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Fleets on the streets: How number, affiliation and purpose of shared-lane automated vehicle convoys influence public perception and blame

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ABSTRACT

Automated vehicles (AVs) may have broad uses in society, but some applications may be more acceptable than others. Determining contexts in which AVs can acceptably operate is a substantial challenge for policy makers. In an online YouGov survey (N = 1175) with text-and-image vignettes of a one- or three-lane road section, AV convoys that shared lanes with a normal vehicle were perceived less positively and led to greater blame toward their owning institutions than lone AVs. AVs affiliated with a private commercial company were perceived less positively than those affiliated with a public transit agency. AVs used to regulate traffic of the vehicles behind them were blamed more than AVs used to navigate through traffic to reach a destination. These results suggest that numerical balance, vehicle affiliation and intended purpose are aspects of future AV policies for mixed traffic in shared lanes that will influence people's impressions of automated vehicles on public roads.

1. Introduction

Research on public perception of automated vehicles has largely focused on surveys which directly or indirectly assume a model of private vehicle ownership. For example, such surveys frequently ask participants whether they would personally want to purchase an automated vehicle, and how much they would be willing to pay for one, or if they enjoy driving manually (Kyriakidis et al., 2015, Schoettle & Sivak, 2014, Pöllänen et al., 2020) (cf. Mara & Meyer, 2022). Public opinion surveys that have included specific behaviors or use cases of automated vehicles (e.g., Kaur & Rampersad, 2018, Kassim et al., 2019, Bonnefon et al., 2016, Li et al., 2016, Pöllänen et al., 2020) have focused on situations involving single, privately owned AVs (e.g., daily commute, congested traffic, accidents) rather than situations that broadly transform traffic experiences of other road users. However, due to the high cost of automated vehicle technology, the way that most people will first encounter highly automated vehicles (Level 4 and above, by the SAE J3016 Standard (Society of Automotive Engineers, 2021)) will be as observers rather than direct users (Li et al., 2015) (cf. Rogers, 1962), and the vehicles they are likely to encounter will be owned by fleets rather than private individuals (Marshall, 2021). Fleets of automated vehicles are likely to be owned by larger corporate or governmental entities, and may be controlled to

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dynamically coordinate their behavior for traffic regulation of human-driven (non-automated) vehicles (e.g., see Cao et al., 2021, Wu et al., 2017). People's everyday driving experiences—the daily commute, for example—will be more directly impacted, sooner, by their experience of other vehicles and those vehicles' behavior: the purpose/application of the automated vehicles, how many of them are on the road or their affiliation (Vinitsky, Parvate, et al., 2018, Gilbert et al., 2022). For practical issues about how to deploy automated vehicles onto roads in the future—and who should do that—understanding public opinion about the context about which automated vehicles are present on public roads in the first place is paramount.

The current work offers an initial exploration of how three policy-related factors—the number of vehicles, the affiliated institution and the purpose of the automated vehicle(s) on the road—influence public perception and responsibility allocation of the vehicles. We present the design and results of a ($N = 1175$) survey study[1] performed online to understand how these factors affect the public perception of automated vehicles and blame attribution for accidents involving these vehicles. This study is the first of its kind, looking at public perception and blame attribution of automated vehicle fleets in specific scenarios. Given the importance of public perception of automated vehicles to vehicle adoption and responsibility attribution to vehicle manufacturers, this work may aid the development of policy decisions related to the presence, purpose and affiliation of single automated vehicles and coordinated platoons[2] of automated vehicles on public roads.

2. Literature review

2.1. Perception and responsibility with groups of vehicles

A large literature has explored public perception as a key measure of public opinion for automated vehicles (e.g., Cunningham et al., 2019, 2018, Kyriakidis et al., 2015, Schoettle & Sivak, 2014). Past public opinion surveys of automated vehicles have predominantly evaluated public perception of singleton automated vehicles or have assessed general attitudes towards the concept of automated vehicles (e.g., Hulse et al., 2018). However, allowing groups of coordinated automated vehicles on public roadways is a key policy consideration, since coordinated automated passenger vehicles can improve throughput and relieve traffic congestion by regulating normal vehicle traffic behind them (based on simulation and small scale road tests; cf. Vinitsky, Parvate, et al., 2018). Groups of automated trucks are likely to replace many long-distance drivers, while groups of automated passenger vehicles are being proposed in the U.S. (Viscelli, 2018, Rice, 2019). How will the presence of groups of automated vehicles on public roadways affect people's perception of AVs?

Transportation literature has identified trends in public opinion toward groups of automated vehicles. Automated truck platoons are accepted by 70% of U.S. and German adults, with acceptance defined as approval, conditional approval, tolerance or indifference toward the platoons (Castritius, Lu, et al., 2020). Professional drivers also support automated truck platoons (Castritius, Hecht, et al., 2020). Companies with smaller number of vehicles reported being more likely to support Level 5 (i.e., high) automation in their vehicle fleets (Talebian & Mishra, 2022). Similarly, people are willing to pay more to use shared automated passenger vehicle fleets and to own individual AVs versus normal vehicles (Bansal & Kockelman, 2018, Bansal et al., 2016). However, a driving simulation study found that participants who drove a normal vehicle reported low comfort and caused accidents when trying to merge into a highway in which an automated passenger vehicle platoon was passing by, particularly if the platoon's inter-vehicle distance was narrow (Aramrattana et al., 2021). Participants reported that interacting with a platoon was rated as highly demanding and that the platoon's behavior was difficult to anticipate, even among drivers who usually have little difficulty entering highways (Aramrattana et al., 2021). We therefore test how the public will perceive automated vehicle convoys.

Research Question 1 (Perception of Convoys): Will people perceive the presence of automated vehicle convoys as more or less positive than the presence of a lone automated vehicle?

Responsibility allocation (or "blame attribution") is a second key consideration in people's opinion of automated vehicles. Assigning responsibility for AV accidents has both moral implications (cf. Elish, 2019) and is influenced by design considerations (e.g., Bigman et al., 2019). Empirical surveys have evaluated how the public assigns blame to various parties (e.g., manufacturers, owners, drivers, the government), primarily comparing levels of automation (e.g., Pöllänen et al., 2020, Bennett et al., 2020) or comparing blame assigned to human drivers versus automated vehicles (e.g., Liu & Du, 2022, Copp et al., 2021). While level of automation is an important technical consideration in AVs, people's perceptions of blame may also be influenced by policy decisions such as groups versus singleton AVs.

Although no past work to our knowledge has looked at the effect of number of vehicles on blame assignment, past work in sexual assault cases found that as the number of perpetrators increases, greater blame is assigned to the victim (i.e., victims of offenses with multiple perpetrators are blamed more than victims of a single perpetrator) (Lim, 2018); groups are also less likely to be assigned blame than individuals for organizational failures (Gibson & Schroeder, 2003). Moreover, multi-vehicle crashes found that not all drivers are responsible for the accident (Yau et al., 2006), suggesting that responsibility allocation may be different. We explore whether this effect may be present with assigning blame to parties involved in accidents with varying numbers of AVs.

[1] Although past AV surveys have used one survey per independent variable of interest (e.g., Bonnefon et al., 2016 used separate studies for number of sacrificed lives and type of family members), the current work uses one study to explore all variables to account for interaction effects, which are not expected (based on prior work) but are considered for completeness.

[2] We use the terms "convoy" and "platoon" interchangeably to refer to automated vehicles that are proximate to each other.

Research Question 2 (Responsibility of Convoys): Will people assign responsibility differently for accidents involving automated vehicle convoys compared to a lone automated vehicle?

2.2. Perception and responsibility with government or corporate automated transit systems

Automated vehicles have been proposed for operation by organizations with public affiliation as well as those with private affiliation. Government-affiliated platoons that coordinate vehicles in order to improve efficiency have been proposed to solve many public problems related to the future of transportation (Watanabe et al., 2021, Sivanandham & Gajanand, 2020, Wu et al., 2017), including the use of fleets of AVs as "public urban vehicles" in France, Singapore and other countries as early as the 1990s (Daviet & Parent, 1997). Commercial (private company) affiliated platoons of heavy duty vehicles have also been proposed, such as automated trucks affiliated with different commercial companies or platooning services that may coordinate with one another (cf. Farokhi et al., 2017, Nissenbaum, 2009). Past work about either government affiliated or commercial affiliated automated transit systems have typically addressed public opinion of one or the other but not both. Government-affiliated automated vehicles' comfort and speed have been compared to existing public transportation modes (Nguyen et al., 2019), assessed for traffic control and energy consumption (Sethuraman et al., 2019) and investigated using focus groups that identify concerns about how pedestrians and platoon pods would interact, including whether or how people would be prevented from crossing between them (Woodman et al., 2019). Stakeholder interviews found that public transit AV shuttles are the largest opportunities for U.S. cities, whereas private service passenger service pilots are unable to be appraised due to low information (Chatman & Moran, 2019). However, these works did not experimentally compare how people's perceptions of automated vehicles would change depending on the public/governmental versus private/commercial affiliation of the vehicles. Thus, a major unanswered question is how people's perceptions of automated vehicles on public roads is influenced when the vehicles are designed or managed by public/governmental versus private/commercial companies.

In a related public opinion survey on artificial intelligence (AI) algorithms that explored public versus private affiliation, 2000 U.S. YouGov respondents did not have high confidence in any type of organization to develop and manage AI (Zhang & Dafoe, 2020). University researchers and the U.S. military were the most trusted groups to *develop* AI in the public interest, followed by large tech companies (e.g. Google, Microsoft, Facebook) (Zhang & Dafoe, 2020); non-government organizations and companies were the most trusted to *manage* AI; and the U.S. state and federal government were the least trusted (note that trust was generally low). To extend such research into public opinion of automated vehicles' management, we filter the key categories used in Zhang and Dafoe (2020) to only include affiliated organizations that are actively developing automated vehicle platoons based on the literature reviewed (i.e., public transport authorities and private companies).

Research Question 3 (Perception of Affiliations): Will people perceive automated vehicles affiliated with a public transit agency as more or less positive than those affiliated with a private commercial company?

Among work that has looked at the effect of affiliation on responsibility attribution, Copp et al. found that larger companies were blamed less than smaller companies in an AV accident (Copp et al., 2021). Lima et al. states that public or private organizations (e.g., National Highway Traffic Safety Administration or vehicle manufacturers) act as trusted authorities in taking responsibility to certify AVs and their corresponding ecosystems (Lima et al., 2016). Faisal et al. mentions that in the U.S., liability for AV accidents is determined by state governments, but that some states have drafted terms suggesting that AV manufacturers can be held liable for accidents (Faisal et al., 2019). Law experts mention that AV operators (i.e., owners or manufacturers) may be liable for AV accidents but that liability should be limited (Gless et al., 2016). Analysis of a crash involving a normal vehicle Uber modified into an automated vehicle attributed responsibility for the accident to Uber as the self-driving system developer and operator who disabled the car's emergency braking function, as well as partial attribution to Arizona's lax regulations (He, 2021). We therefore also explore how two main affiliations of automated vehicles affect responsibility allocation for accidents.

Research Question 4 (Responsibility of Affiliations): Will people assign responsibility differently for accidents involving automated vehicle(s) affiliated with a public transit agency versus a private commercial company?

2.3. Automated vehicle purpose

Past research has investigated various purposes and application domains of automated vehicles. Researchers are increasingly studying the public opinion on AVs for different destination-transporting applications (i.e., applications in which the AV transports people or items), including private AVs (Zou et al., 2022), public transportation (Pakusch & Bossauer, 2017), automated shuttle services (Berrada et al., 2020, Hilgarter & Granig, 2020) and automated trucking (Kishore Bhoopalam et al., 2021). Riders transported using an automated shuttle were accepting of automated vehicle fleets as an alternative means of transportation (Hilgarter & Granig, 2020). Many nations examine public perception about automated vehicles for the purpose of public transportation, including the US, the UK, Australia, New Zealand, Singapore, and China (Chng & Cheah, 2020, Cunningham et al., 2018, 2019, Schoettle & Sivak, 2014, Zhu et al., 2020).

As an emerging purpose of AVs, both real world trials and simulated results from the intelligent transportation systems literature have shown that as automated vehicle fleets increase in scale and capacity, they will become capable of another function: traffic regulation (i.e., setting the pace of traffic) (Čičić & Johansson, 2018, Zhou et al., 2019). This role may be passive, as human drivers

and other road users learn to adjust their driving as the fleet's style becomes prevalent on public roads (Gilbert, 2021). Simulator studies with multiple AVs have found that the presence of an automated platoon can affect the behavior of upstream (i.e., following) normal vehicles, the drivers of which use reduced time headway (Gouy et al., 2014). It may instead be active, if automated vehicles intentionally nudge other drivers in order to control either local interactions or the citywide flow of traffic (Fisac et al., 2019, Wu et al., 2017). Real-world field tests with a single, active-control AV driving in front of normal vehicles in a single lane have found that AVs can affect the behavior of upstream traffic by improving flow and reducing phantom jams and shock waves (Stern et al., 2018) (cf. Vahidi & Sciarretta, 2018, Aria et al., 2016); such Langrangian-actuated AVs can be extended to multi-lane traffic control (cf. Stern et al., 2018). Either way, the role of traffic regulation may be traced back to design choices overseen by automated vehicle developers, raising new problems at the intersection between the specification of fleet behavior and public policy (Gilbert et al., 2022). An open question is how the perception of automated vehicles depends on their purpose of *accommodating* traffic flow (as is the case when AVs transport to a destination and drives around other vehicles) vs. *regulating* overall traffic flow (as is the case when AVs purposely control the speed of human-driven vehicles behind them). There is a pressing need to fill gaps in past work that have not explicitly included traffic regulation as an emerging purpose of AVs.

Research Question 5 (Perception of Traffic Regulation): Will people perceive automated vehicles whose purpose is traffic regulation as more or less positive than those whose purpose is destination transport?

Past work on blame attribution and traffic regulation primarily involves normal vehicles. A large analysis of U.S. highway accidents found that road freight transportation accidents are often caused by failure to slow in response to a lead vehicle or following distance to a lead vehicle (Newnam & Goode, 2015). More specifically, these situations can be caused by environmental factors like road furniture (such as when highway patrol uses confusing road signs) and traffic conditions (such as when traffic ahead abruptly slows because of heavy traffic) (Newnam & Goode, 2015). Although not explicitly involving automated vehicles, such literature confirms that slow-downs and potential confusing actions in the road ahead—which may be more likely with AVs that perform traffic regulation—are a common cause of traffic accidents. Moreover, even though the following vehicle is at fault, road conditions can nevertheless be identified as contributing to the accident—suggesting that blame may be shared between both a leading, automated vehicle and a normal following vehicle in a rear-shunt accident. Similarly, in accidents where a bicyclist is hit by a vehicle, the intoxication of the bicyclist is more correlated with bicyclist injury than driver fault and can lead to the bicyclist being at fault (Kim et al., 2007). We therefore test whether erratic behavior of a traffic regulating AV may share some of the blame in a rear-shunt accident.

Research Question 6 (Responsibility of Traffic Regulation): Will people assign responsibility differently for accidents involving automated vehicles for traffic regulation compared to destination transport?

3. Materials and method

3.1. Participants

We recruited 1204 participants from the YouGov survey platform. YouGov is a representative sampling platform that matches a randomly-drawn sampling frame of the U.S. population with members from their opt-in respondents based on a large set of variables (cf. Iyengar, 2013, Peterson & Iyengar, 2021); the platform has been widely validated (cf. Memmott et al., 2021). Twenty-nine participants (2.4%) who incorrectly answered the attention check question "What technology is this survey about?" (e.g., "virtual reality" instead of "automated vehicles") were excluded, leaving 1175 participants total (643 women, 510 men, 9 non-binary, 13 prefer not to answer) ages 19 to 68 (mean $M = 55$, standard deviation $SD = 13$). Participants' ethnicity was 907 White or Caucasian, 93 Black or African American, 65 Hispanic or Latino, 25 Asian or Pacific Islander, 13 Native American or Alaskan Native, 35 Multiracial or Biracial, 10 A race/ethnicity not listed here, 27 Prefer not to answer. Participants' highest education was 15 Less than a high school diploma, 168 High school degree or equivalent (e.g. GED), 268 Some college, no degree, 138 Associate degree (e.g. AA, AS), 343 Bachelor's degree (e.g. BA, BS), 158 Master's degree (e.g. MA, MS, MEd), 53 Professional degree (e.g. MD, DDS, DVM), 32 Doctorate (e.g. PhD, EdD).

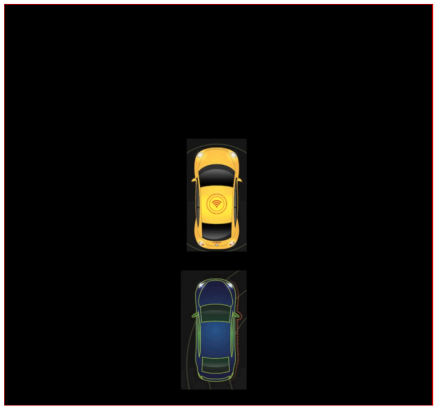
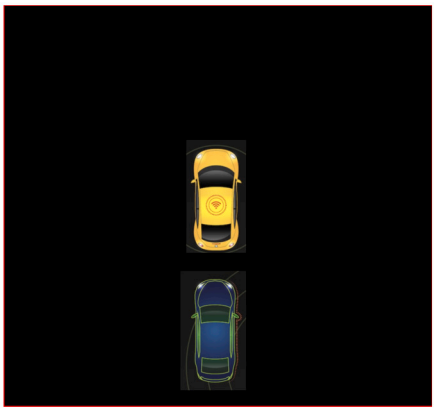
3.2. Study design

In this study, we conducted a 2 (vehicle number: single versus group) x 2 (vehicle affiliation: private versus public) x 2 (vehicle purpose: traffic regulation or destination arrival) between-participants online experiment. Participants were randomly assigned to read one of eight text-and-image-based vignettes describing either a single or group of automated vehicles that were either operated by a private or public organization and that were either being used to regulate traffic or to transport to a destination.

3.3. Stimuli

Text in the vignettes was designed to vary only in the manipulated variables, to mention each variable at least once in each vignette, and was matched for word count and style (please see Table 1). Images used visual depictions of road traffic with a normal vehicle behind a lone AV in a single lane for the lone AV condition or behind multiple AVs across three lanes for the AV fleet

Table 1
Vignette text and image based on vehicle purpose (column header), number of vehicles (row grouping) and vehicle affiliation (row header) of yellow fully-automated vehicle(s) in a one- or three-lane road section. (For interpretation of the colors, the reader is referred to the web version of this article.)

	Traffic regulation	Destination transport
Single vehicle:		
Public affiliation	A public transit agency's autonomous vehicle is driving in front of other vehicles and adjusts its speed to *regulate traffic*. The public transit agency's autonomous vehicle modifies its speed to *control the speed of the vehicles behind it.*	A public transit agency's autonomous vehicle is driving in front of other vehicles and adjusts its speed to *reach its destination*. The public transit agency's autonomous vehicle modifies its speed to *navigate through the vehicles in front of it.*
Private affiliation	A private commercial company's autonomous vehicle is driving in front of other vehicles and adjusts its speed to *regulate traffic*. The private commercial company's autonomous vehicle modifies its speed to *control the speed of the vehicles behind it.*	A private commercial company's autonomous vehicle is driving in front of other vehicles and adjusts its speed to *reach its destination*. The private commercial company's autonomous vehicle modifies its speed to *navigate through the vehicles in front of it.*
Group of vehicles:		
Public affiliation	A public transit agency's **convoy of five** autonomous vehicles is driving in front of other vehicles and adjusts its speed to *regulate traffic*. The public transit agency's autonomous vehicles modify their speed to *control the speed of the vehicles behind them.*	A public transit agency's **convoy of five** autonomous vehicles is driving in front of other vehicles and adjusts its speed to *reach its destination*. The public transit agency's autonomous vehicles modify their speed to *navigate through the vehicles in front of them.*
Private affiliation	A private commercial company's **convoy of five** autonomous vehicles is driving in front of other vehicles and adjusts its speed to *regulate traffic*. The private commercial company's autonomous vehicles modify their speed to *control the speed of the vehicles behind them.*	A private commercial company's **convoy of five** autonomous vehicles is driving in front of other vehicles and adjusts its speed to *reach its destination*. The private commercial company's autonomous vehicles modify their speed to *navigate through the vehicles in front of them.*

condition (please see Table 1). (The single-lane, single-AV image was based on single shared-lane mixed traffic, e.g., Fig. 3b in Sadigh et al. (2016) and Fig. 1 in Stern et al. (2018), while the multi-lane, multi-AV image was based on three-shared-lane scenarios of mixed traffic, e.g., Fig. 2 in Woo and Skabardonis (2021) and Fig. 15.1 in Wagner (2016)). Images differed only in the number of vehicles manipulation, as in figures from past work (e.g., Woo & Skabardonis, 2021). The vignettes were designed to assess initial impressions of the concepts of vehicle purpose, affiliation and number of vehicles, so used general wording and images. To account for contextual effects apart from the ones being analyzed, vignettes were standardized to use a yellow automated sedan and blue normal sedan (colors selected for contrast) and road type (i.e., general road with lanes) and the context noted in our descriptions of stimulus samples (Cummings & Reeves, 2022).[3] A single stimulus for the image and text description for each manipulation was sampled based on prominence in literature. Research integrity was enhanced using detailed specification of stimulus categories (cf. Cummings & Reeves, 2022, pp. 216): the vehicle number category was defined as a depiction of shared-lane AV(s) (spread across multiple lanes in the case of multiple AVs) in front of a single normal vehicle; the vehicle affiliation category was the operator of the AV(s), stated as a short three-word descriptor without any proper nouns; and the vehicle purpose category was the purpose of the AV(s), stated as a short two-word descriptor followed by a description of the vehicle's driving behavior related to that purpose.

To assess responsibility attribution, participants viewed a follow-up text-based vignette (see Table 2) that described an accident with a non-automated vehicle having a rear-end shunt with the automated vehicle (i.e., the AV's rear end is impacted by the human-driven vehicle) due to unpredictable AV behavior. To motivate this accident scenario, past literature has suggested that AVs may navigate traffic situations in ways that upstream human drivers cannot easily interpret (Aramrattana et al., 2021, Fridovich-Keil et al., 2020). Results in simulation show that new techniques like inverse reinforcement learning can lead to AVs that actively take atypically aggressive or defensive actions near human drivers in order to better control traffic situations (Sadigh et al., 2016). A range of hybrid modeling approaches can combine AVs' capacity for long- and short-term planning to induce and control a variety of situations dynamically (Fisac et al., 2019), which may not match how people typically drive. Participants were assigned to the same condition for the follow-up vignette as for the primary vignette.

3.4. Procedure and measures

Participants were asked about public perception of the automated vehicles depicted in the vignette after the primary vignette and responsibility attribution in an accident after the secondary vignette. All procedures were approved by the research ethics board at Anon. University and preregistered on osf.io (link for peer review).

Public perception was measured with a 6-item scale, consisting of 1 item about general impression ("What is your immediate feeling toward the AV(s) pictured in this survey?" 1 = "very negative," 6 = "neutral," 11 = "very positive"); modified from Clothier et al. (2015), Schoettle and Sivak (2014)), 1 on benefit to self ("How beneficial do you believe the specific AV(s) pictured in this survey could be to you?" 1 = "no benefit to you at all," 6 = "moderate benefit to you," 11 = "large and direct benefit to you"; modified from Clothier et al. (2015)), 1 on benefit to society ("How beneficial do you believe the specific AV(s) pictured in this survey could be to society?" 1 = "no benefit to society at all," 6 = "moderate benefit to society," 11 = "large and direct benefit to society"; modified from Clothier et al. (2015)), 2 on perceived safety and risk ("How strongly do you agree that the autonomous vehicle(s) pictured in this survey is safe?" 1 = "strongly disagree," 6 = "neutral," 11 = "strongly agree"; "How strongly do you agree that the AV(s) pictured in this survey is risky?", reverse-coded; modified from Clothier et al. (2015), Schoettle and Sivak (2014), Kassim et al. (2019)), and 1 on risk acceptability ("To what extent do you think the risks associated with the use of the AV(s) pictured in this survey are acceptable?" 1 = "not acceptable at all," 6 = "neither acceptable nor unacceptable," 11 = "definitely acceptable"; modified from Clothier et al. (2015)); we use the general term "perception" because of the exploratory nature of the scale used. We harmonized the questions (e.g., changing "Describe your immediate feeling" to "What is your immediate feeling") for consistency with the other questions, and using 11-point Likert scales for all items, regardless of the original scale. Questionnaire items about enjoyment, ease of use and interest/willingness to buy (Schoettle & Sivak, 2014, Kyriakidis et al., 2015, Kassim et al., 2019) were excluded as the current study specified organization (rather than individual) ownership of the automated vehicles; similarly, trust in safety items (Kassim et al., 2019) were addressed by the safety item, while items about specific concerns (e.g., hacking, privacy, level of automation) (Schoettle & Sivak, 2014, Kyriakidis et al., 2015, Kassim et al., 2019) were too narrow for the current study. Scale internal consistency was Cronbach's $\alpha = 0.922$ (6 items, 1175 samples).

Participants were asked to assign relative responsibility to the AV(s)' owner and the normal car's driver after reading the follow-up vignette in Table 2 ("How much are each of the following parties to blame for the traffic accident?"; 11-point Likert scale, 1 = "no blame at all", 6 = "moderate blame", 11 = "Full Blame", followed by the two parties; "How much are each of the following parties at fault for the traffic accident?", followed by the two parties; modified from Pöllänen et al. (2020), Li et al. (2016) to an 11-point Likert scale and two parties[4] for simplicity). Scale internal consistency with driver fault/blame items reverse-coded[5] was Cronbach's

[3] The omission of a specific road type is in line with past vignettes that used a "main road" (Bonnefon et al., 2016) or "road" (Li et al., 2016), although we note that some work has used specific road type (e.g., "two-way mountainside road" (Awad et al., 2020) or "city street" (Li et al., 2016)).

[4] Five parties (the driver/user/owner, vehicle, other road users, manufacturer, and government) were used in past work that involved accidents between an AV and road users such as pedestrians (Pöllänen et al., 2020, Li et al., 2016); we reduced it to two parties since some work suggests that human drivers and companies are the primary parties found at fault (e.g., Li et al., 2016, Copp et al., 2021) and the accidents in our vignettes were between two vehicles.

[5] This study was designed assuming fault was zero-sum across the two parties, so we used reverse coding to obtain a single measure of blame; however, we performed separate analyses for each party as exploratory tests to check this assumption (and because past work looking at five or more parties analyzed each party separately; e.g., Li et al., 2016).

Table 2
Follow-up vignette text for rear shunt (crash) scenario and image based on vehicle purpose (column header), number of vehicles (row grouping) and vehicle affiliation (row header) of yellow, fully-automated vehicle(s) in a one- or three-lane road section.

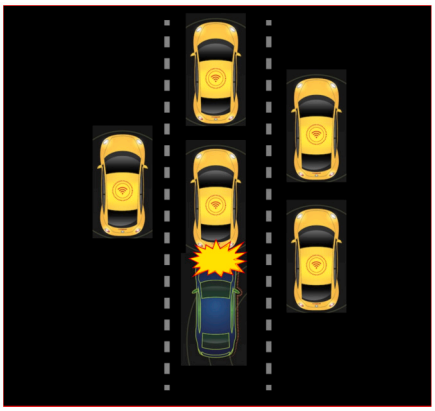
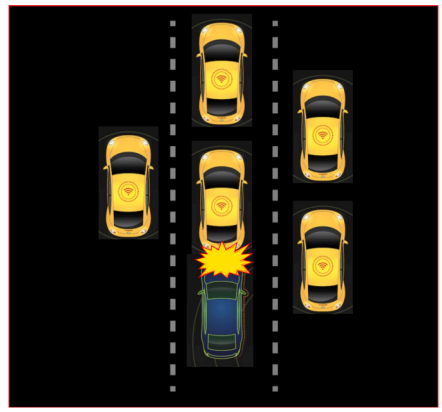
	Traffic regulation	Destination transport
Single vehicle:		
Public affiliation	While the public transit agency's autonomous vehicle modifies its speed to *regulate traffic,* the car behind the autonomous vehicle has difficulty anticipating the behavior of the autonomous vehicle in front and as a result, collides with it.	While the public transit agency's autonomous vehicle modifies its speed to *reach its destination,* the car behind the autonomous vehicle has difficulty anticipating the behavior of the autonomous vehicle in front and as a result, collides with it.
Private affiliation	While the private commercial company's autonomous vehicle modifies its speed to *regulate traffic,* the car behind the autonomous vehicle has difficulty anticipating the behavior of the autonomous vehicle in front and as a result, collides with it.	While the private commercial company's autonomous vehicle modifies its speed to *reach its destination,* the car behind the autonomous vehicle has difficulty anticipating the behavior of the autonomous vehicle in front and as a result, collides with it.
Group of vehicles:		
Public affiliation	While the public transit agency's **convoy of five** autonomous vehicles modifies its speed to *regulate traffic*, the car behind the autonomous vehicles has difficulty anticipating the behavior of the autonomous vehicles in front and as a result, collides with **one of them**.	While the public transit agency's **convoy of five** autonomous vehicles adjusts its speed to *reach its destination*, the car behind the autonomous vehicles has difficulty anticipating the behavior of the autonomous vehicles in front and as a result, collides with **one of them**.
Private affiliation	While the private commercial company's **convoy of five** autonomous vehicles modifies its speed to *regulate traffic*, the car behind the autonomous vehicles has difficulty anticipating the behavior of the autonomous vehicles in front and as a result, collides with **one of them**.	While the private commercial company's **convoy of five** autonomous vehicles modifies its speed to *reach its destination*, the car behind the autonomous vehicles has difficulty anticipating the behavior of the autonomous vehicles in front and as a result, collides with **one of them**.

Table 3
Descriptive statistics for each dependent measure in each "vehicle number" group and ANOVA results for the main effect of vehicle convoys.

Dependent measure		Five		One		ANOVA: main effect of number			
		n	*M (SD)*	*n*	*M (SD)*	*df*	*F value*	*p value*	η_p^2
Perception		586	4.3 (2.4)	589	4.7 (2.4)	1, 1167	6.83	.009	.006
Blame	Composite score	586	5.8 (2.8)	589	5.2 (2.8)	1, 1167	11.48	<.001	.010
	Toward AV affil.	586	6.4 (3.3)	589	5.8 (3.4)	1, 1167	11.92	<.001	.010
	Toward NV driver	586	6.9 (2.9)	589	7.3 (2.9)	1, 1167	6.90	.009	.006

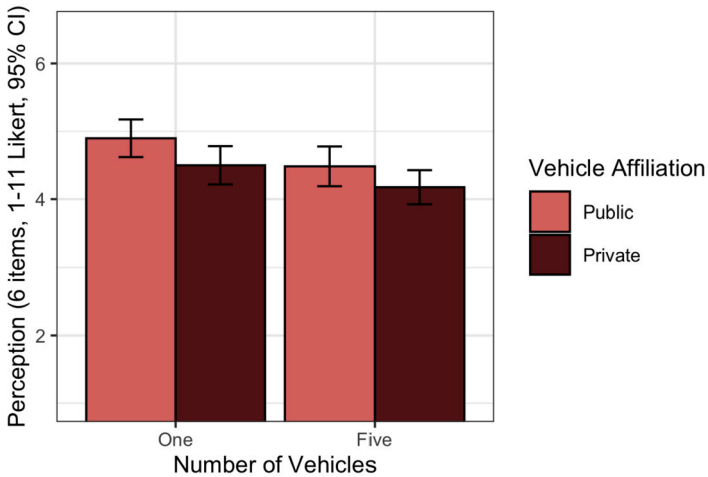


Fig. 1. Bar plot of public perception of automated vehicles versus number of vehicles, grouped by vehicle affiliation. Error bars are 95% CIs.

α = 0.889 (4 items, 1175 samples). An exploratory factor analysis with all survey items demonstrated a three-factor structure corresponding to public perception items, driver blame items and affiliation blame items (see Appendix A).

3.5. Analysis

We used a 2 x 2 x 2 Analysis of Variance (ANOVA) with three between-participant factors (number of, purpose of and affiliation of vehicle(s)) to analyze our results. One ANOVA was done for the measure of public perception and one ANOVA was done per judgment target for responsibility attribution. We used linear regression models as post-hoc tests to compare specific cells in our study design with other specific cells, to do follow-up comparisons for any aggregate ANOVA effects we find. We performed case-wise exclusion for missing data. All statistical analyses, including the factor analyses above, which used lavaan, were done in R version 4.0.5 and RStudio version 1.4.1106.

4. Results

4.1. Effect of convoys

Research Question 1 asked whether people perceived the presence of vehicle convoys as more or less positive than lone automated vehicles. In support of an affirmative answer to this question, an ANOVA on perception with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle number (Table 3, first row). Participants rated a convoy of five automated vehicles as perceived less positively than a lone automated vehicle (Fig. 1). No interaction effects were found, all *ps* > 0.39. Automated vehicle convoys were therefore rated less positively than lone automated vehicles.

Research Question 2 asked whether people assign responsibility differently for accidents involving automated vehicle convoys compared to a lone automated vehicle. In support of an affirmative answer to this question, an ANOVA on blame with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle number (Table 3, second row). Participants assigned greater blame to automated vehicle convoys than to lone automated vehicles (Fig. 2). No interaction effects were found, all *ps* > 0.73, except the interaction between vehicle number and affiliation, which had p = 0.09. Greater blame was assigned to the owner of convoys of automated vehicles than the owner of a lone automated vehicle for an accident in which a normal vehicle driver rear shunted an automated vehicle, accounting for the affiliation of the automated vehicle(s).

An exploratory test for Research Question 2 was performed to separately look at blame attribution to the automated vehicle affiliation versus to the driver of the normal vehicle. An ANOVA on blame toward AV affiliation with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle number (Table 3, third row). Participants assigned

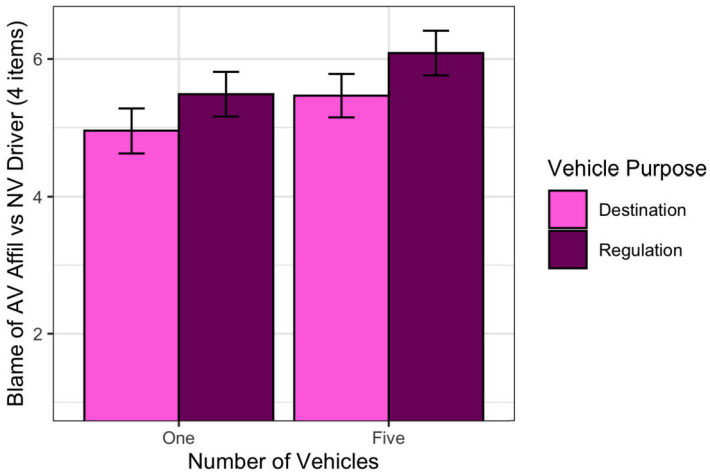


Fig. 2. Bar plot of blame toward automated vehicle affiliation (rather than normal vehicle driver) versus number of vehicles, grouped by vehicle purpose. Error bars are 95% CIs.

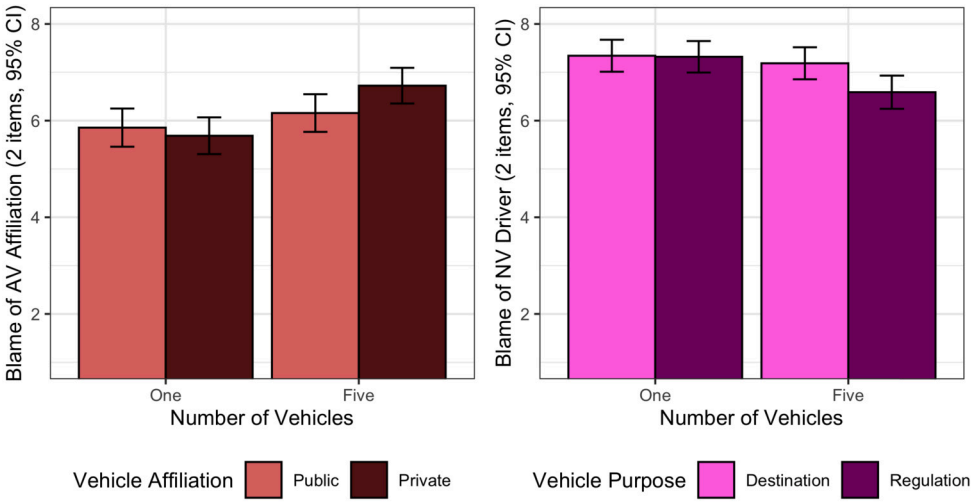


Fig. 3. Left: Bar plot of blame toward automated vehicle (AV) affiliation versus number of vehicles, grouped by vehicle affiliation. Right: Bar plot of blame toward normal vehicle (NV) driver versus number of vehicles, grouped by vehicle purpose. Error bars are 95% CIs.

greater blame to organizations affiliated with automated vehicle convoys than to those affiliated with lone automated vehicles. The interaction between vehicle number and affiliation was not significant, $p = 0.056$; however, based on the p-value, a post-hoc Tukey's HSD test found significantly greater AV affiliation blame toward a convoy versus lone vehicle when the vehicles were from a private company, $p < 0.001$, $0.3 < \mu_{five} - \mu_{one} < 1.7$, but not when they were from a public agency, $p = 0.71$, $-0.4 < \mu_{five} - \mu_{one} < 1.0$ (Fig. 3, left). A separate ANOVA on blame toward the normal vehicle's driver with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle number (Table 3, bottom row). Participants assigned less blame to drivers who hit automated vehicle convoys than to those who hit lone automated vehicles. The interaction between vehicle number and purpose was not significant, $p = 0.09$; however, based on the p-value, a post-hoc Tukey's HSD test found significantly lower blame of a normal vehicle driver who rear shunted a convoy versus a lone vehicle used for traffic regulation, $p = 0.01$, $-1.3 < \mu_{five} - \mu_{one} < -0.1$, but not when used for destination transport, $p = 0.91$, $-0.8 < \mu_{five} - \mu_{one} < 0.5$ (Fig. 3, right). Thus, the exploratory test showed that automated vehicle number affected both blame attribution to the automated vehicles and to the normal vehicle driver.

4.2. Effect of affiliations

Research Question 3 asked whether people perceived automated vehicles affiliated with a public transit agency as more or less positive than those affiliated with a private commercial company. In support of an affirmative answer to this question, an ANOVA on perception with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle

Table 4
Descriptive statistics for each dependent measure in each "vehicle affiliation" group and ANOVA results for the main effect of vehicle affiliation.

Dependent measure		Private		Public		ANOVA: main effect of affil.			
		n	*M (SD)*	*n*	*M (SD)*	*df*	*F value*	*p value*	η_p^2
Perception		592	4.3 (2.3)	583	4.7 (2.5)	1, 1167	6.21	.013	.005
Blame	Composite score	592	5.4 (2.9)	583	5.6 (2.8)	1, 1167	.73	.390	-
	Toward AV affil.	592	6.2 (3.3)	583	6.0 (3.4)	1, 1167	1.00	.320	-
	Toward NV driver	592	7.1 (2.8)	583	7.2 (3.0)	1, 1167	.26	.600	-

Table 5
Descriptive statistics for each dependent measure in each "vehicle purpose" group and ANOVA results for the main effect of vehicle purpose.

Dependent measure		Regulation		Destination		ANOVA: main effect of purpose			
		n	*M (SD)*	*n*	*M (SD)*	*df*	*F value*	*p value*	η_p^2
Perception		587	4.4 (2.5)	588	4.6 (2.3)	1, 1167	1.10	.290	-
Blame	Composite score	587	5.8 (2.9)	588	5.2 (2.8)	1, 1167	12.41	<.001	.010
	Toward AV affil.	587	6.5 (3.4)	588	5.7 (3.3)	1, 1167	19.11	<.001	.020
	Toward NV driver	587	7.0 (2.9)	588	7.3 (2.9)	1, 1167	3.37	.070	-

affiliation (Table 4, first row). Participants rated automated vehicles affiliated with a private commercial company less positively than those affiliated with a public transit agency (Fig. 1).

Research Question 4 asked whether people assign responsibility differently for accidents involving automated vehicle(s) affiliated with a public transit agency versus a private commercial company. An ANOVA on blame with vehicle number, affiliation and purpose as between-participant variables did not find a significant effect of vehicle affiliation (Table 4, second row). No support was found for assigning blame differently between automated vehicle(s) affiliated with a public transit agency versus a private commercial company.

An exploratory test for Research Question 4 was performed to separately look at blame attribution to the automated vehicle affiliation versus to the driver of the normal vehicle. An ANOVA on blame toward AV affiliation with vehicle number, affiliation and purpose as between-participant variables did not find a significant effect of vehicle affiliation (Table 4, third row). However, a post-hoc Tukey's HSD test suggested that the influence of number on AV affiliation blame may have been stronger for private companies than for public agencies (as presented in Section 4.1 and Fig. 3, left). A separate ANOVA on blame toward the normal vehicle's driver with vehicle number, affiliation and purpose as between-participant variables did not find a significant effect of vehicle affiliation (Table 4, bottom row). No interactions involving vehicle affiliation were found, all $ps > 0.26$. Thus, the exploratory test did not find consistent evidence of AV affiliation affecting blame assignment toward the affiliation and toward a normal vehicle driver.

4.3. Effect of vehicle purpose

Research Question 5 asked whether people perceived automated vehicles whose purpose is traffic regulation as more or less positive than those whose purpose is destination transport. An ANOVA on perception with vehicle number, affiliation and purpose as between-participant variables did not find a significant effect of vehicle purpose (Table 5, first row). No support was found for rating automated vehicles used for traffic regulation more or less positively than those used for destination transport.

Research Question 6 asked whether people assign responsibility differently for accidents with automated vehicles for traffic regulation versus those for destination transport. In support of an affirmative answer to this question, an ANOVA on blame with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle purpose (Table 5, second row). Participants assigned greater blame to automated vehicles used for traffic regulation than to automated vehicles used for destination transport (Fig. 2). Greater blame was assigned to the affiliated owner of an automated vehicle(s) versus the driver of a normal vehicle who rear shunted the automated vehicle when the automated vehicle(s) were regulating traffic than when they were driving to reach a destination.

An exploratory test for Research Question 6 was performed to separately look at blame attribution to the automated vehicle affiliation versus to the driver of the normal vehicle. An ANOVA on blame toward AV affiliation with vehicle number, affiliation and purpose as between-participant variables found a significant effect of vehicle purpose (Table 5, third row). Participants assigned greater blame to automated vehicles for traffic regulation than to automated vehicles for transport. No interactions involving vehicle purpose were found, all $ps > 0.3$. A separate ANOVA on blame toward the normal vehicle's driver with vehicle number, affiliation and purpose as between-participant variables did not find a significant effect of vehicle purpose (Table 5, bottom row). However, a post-hoc Tukey's HSD test suggested that participants may have assigned less blame to drivers who hit an automated vehicle convoy than those who hit a lone automated vehicle specifically for vehicles used for traffic regulation (as presented in Section 4.1 and Fig. 3, right). Thus, the exploratory test showed that automated vehicle purpose primarily affected blame attribution to the owner affiliated with the automated vehicle rather than to the normal vehicle driver.

5. Discussion

5.1. Summary of results

Automated vehicle convoys in shared lanes were less positively perceived and led to greater blame of their owning organizations (and less blame to a normal vehicle driver) in the event of a rear shunt accident than lone automated vehicles in a single lane of mixed traffic. Automated vehicles affiliated with a private commercial company were perceived as less positive than those affiliated with a public transit agency. In a rear shunt accident that occurred in shared lanes, the organization affiliated with automated vehicles that regulated traffic was blamed more than when the automated vehicles were used for transportation purposes.

5.2. Policy implications

Simulated results already show that automated vehicle convoys will be able to control highway bottlenecks once they reach 10 percent of all vehicle traffic, acting as moving road obstacles that would restructure the behavior patterns of other road users (Vinitsky, Kreidieh, et al., 2018). Moreover, in our study the number of collocated automated vehicles was the most important policy factor among the three investigated–influencing both participants' perception of automated vehicles and blame attribution toward the organizations affiliated with those vehicles. Together, these facts suggest the importance of maintaining numerical balance in mixed autonomy traffic, particularly in traffic situations where the experience of human road users is directly impacted.

In the event of an accident, automated vehicles whose purpose was to regulate traffic led to greater blame of their owners than did automated vehicles used for destination transportation. This may mean that organizations that wish to use automated vehicles to regulate traffic face harsher moral standards than those that aim to focus on transportation of persons or items. However, the purpose of automated vehicles did not influence participants' valence of perception of the vehicles, suggesting that people evaluating the general concept of AVs in a poll (rather than actually driving behind automated vehicles) may not particularly care about why those automated vehicles are on the road. Meanwhile, existing surveys show very low consumer knowledge about the capabilities of fully-automated vehicles (Boor et al., 2022), suggesting this variable may not yet enter the minds of survey respondents. To move beyond the limits of general concept polling (e.g. Zmud et al., 2016), future public surveys should address this discrepancy by distinguishing possible intended purposes of vehicle automation when asking participants to evaluate AVs.

Participants were influenced by the ownership of automated vehicles when determining their perception of the vehicles. Automated vehicle affiliation may therefore influence public trust (as has been previously demonstrated for AI algorithms (Zhang & Dafoe, 2020))—with private corporations requiring greater public relations effort than public agencies. However, affiliation did not influence blame attribution for a rear shunt of an automated vehicle, perhaps because ownership is less important than facts relevant to an accident.

5.3. Implications for theory

Convoys of automated vehicles led to lower valence of perception and higher blame than lone automated vehicles. This finding extends past results that found driving simulator participants were uncomfortable with driving in the presence of a nearby AV platoon (Aramrattana et al., 2021) by showing people's general perception of AV platoons was lower than of lone AVs. Past work that found public support for AV platoons generally used text surveys or interviews rather than images or simulations (e.g., Castritius, Lu, et al., 2020).

People perceived organizations affiliated with AVs as more blameworthy in accidents involving an AV convoy versus a lone AV—even in a rear shunt accident where the AV gets shunted, which is usually considered the fault of the following rather than leading vehicle. This extends past work that finds automated vehicles lead people to assign greater responsibility to their owning organizations for accidents involving another party even when the other party is at fault (e.g., Li et al., 2016). A possible explanation is that a greater number of automated vehicles increases system complexity, which increases the difficulty of determining legitimate targets of responsibility for accidents caused by autonomous systems (Santoni de Sio & Mecacci, 2021). People therefore increasingly use speculative moral judgment (Danaher, 2016), since traditional means of responsibility ascription are incompatible with complex autonomous systems (Matthias, 2004).

These results point to the significance of the fleet ownership model on opinions around AVs—whereas past work on individual AVs primarily considered consumer choices as the rationale for deploying AVs (e.g., whether purchasers would prefer sacrificial AVs (Bonnefon et al., 2016) or network-connected AVs (Maeng et al., 2021)), AV fleets highlight deployment rationales beyond AV ownership to include AVs as 'material' objects that have spatial presence and behaviors to contend with on the road. AV convoys and their everyday driving behaviors affect public opinion, which extends existing work on how AVs may alter urban space use (Okeke, 2020, Silva et al., 2021) and calls for framing AV survey research around scenarios which are the most salient to other road users and most likely to take place on public roads first—such as spatial conflicts between automated and non-automated vehicles—since negative sentiment towards fleet-owned AVs might change opinions people have towards driving in the presence of AVs.

5.4. Limitations and future work

5.4.1. External validity

This work relied on an online poll to assess perception and blame attribution in public use of automated vehicles. Some of the variables explored here may be more salient in a real world study. For example, it is currently unclear whether automated vehicle

fleets will be deployed for traffic control at scale, so this work is meant to gauge opinion of traffic control demonstrated by past field and simulator studies prior to broader deployment. Similarly, automated vehicle purpose may have a greater effect on participants who experience driving behind such a vehicle, since they would be an active party in the traffic scenario rather than evaluating the scenario online and in the role of a neutral citizen. Moreover, our results only apply to the scenario in which AVs share multiple lanes with normal vehicles. Uncertainties with human-driven vehicles have led to proposals for dedicated lanes and phases for AVs to reduce safety and operational concerns (cf. Ma et al., 2022), which may result in higher valence of perception of AV platoons than if they shared multiple lanes with normal vehicles. However, dedicated lanes for AVs and AVs that form "lines" in a single lane may cause speed reductions due to increased lane changes to enter and exit the dedicated lane or line in a shared lane; they also exhibit poor performance under low AV penetration conditions (Xiao et al., 2020). Limitations of dedicated and single-line lanes have led researchers to propose partially-dedicated lanes in which normal vehicles may follow a group of collocated AVs across multiple lanes (cf. Woo & Skabardonis, 2021, pp. 4) and to remark that "the future of traffic control lies in the vehicle" (Taj, 2019). Future work is needed to determine whether the effects found here extend to AV convoys in dedicated lanes.

5.4.2. Construct validity

The current study was a single-stimulus study in that it used a single instance of text wording and image per condition, which may pose a threat to construct validity. Construct validity is "the inability to generalize the results of a study with few or even a single stimulus…because we do not know whether the effects observed are due to an unstated stimulus feature" (Cummings & Reeves, 2022, pp. 211). We addressed the potential threat to construct validity due to stimulus sampling by defining stimulus criteria in Section 3.3 and by reducing variability across stimuli in different conditions (homogenizing the length and frequency of the text descriptors as well as the graphic elements in the images, such that only the specific words of the condition like "public transit agency" vs. "private commercial company," differed across conditions)—two of the methods suggested by Cummings and Reeves (2022). While we believe the effects found in this study were attributed to number, affiliation and purpose of the automated vehicles, we recommend that future work explores the effect of stimulus characteristics on public perception and accident responsibility involving AV fleets.

5.4.3. Additional considerations

This work looked at how AV policy factors influence the perception of AVs and the responsibility allocated to automated vehicles versus human drivers in rear shunt collisions. However, we did not explore potential reasons or models for why this may be the case. Research suggests that upstream drivers in a simulator task who tried to merge into traffic with AV platoons felt that the task was demanding (Aramrattana et al., 2021) and that perceived ease of use subsequently influences people's acceptance of AVs (Nordhoff et al., 2019). Similarly, vehicle behavior and characteristics can influence a person's intention to accept or not accept an automated vehicle (Nordhoff et al., 2019). In particular, studies have shown that humans make judgments about and assign responsibility for consequential decisions based on their perception of "agency" and "patiency" in moral dilemmas (Gray et al., 2012). This suggests that flipping a given vehicle's role from patient (e.g., transporting people/goods) to agent (e.g., regulating traffic) might alter how bystanders perceive and evaluate its agency, and in turn its role and responsibility in accident situations. Yet another influencing factor may be trust, since opinions about different affiliations may be related to user trust (Zhang & Dafoe, 2020). However, the current survey did not consider any potentially mediating factors, such as perceived authority, agency or trust, which could help explain why policy factors in AV use on public roads affect public opinion. Moreover, public perception was used as a general overarching measure consisting of perceived safety, benefit and other items that could be separately analyzed with other measures found in AV literature (e.g., Pigeon et al., 2021, Benleulmi & Ramdani, 2022, Liu & Xu, 2020). More advanced causal modeling is therefore left as future work.

Our results also indicate that in a rear-shunt accident, the organization affiliated with the leading automated vehicle can be blamed nearly as much as the following normal vehicle. Future work involving a control in which a normal vehicle rather than an automated vehicle is the lead vehicle could identify how much additional blame is placed on automated vehicle versus normal vehicle victims of rear shunt accidents, as well as whether an organization that has a policy to hire human drivers to regulate traffic is believable for participants.

6. Conclusion

Some of the first large-scale deployment of automated vehicles are likely to be of fleet-owned vehicles, which can be deployed in multiples and behave in a coordinated fashion. To anticipate practical issues of public opinion which are likely to occur in response to these automated vehicles, we have conducted a survey study examining the effects of shared-lane convoys, government or corporate ownership, and vehicle purpose on perception and responsibility attribution in a rear-shunt scenario. We found that people found automated vehicle convoys in shared lanes to be less positively perceived than lone automated vehicles, and to have greater responsibility for accidents in which a normal vehicle driver rear-shunted an automated vehicle. Public transit AVs were perceived more positively than private commercial AVs, and AVs performing traffic regulation were blamed more than AVs used for transportation purposes. This study indicates that the number, ownership and use scenario of automated vehicles in shared lanes are likely to have strong impact on public opinion during deployment, and suggests that further research looking at scenarios and use cases around fleet, convoy, and platoon scenarios for other road users will be important to predict and inform the public response to autonomy.

Table 6
Factor loadings for 3-factor structure and 2-factor structure; note: only red numbers are loaded, others are included for completeness and not loaded.

	3-Factor Structure			2-Factor Structure	
Item	F1	F2	F3	F1	F2
Feel	0.79	-0.00	-0.00	0.80	0.00
BenefitSelf	0.89	0.06	-0.01	0.88	0.04
BenefitSociety	0.89	0.01	-0.03	0.89	-0.03
Safe	0.86	-0.04	0.01	0.87	-0.01
Risk (rev. coded)	0.55	-0.14	0.02	0.58	-0.07
Accept	0.86	-0.00	0.01	0.86	0.02
BlameAffil	0.03	0.96	-0.00	-0.14	0.62
BlameDriver	0.02	-0.01	0.96	0.03	0.91
FaultAffil	-0.02	0.81	0.10	-0.16	0.63
FaultDriver	-0.01	0.08	0.85	0.00	0.93

CRediT authorship contribution statement

Thomas Krendl Gilbert: Conceptualization, Methodology, Project administration. **Noah Zijie Qu:** Investigation, Methodology, Resources. **Wendy Ju:** Methodology, Supervision, Writing – review & editing. **Jamy Li:** Conceptualization, Formal analysis, Methodology, Writing – original draft.

Data availability

Data will be made available on request.

Appendix A. Exploratory factor analysis

An exploratory factor analysis (EFA) with a putative 3-factor structure to the 10 questionnaire items using geomin oblique rotation and the lavaan R package, found factor loadings in which all perception items loaded on one factor and non-loading items had loadings less than 0.03; the second and third factors had loadings for affiliation blame and driver blame, respectively (Table 6). As per parallel analysis (Schmitt, 2011), a 2-factor structure was modeled that resulted in a perception factor with -0.16 non-loadings and a responsibility attribution factor with -0.07 non-loadings, while a 4-factor structure resulted in less interpretable loadings, such as regression coefficients for factor loadings that were smaller than non-factor loadings (not shown). The 3-factor EFA was modeled in lavaan as "efa('block1')*F1 + efa('block1')*F2 + efa('block1')*F3 = ~ [all items]".

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