range of 31%–95% [4, 7, 15]. On the other hand, AV taxis can lead as can lead to higher ve to higher vehicle miles traveled (VMT)
as they provide a flexible yet affordable transportation to travelers who previously had limited mobility such as the elderly, disabled or those with no license [8, 12, 31, 41].

Literature has begun to explore the potential impacts of AVs on travel behavior [6, 18]. Broadly, the literature focuses on consumer preference towards AVs, in the context of attitudes and interests. Bansal and Kockelman [3] showed that around 80% of their survey respondents are unwilling to use shared AVs if they cost higher than current available car-sharing options, and 40% were not interested in using shared AVs. In general, the literature suggests a substantial shift towards on-demand mobility services. Pakusch et al [28] performed an online survey in Germany with 302 participants to explore the consumer preference regarding various transportation alternatives. Respondents were only presented with two alternatives at a time. Their analysis presented a comparison matrix where private owned vehicles ranked first, followed by private owned AV, traditional car sharing, autonomous car sharing and lastly public transportation. The authors concluded that public transportation will be a loser with vehicle automation, specifically the preference for public transportation will decrease significantly as compared to that of car-sharing (traditional and automated). Recently, Weiss et al [38] performed empirical analysis using stated-preference survey in the Greater Toronto Area (Canada) to provide some intuition on commuter’s decision towards AVs. The authors considered seven different modes of transportation with AVs (private and shared) and personal vehicles (private and shared). A multinomial logit model was formulated to present some preliminary analysis on impact of cost, gender and age. The large number of alternatives added to the complexity of the survey. The authors found that AVs and ride hailing have larger value of time (VOT) compared to other options, which is counter intuitive.

Clearly, the adoption of AVs is accompanied with several travel behavior changes and the analyses of consumer attitudes towards AVs is crucial in identifying such changes. However, an essential piece of the story is yet missing. The caveat here is that the presence of AVs will bring along several trade offs, most importantly, environmental trade offs. Knowing that the transportation system is responsible of 28% of greenhouse gas (GHG) emissions in the United States [14], the environmental impacts of AV adoption becomes a momentous barrier towards the goal of achieving a sustainable transportation system. The conjuncture is that AV adoption is likely to cause transportation mode shifts resulting in reduced usage of more environmentally preferred options: transit or bus systems. Scarce research have investigated the environmental impacts of AVs, focusing predominantly on the technology by itself rather than the trade offs it present as a result of mode shifts. For instance, Taebat et al [33] presented a review of the environmental impacts of AV’s at four distinct levels: vehicle, urban system, society and transportation system. The paper concludes that environmental implications of AVs are greatly impacted by the shift in travel patterns and vehicle utilization. Additionally, Miller and Heard [26] details how adoption patterns of AVs are a major influence on their environmental impacts. Several studies have shown that the adoption of automated vehicles is likely to increase vehicle utilization and total VMT by commuters, due to the elimination of driving burden and increase in accessibility [9, 15, 26, 33]. This translates directly into travel pattern change at the society level, as automated vehicles are expected to compete with mass transit systems resulting in a decrease in transit users [11, 26, 27, 33, 39]. On the other hand, some studies expect a reduction in commuters car ownership with the adoption of AVs and thus a decrease in the associated raw materials and manufacturing environmental impacts. While this may be expected, the biggest environmental impact of automobiles is in the use phase [23]. As the environmental impact per person-mile is greater when traveled as a single passenger in an automobile than on mass transit that is carrying a larger number of passengers.

In this paper, we differ from previous research studies by presenting a comprehensive empirical and analytical approach into quantifying the environmental trade offs resulting from the adoption of AVs as a function of modal shifts and use phase. We design a stated preference (SP) survey to gather data into commuter’s mode preference in presence of AV. Four different mode choices are considered: privately owned vehicle, AV taxi, bus, and bicycle. Consequently the use phase environmental impacts of AVs are derived directly from modal shifts using well-to-wheel (WTW) life cycle analysis (LCA). Four different environmental categories are considered: energy consumption, GHG emission, particulate matter and pollutants emissions. In section 2 we provide the survey design, analytical modeling of mode choice selection and environmental modeling. Section 3 provides results and discussion. Finally, section 4 concludes.

2. Methods and modeling

2.1. Survey design and data collection

A web-based survey is conducted to collect mode preference data from respondents in Madison, Wisconsin. Madison is a medium sized metropolitan area with the University of Wisconsin-Madison being the major driver of the economic and travel activities in the city. A total of 805 responses were received, and the final data set was reduced to 614 after necessary filtering.

The first part of the survey included a set of questions designed to collect socio-demographic
information and general travel characteristics. The second part was designed to obtain measurements on respondent’s mode choice preference, featuring a SP survey. Traditionally, SP surveys are widely used in transportation and marketing research. In general, these surveys expose the respondent to a series of choice experiments. The choice experiments were carefully designed to depict realistic travel scenarios for any commuter and any trip type in Madison city.

The survey considers four different mode choices: personal vehicle, AVs (as AV taxi), bus, and bicycle. Then, the mode choices are set to vary across a set of attributes: travel cost, travel time, waiting time, and walking time. Additionally, these attributes were set to vary across different levels (small, medium, large). Such level design prevents any mode to dominate the set of choice experiments.

Consequently, a set of hypothetical scenarios were designed to depict realistic trips in Madison. Trips were designed according to three levels of: short length trip (3 miles), medium length trip (9 miles), and long length trip (15 miles). Accordingly, the attribute values of the hypothetical trips varied across choices. Travel times of the hypothetical scenarios are calculated from Google maps and scaled for each mode of transportation to incorporate uncertainty due to potential traffic jam. Travel cost is calculated based on cost-per-mile estimates. AV taxes have a cost-per-mile of 85 cents [22], personal vehicles 43 cents (in accordance with AAA estimate), and for bus cost it matches Madison metro transit fare ($2). Parking estimates were also added to the travel cost. These were estimated considering different types of parking and rates in Madison (on street, hourly based, yearly based). Note that there is no parking cost for AV choice as it is considered an AV taxi. Waiting time were chosen as: 2, 5, and 8 min. As for waiting time, they varied depending on transportation mode, and were estimated based on repeated measurements from real-life systems (Madison bus, and ride hail services for AVs). For AV waiting times are: 1, 3 and 5 min. For buses, 5, 10 and 15 min. Finally, a factorial experimental design was used to obtain different choice experiments. Each respondent was randomly assigned 10 choice experiments, meaning consequently 6140 choice responses were recorded.

Survey instrument can be seen in the supplementary information (SI) (available online at stacks.iop.org/ERL/16/064010/mmedia).

2.2. Mode choice modeling

A random utility maximization is employed to analyze the choice experiments for respondents. This modeling framework has become the state-of-the-art in applications of SP survey, especially when dealing with heterogeneity between population and sample data [13, 24, 34]. A generic utility model associated with respondent choosing transportation mode \( m \), given a set of modal attributes (travel cost, travel time, waiting time, walking time, etc.) relative to choice scenario \( k \in [1, ..., k_n] \) of individual \( n \), is given by equation (1):

\[
U_{nk} = V_{nk} + \epsilon, \tag{1}
\]

where \( V_{nk} \) is a systematic utility estimated as \( V_{nk} = \beta'X_{nk} \), where \( X_{nk} \) represents a vector of observed explanatory variables, \( \beta' \) is a vector of coefficients for each explanatory variable, \( \epsilon \) captures unobserved parts of the utility (assumed to be identically distributed (iid)).

Assuming the error term \( \epsilon \) follows the Gumbel distribution, and using the density function of \( \beta' \) is \( f(\beta, \theta) \), where \( \theta \) is a vector of parameters describing the distribution of \( \beta' \). Then the unconditional probability that respondent \( n \) chooses mode choice \( m \) in a choice experiment, is given by equation (2):

\[
P_{nk} = \frac{1}{\beta} \sum_{m} e^{\beta'X_{nk}} f(\beta, \theta) d\beta. \tag{2}
\]

Additionally, in this framework we adopt the panel mixed-logit to extend the correlation of error between random coefficient estimates into correlation between repeated choice experiment \( k \) for respondent \( n \) [32, 34]. This comes naturally as each respondent in the developed survey is given a set of 10 choice experiments. Accordingly, the joint probability for \( K_n \) repeated measures for individual \( n \) is given as in equation (3):

\[
P_{nk} = \prod_{k=1}^{K_n} \prod_{y=1}^{m} \frac{1}{\sum_{j} e^{\beta'X_{nk,j}}} \tag{3}
\]

2.3. Life cycle assessment

LCA presents a powerful systematic tool to analyze the environmental impacts of transportation modes during their usage phase. The application of LCA is widely seen across different engineering systems. However, the adoption of WTW LCA to analyze AV impacts presents a unique advantage, so far missing in the literature, allowing the linkage between different transportation modes to their respective use phase environmental impacts.

The use phase environmental analysis is then based on the WTW-LCA. The system boundary is shown in figure 1. The principal idea here is to look at the environmental impacts of vehicles during their usage phase, which entails assessing the environmental impacts of fuel cycle from extraction till usage. Accordingly, the Greenhouse Gases Regulated Emissions and Energy Use in Technologies Model (GREET [37]) is used to obtain estimates of WTW environmental impacts. GREET is an LCA analytical tool that simulates energy use and emissions of various vehicle and fuel combinations throughout their use phase. In this work, personal vehicles and AV are modeled as spark ignition (SI) internal combustion engines, running on a mixture of 10% ethanol
and 90% gasoline by volume. This fuel mix is widely used in Madison. Busses are modeled as compression-ignition direct injection, running on low sulfur diesel. The busses depict those available at Madison metro system. We note that vehicles modeled in here depict current vehicular conditions, however with advancement in vehicular technology it is expected that emerging vehicles might have some new characteristics in the future. Yet, this remains outside the scope of our analysis and we refer readers to the SI for further discussion on that. Consequently, four different environmental impact factors were extracted from GREET and analyzed: energy consumption (kJ), GHG emissions (kg), particulate matter (PM2.5) (mg), $SO_x$ emissions (mg), and $NO_x$ emissions (g).

The environmental impacts are quantified as the product between mode usage (mode split percentage) and the impact factors extracted from GREET model. These are computed per mile bases for autonomous and personal vehicle, and per passenger mile for busses. An average of 13 people in a bus is assumed (based on observed data of bus ridership from Madison city), while AVs and personal vehicles carry only one person. Bicycles are not considered in the analysis as they do not pose any significant impacts (during use phase), yet their influence lies in offsetting the distribution of mode usage. Accordingly, the environmental impacts are calculated for modal splits observed in the survey and hypothetical scenarios seen in figure 2. These impacts are then

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**Figure 1.** LCA—WTW system boundary for use phase environmental impacts of AVs.

**Figure 2.** Modal shifts for prediction scenarios.
compared to a baseline situation, denoted as current situation (CS). The mode splits in CS are extracted from an exhaustive biennial transportation survey report published by UW-Madison [1]. The survey collects commuting characteristics for over 2000 personnel affiliated with UW-Madison (students, faculty, and staff). From the survey, the mode splits of the CS (with no presence of AVs) are 57% personal vehicles, 18% bus, and 25% bicycle.

3. Results and discussion

3.1. AV adoption patterns and analysis

The results of the empirical mode choice model estimated from the choice experiments are presented in table 1. In the choice experiments from the survey, 31% of the time respondents chose AV as their mode of transportation, 32% personal vehicle, 16% bus and 21% bicycle.

The developed model allows to calculate the VOT for each mode of transportation. VOT represents the price travelers are willing to pay to reduce the travel time, and thus an important factor in commuter mode decisions. Typically, VOT is calculated as the ratio between time and cost coefficients (i.e. $\beta_{\text{time}} / \beta_{\text{cost}}$). However, in the mixed-logit framework, the cost and time variables are regarded as random parameters and thus the $E[\beta_{\text{time}} / \beta_{\text{cost}}]$ can be estimated through mean and variance using techniques from [29]. In the final model, the estimated coefficients for cost and time were all found to be statistically significant and follow the expected sign (negative; as we expect probability of choosing a mode to decrease if the cost or travel time increase). As expected, the AV present the overall lowest VOT ($16.31 \, \text{h}^{-1}$). This is due to the attractive features of such mode of transportation with commuters, given that they can wait at their origin and no significant walking/waiting times are needed. Conversely, the bus has significantly longer access time (waiting, walking) and travel time which is reflected by the large VOT; $26.8 \, \text{h}^{-1}$ for travel time, $6.5 \, \text{h}^{-1}$ for waiting time and $5.9 \, \text{h}^{-1}$ for walking time. Interestingly, personal vehicles present a midway alternative, with a travel time VOT of $20.4 \, \text{h}^{-1}$. Yet with significant walking time VOT of $2.2 \, \text{h}^{-1}$. This is reflective of commuters having to park their cars far away from their desired destination. Note that the waiting time and walking time for AV were found to be insignificant possibly due to the relatively short duration whereby respondents disregarded it.

Table 1 reveals important observations of travel choices and potential users of AVs. Interestingly, the results show that those with high frequency usage of rides hailing are significantly (from a statistical point of view) more likely to choose an AV as their mode of transportation. This emphasizes on the favorability of mobility-at-demand options which can potentially gain more ground with the adoption of AVs. Additionally, commuters who desire a high level of freedom while traveling are significantly more likely to choose an AV. This is rather expected, as AVs rid commuters of all driving responsibility, providing them with increased freedom. Additionally, females are seen to be less likely to choose an AV, and more likely to choose a personal vehicle. This might be traced back to female’s affinity to adopt new technologies as compared to males [19]. Concerning commuters age, it was found that young adults aged 15-19 are also more likely to choose AVs. While older ages were more likely to rely on private vehicles or busses. As for income no strong statistical significance is seen, however high income earners ($75,000 +$) were more likely to travel in personal vehicles rather than AV. Commuters living in central business districts are shown to rely more on bicycles and busses rather than personal or AV. This is expected, as CBD are typically a vibrant hub of close by amenities where commuters do not need to travel far to get to their typical destinations. Finally, the model reveals that commuters who currently own a personal vehicle are significantly less likely to choose AVs. This is an important realization as it shows that AVs are not fully capable of overtaking personal vehicle usage, yet they compete with the transit system which might result in increased environmental impacts. However, this remains a short-term insight as behavior evolves through time, especially after AVs become a reality.

3.2. Predictions for different scenarios

In efforts to assess the potential impacts of different policies and service changes, modal shifts were predicted through a simulation with (-20%, 20%) change in attribute values (cost, travel time, waiting and walking time). The change in attribute values was restricted between (-20%, 20%) to preserve the elasticity around predicted values, as discussed in [20]. A number of different scenarios were simulated, and finally seven scenarios were chosen. Table 2 presents a summary of these scenarios.

The scenarios are chosen to reflect realistic and anticipated changes in travel characteristics of transportation modes as a result of different policies. Specifically, the scenarios improve (or reduce) the utility of each mode of transportation causing a modal shift. Since AVs are not currently an available mode their cost (fare) projection is likely to vary, this is reflected in Sc1 and Sc2. Also, Sc3 and Sc5 are designed to increase the utility of busses by decreasing the access time and travel time (e.g. dedicated bus lane). Given that busses typically have the highest travel time and access time, compared to other transportation modes, this scenario presents valuable information on the impact of enhancing the bus system. On the contrary, Sc6 is designed to decrease the utility of personal vehicles and AV as to gain insights on the impact this has on bus ridership. The mode shifts percentages for each of these scenarios are presented in figure 2.
Table 1. Mixed-logit model estimation (p-value: 0***, 0.001 ***, 0.01 *, 0.05 −, 0.1 −, 1).

| Coefficients                        | Estimate (standard error) | Autonomous vehicle | Personal vehicle | Bicycle | Bus |
|-------------------------------------|---------------------------|--------------------|------------------|---------|-----|
| Alternative specific constant       |                           |                    |                  |         |     |
| Intercept                           | 4.700 (1.15***            | 4.656 (1.11***     | 3.983 (1.18**   | Base    |
| Generic modal attributes            |                           |                    |                  |         |     |
| Cost ($)                            | −0.218 (0.009***          | NA                 | NA               | NA      |
| Bus waiting time (min)              | NA                        | NA                 | NA               | −0.017 0.010** |
| AV waiting time (min)               | −0.035 (0.054             | NA                 | NA               | NA      |
| Alternative specific attributes     |                           |                    |                  |         |     |
| Travel time (min)                   | −0.052 (0.003**           | −0.067 (0.0031***  | −0.075 (0.002* | −0.089 0.0012*** |
| Walking time (min)                  | −0.497 (0.357             | −0.00436 (0.0024*  | −0.137 (0.507 | −0.0175 0.0103* |
| Indicator variables                 |                           |                    |                  |         |     |
| Personal vehicle usage frequency    | −0.0076 (0.029            | 0.085 (0.028**     | −0.009 (0.033 | Base    |
| Bus usage frequency                 | −0.163 (0.024***          | −0.142 (0.0239***  | −0.166 (0.0282** | Base    |
| Bicycle usage frequency             | −0.014 (0.0252            | −0.085 (0.0255***  | 0.144 (0.0289** | Base    |
| Ridehail usage frequency            | 0.115 (0.036**            | −0.08 (0.0368*     | −0.196 (0.044** | Base    |
| Commute activities level (base: low)| 0.0587 (0.0034**          | −0.179* (0.104     | −0.1338 (0.126 | Base    |
| Gender (base: male)                 | −0.215 (0.1036**          | 0.153 (0.1026     | −0.359 (0.124** | Base    |
| Age (base: 20–24)                   |                           |                    |                  |         |     |
| Age: 15–19                          | 0.263 (0.147              | −0.146 (0.141*     | 0.0282 (0.17)  | Base    |
| Age: 25–29                          | 0.06 (0.167               | −0.398 (0.16*      | −0.452 (0.1998 | Base    |
| Age: 30–34                          | −0.241 (0.292             | −0.243 (0.286     | −0.525 (0.329 | Base    |
| Age: 35+                            | −0.337 (0.291             | 0.234 (0.284     | −0.314 (0.408 | Base    |
| Annual household Income (base: < $10 000) |                           |                    |                  |         |     |
| Income: $75 000 +                   | −0.388 (0.22             | 0.699 (0.216**    | 0.084 (0.252 | Base    |
| Income: 35 000 – 75 000             | 0.3397 (0.183            | −0.068 (0.18*)    | 0.527 (0.262*) | Base    |
| Housing location (base: rural)      |                           |                    |                  |         |     |
| Housing: CBD                        | −0.616 (0.35              | −0.275 (0.35      | −0.834 (0.421* | Base    |
| Housing: suburban                   | 0.003 (0.302              | 0.227 (0.291     | 0.267 (0.341 | Base    |
| Personal vehicle availability (base: yes) | −0.251 (0.127*          | −0.475 (0.122***  | 0.189 (0.146 | Base    |

(Continued.)
| Coefficients                                | Estimate (standard error) | Autonomous vehicle | Personal vehicle | Bicycle | Bus |
|---------------------------------------------|---------------------------|---------------------|------------------|---------|-----|
| Buss pass availability (base: yes)          | 0.457 (0.206*)            | 0.149 (0.204)       | 0.743 (0.225***) | Base    |
| Bicycle availability (base:yes)             | 0.133 (0.123)             | 0.11 (0.121)        | -0.339 (0.143*)  | Base    |
| SD of random parameters(normally distributed)|                           |                     |                  |         |
| Cost ($)                                    | 0.134 (0.009*** )         | NA                  | NA               | NA      |
| Travel time (min)                           | 0.012 (0.001*** )         | 0.051 (0.006*** )   | 0.037 (0.0081***)| 0.03 (0.0054***)|
| Walking time (min)                          | 0.018 (0.003*** )         | 0.0203 (0.005*** )  | 0.157 (0.0098***)| 0.213 (0.0087***)|
| Bus waiting time (min)                      | NA                        | NA                  | NA               | 0.091 (0.007***)|
| AV waiting time (min)                       | 0.151 (0.022*** )         | NA                  | NA               | NA      |
| Quality of fit                              |                           |                     |                  |         |
| Log-Likelihood                              | -5221.40                  |                     |                  |         |
| McFadden R2                                  | 0.38                      |                     |                  |         |
| Likelihood ration test: Chis2               | 5418.10                   |                     |                  |         |
Table 2. Prediction scenarios description.

| Scenario | Description |
|----------|-------------|
| Sc1      | 20% increase in AV travel cost |
| Sc2      | 20% decrease in AV travel cost |
| Sc3      | 20% decrease in bus access time (walking and waiting) |
| Sc4      | 20% increase in personal vehicle travel cost |
| Sc5      | 20% decrease in bus travel time |
| Sc6      | 20% increase in personal vehicle and AV travel time |
| Sc7      | 10% increase in AV travel cost with 20% decrease in its travel time |

Note that survey base case (SB) denotes the choice results from the survey. It is evident how AVs compete with bus ridership, specifically when the utility of AVs is increased (Sc2, Sc7). Interestingly, the decrease in travel time of bus results in significant increase in its ridership.

Figure 3. Environmental impacts across different categories as function of modal shifts.

3.3. Environmental impacts

The resulting environmental impacts can be seen in figure 3. The analysis reveals an expected increase in environmental impacts across all categories and scenarios studied (see the trend line in red which shows the aggregate impact over all transportation modes in a given scenario). AVs present an attractive mode of transportation, that causes an increase ridership of vehicles with its introduction. This comes at the expense of bus ridership which is considered the environmentally preferred transportation mode. Given this shift in ridership between CS and the survey base case (SB), it is expected that energy consumption increases by 5.94%, GHG by 5.72%, PM2.5 by 6.8%, 6.85% increase in SO₂ emissions and 5.7% increase in NOₓ. This is due to the fact that vehicles have significantly higher environmental impacts during their use phase compared to busses. Across all the studied environmental factors, busses have 35%–65% less impact. More details can be found in the SI.

A comparison of environmental impacts with CS scenario is summarized in table 3. It is evident that variations in travel time and travel cost can affect the observed environmental impacts, yet not fully capable of offsetting them. In the scenarios where the appeal of AVs is increased through decreasing cost or travel time, a larger spike in environmental impacts is noticeable (Sc2, Sc6, Sc7). This is expected, as percent of AV commuters increases at the expense of other transportation modes, mainly busses. Specifically, a decrease in cost of AVs leads to the highest environmental impacts (Sc2). Conversely, in Sc1 where the cost of AV is significantly increased the ridership for bus increases which leads to a slight mitigation of environmental impacts. Nonetheless, Sc4 presents an interesting insight. When personal vehicles are less attractive (cost of travel increases), commuters tend to switch towards AVs rather than buses. This signifies that with the presence of AVs, policies that aim to reduce commuting in personal vehicles might not be fully successful in altering the environmental impacts. Interestingly, the ridership for bus can be increased through providing commuters with incentives on time savings (as seen in Sc3 and Sc5). Specifically,
Table 3. Comparison of environmental impacts with current situation.

| Environmental impact       | Survey (SB) | Sc1  | Sc2  | Sc3  | Sc4  | Sc5  | Sc6  | Sc7  |
|---------------------------|------------|------|------|------|------|------|------|------|
| Energy consumption (kJ mile$^{-1}$) | +5.93%     | +3.81% | +8.81% | +5.66% | +8.41% | +4.17% | +7.64% | +7.82% |
| GHG-100 (kg mile$^{-1}$)   | +5.72%     | +3.68% | +8.47% | +5.48% | +8.14% | +4.30% | +7.47% | +7.51% |
| PM 2.5 (mg mile$^{-1}$)    | +6.80%     | +4.39% | +10.20% | +6.36% | +9.52% | +3.51% | +8.31% | +9.14% |
| SO$_x$ (mg mile$^{-1}$)    | +6.85%     | +4.41% | +10.26% | +6.40% | +9.56% | +3.47% | +8.34% | +9.19% |
| NO$_x$ (g mile$^{-1}$)     | +5.70%     | +3.67% | +8.44% | +5.47% | +8.12% | +4.35% | +7.46% | +7.58% |

Figure 4. Environmental offsets with adoption of E-AV.

in Sc5 the decrease in travel time of bus acts as an effective incentive for commuters to favor the bus, leading to a positive environmental impacts. Notably, it is observed from Sc3 that a decrease in travel time of bus (e.g. through bus rapid transit) is environmentally more effective than a decrease in access time. This suggests that the travel time of a bus is hindering its potential to compete with other modes of transportation, specifically with the adoption of AVs.

3.4. Electric AVs as offsetting strategy

In efforts to offset the increase in environmental impacts upon the adoption of AVs, we examine the environmental benefits of replacing AV as traditional vehicles with an electric AV (E-AV). Recently, EVs have been gaining considerable ground in transportation systems due to their potential in reducing pollutant emissions, and the drastic development in the EV technology. Thus, E-AVs are considered a viable option that can potentially replace traditional AVs.

Given the nature of EVs, their use phase environmental impacts are dependant on the electricity mix generation and the adoption rate. Accordingly, two different types of E-AVs are analyzed and their respective WTW impacts are extracted from the GREET model. We note that emissions relative to electricity mix generation are average emissions and not marginal. First type assumes that electricity used to power the AV is based on the Wisconsin electricity mix, while the second type assumes U.S. general mix. Full details on each of these mixes can be seen in [35]. Essentially, the Wisconsin electricity generation mix is dependent mainly on coal (42.0%) while the general mix in the U.S. is dependent on natural gas (38.54%). It is important to note that the environmental impacts of batteries or any other vehicle equipment are not considered, as the focus is primarily on the use phase of the vehicle. Further, we note that the distribution of the electricity mixes can alter with time and thus the underlying emissions can change. While, such analysis is outside the scope of this work, we provide a sensitivity analysis of expected emissions from different electricity generation sources in the SI. This allows to gain more insights into the expected change in environmental impacts of E-AVs.

Figure 4 compares the environmental impacts after replacing AVs with E-AVs for different adoption rates. Note that the $y$-axis presents the environmental impacts of $SB-CS$, a value $< 0$ ($> 0$) signifies a decrease (increase) in environmental impacts. Also, adoption rate refers to the percentage of AVs (observed in survey base scenario) that are E-AVs.
Interestingly, the adoption of E-AVs is effectively capable of offsetting some environmental impacts incurred in the adoption of AVs. While AVs present an attractive mode of transportation for commuters, E-AVs are overall environmentally desirable. This observation is of crucial importance to transportation planners and policy makers. However, figure 4 suggests that the extent of environmental benefits is dependent on the electricity mix generation and the adoption rate. For instance, E-AVs with ≈ 30% adoption rate results in positive impacts for energy emissions, GHG and NO\textsubscript{x} emissions. Additionally, the EVs running on U.S. general mix decrease these environmental impacts beyond that of Wisconsin mix. Generally, it is noticeable that U.S. general electricity mix is desirable over the Wisconsin mix, specifically due to the excessive dependency of the Wisconsin mix on coal. This is reflective in the PM\textsubscript{2.5} and SO\textsubscript{x} graphs. E-AV's running on Wisconsin mix have will lead to higher PM\textsubscript{2.5} emissions during use phase (even at 100% adoption rate) due to the large contribution of coal burning in generating the electricity, which emits significant particulate matter. Conversely, the EVs running on U.S. mix have lower PM\textsubscript{2.5} emissions since such electricity mix reduces coal burning in favor of natural gas, yet ≈ 40% adoption rate is needed to get positive impacts. Additionally, there is an increase in SO\textsubscript{x} for E-AVs profile which is attributed to the high level of SO\textsubscript{x} emissions coming from electricity generation, surpassing that of traditional fuel extraction. We note here that the scenario where E-AV adoption is 100%, refers to a situation whereby the first AV deployed would be an E-AV.

4. Conclusion and future needs

In this study, we quantify the expected environmental impacts of the adoption of AVs. These environmental impacts are computed as function of modal shifts and use phase life cycle assessment. We found that AVs present an attractive mode of transportation, competing with traditional modes. This results in an expected increase in use phase environmental impacts across all studied categories: energy consumption, GHG emission, particulate matter, sulfur and nitrogen oxides. This suggests that the adoption of AVs is likely to cause undesirable environmental trade-offs. However, these trade-offs can be offsetted by replacing AVs as E-AVs, yet the extent of environmental benefits is dependent on the adoption rate and electricity mix generation. Accordingly, cities that seek to deploy AVs in their transportation networks in the future, need to steer their deployment in ways that match commuter adoption patterns and are environmentally beneficial. This comes with challenges on building the needed infrastructure if E-AVs are to be used, assessing the type of AVs used (shared or personal) and monitoring the modal shifts.

This study serves as an important step towards analyzing the impact of AV adoption. The proposed analysis framework reveals the adopters of AVs and quantifies the use phase environmental impacts. Nevertheless, several limitations exist and future research is desired to gain a deeper understanding of this timely topic. Firstly, data collected in this work had a large proportion of participants with age less than 29, and while younger generation tend to be early adopters of emerging technologies, additional data that represent a wider range of population is desired to scale the developed model. Secondly, additional mode choice studies in different geographical areas are needed for extrapolating results on AV adoption at a national level. Another important direction would be expanding the environmental analysis to include predictions of futuristic scenarios. The current work focuses on present-day vehicles and electricity mixes, however, with the continuous advancement of vehicular technology and the increase in renewable energy adoption, it is expected that emissions and energy consumption are set to decrease.

Data availability statement

The data generated and/or analyzed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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ORCID iDs

Soyoung Ahn  \https://orcid.org/0000-0001-8038-4806

Andrea Hicks \https://orcid.org/0000-0002-6426-9717

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