

Acceptance of Automated Vehicles is Lower for Self than Others

ABSTRACT

Road traffic accidents are the leading cause of death worldwide for people aged 2–59. Nearly all deaths are due to human error. Automated vehicles could reduce mortality risks, traffic congestion, and air pollution of human-driven vehicles. However, their adoption depends on consumer acceptance, among other factors. In a nationally representative sample of Americans ($N = 580$) and direct replication ($N = 193$), we find consumers prefer lower levels of vehicle automation for themselves than for others. This difference is mediated by self-enhancing comparative evaluations. Relative to automated vehicles, consumers believe they are safer and more trustworthy drivers than other drivers. In a second experiment ($N = 803$), enhanced assessments of self, not different assessments of automated vehicle capabilities, explained different preferences for self and others. Our findings show how biased self-evaluations reduce the acceptance of automated vehicles. This yields practical insights for policymakers and firms seeking to increase acceptance of automated vehicles.

Road traffic accidents are the leading cause of death worldwide for people aged 2–59 and for Americans aged 1–54 (CDC 2023). Nearly all road traffic accidents (98%) are attributable to human error (NHTSA 2022b). By replacing human drivers, automated vehicles have the potential to substantially reduce this mortality risk and also make roads more accessible, less congested, and less polluted. Unlike infrastructure improvements that can be paid for and mandated by governments, like any new technology, the diffusion of automated vehicles critically depends on consumer perceptions (e.g., Bass, 1969; Meade and Islam, 2006). Beyond practical barriers to adoption such as their price and accessibility (Nastjuk et al. 2020; Raj, Kumar, and Bansal 2020), real psychological barriers exist, as their adoption requires consumers to trust a technology that could, in the event of failure, harm or kill consumers and their loved ones. Psychological barriers to adopting automated vehicles are typically explored through the lens of *algorithm aversion*—the reluctance to trust algorithms, automation, and artificial intelligence due to a prejudiced perception of the vehicles themselves (Bonnefon, Shariff, and Rahwan 2016; Buckley, Kaye, and Pradhan 2018; Raj et al. 2020). Consumers, for example, perceive automated vehicles as more unsafe, unfamiliar, and risky than human-driven vehicles (De Freitas et al. 2023b).

We suggest that psychological barriers do not only reside in the way that consumers perceive automated vehicles, but also in biased perceptions of themselves (Morewedge 2022). Most consumers believe they are better and safer than average drivers (Kruger 1999; Walton and Bathurst 1998). We hypothesize that these self-serving evaluations of driving ability extend to comparisons between self and automated vehicles, which make consumers reluctant to adopt these technologies. Furthermore, we posit that this self-enhancing evaluation will not extend to other human drivers. In other words, we predict that consumers evaluate their driving abilities

more favorably relative to automated vehicles and evaluate the driving abilities of their peers less favorably relative to automated vehicles. Our theory suggests these perceptions lead consumers to believe that other human drivers will benefit more than themselves from automated vehicles. In a quota-based, nationally representative sample of Americans ($N = 580$) and direct replication with a convenience sample ($N = 193$), we find that consumers prefer lower levels of vehicle automation for themselves than for other human drivers and, relative to automated vehicles, they perceive themselves to be safer and more trustworthy than other human drivers. In a follow up experiment ($N = 803$), we independently measure perceived capabilities of the self, others, and automated vehicles, and find that self-enhancing assessments of the abilities of human drivers (self > others)—not different assessments of the capabilities of automated vehicles—explain the asymmetry in acceptance of automated vehicles. Our findings show how biased self-evaluations can impede consumer acceptance of automated vehicles and suggest actionable ways for policymakers and firms to increase consumer acceptance and adoption of these technologies.

THEORETICAL FRAMEWORK

The Case for Automated Vehicles

In 2021, the United States suffered approximately 42,915 fatalities from vehicle traffic accidents (NHTSA 2022a), a 10.5% increase since 2020 and an 18% increase since 2019. These statistics underscore a national public health crisis as well as the staggering economic and emotional burden of vehicle traffic accidents. In 2019 alone, vehicle traffic accidents cost the United States \$340 billion, 1.6% of its gross domestic product and an estimated \$1.4 trillion in societal harm (NHTSA 2023). At least 90% of road accidents are attributable to human errors

(NHTSA 2022b), such as inattention, excessive speed, illegal maneuvers, and falling asleep (Smith 2017).

Automation makes it possible to transform driving, once an exclusively human function, into a fully computerized task. Developers aim to engineer completely automated vehicles, yet these technologies are not capable of performing all driving tasks to date. The Society of Automotive Engineers has created a classification system of Level 0 (no automation) to Level 5 (fully automated), categories indicating the number automated driving tasks. As of mid-2022, Level 1 and Level 2 vehicles are commercially available to consumers. Firms are still testing Level 3 and Level 4 vehicles (De Freitas et al. 2022). Fully automated Level 5 vehicles, which can perform dynamic driving tasks across all driving conditions, are not yet developed. Notwithstanding, even automated vehicles with lower levels of automation can still help avoid crashes. They issue lane departure warnings and take direct actions such as automatic braking and advanced emergency intervention.

Automated vehicles have the potential to eliminate human error because they react faster than human drivers and are immune to unintended and deviant human behaviors, such as mind-wandering and driving under the influence of drugs and alcohol (Sivak and Schoettle 2015). Automated vehicles also offer benefits that extend beyond reducing vehicle traffic accidents such as increasing accessibility for passengers who are disabled, unlicensed, or live far away from public transportation systems (Fagnant and Kockelman 2015); reducing traffic and parking congestion (Kesting et al. 2008); and enhancing ride quality by freeing consumers to converse, work, relax, or drive inebriated (Greenblatt and Saxena 2015). Automated vehicles can generate economic efficiencies for firms by eliminating the need to employ human drivers, yielding cost savings that firms can pass on to consumers.

Unlike infrastructure improvements that policymakers can implement directly, like any technological innovation (Bass, 1969), the adoption and diffusion of automated vehicles hinges on consumer perceptions and consumer acceptance (Newcomb 2012). Even policies mandating automated vehicles will require public support. Public surveys consistently find that consumers prefer to avoid riding in or buying automated vehicles. For instance, 63% of consumers say they would not want to ride in an automated vehicle if given the opportunity (Rainie et al. 2022), 76% feel less safe riding in cars with self-driving features, and 79% would not pay more to own a car with self-driving features (Brennan and Sachon 2022). Consumers express safety concerns about the performance and failures of automated vehicles, and fear of ceding control to a machine (Schoettle and Sivak 2014). Consumer segments also vary in their willingness to adopt automated vehicles. Automated vehicles are most appealing to young, highly educated, and tech-savvy consumers (Haboucha, Ishaq, and Shiftan 2017; Lavieri et al. 2017; Menon et al. 2020).

Psychological barriers due to perceptions of AVs

Investigations of psychological barriers to the adoption of algorithms and automated technologies typically focus on the characteristics of the algorithms and automated technologies, such as concerns regarding their performance and degree of autonomous control (André et al. 2018; Dietvorst, Simmons, and Massey 2018; Longoni, Bonezzi, and Morewedge 2019; Wertenbroch et al. 2020), flexibility in learning from mistakes (Reich, Kaju, and Maglio 2022), complexity (Yeomans et al. 2019), and opacity—aka their “black box” nature (Cadario, Longoni, and Morewedge 2021). These psychological barriers (for a review, see De Freitas et al. 2023a) can be applied to automated vehicles as well. For example, the opacity of their decision-making algorithms raises concerns that automated vehicles will not reflect consumers’ values if

they are confronted with life-and-death situations in which the vehicle has to decide who to harm and save (Bonnefon et al. 2016); even though these concerns are likely misguided (De Freitas et al. 2020; De Freitas et al. 2021).

Corresponding interventions have taken a product-focused approach and aimed to reduce prejudice towards automated products, such as demonstrating that these products can learn (Reich et al. 2022) and by anthropomorphizing them (Castelo, Bos, and Lehmann 2019). In the context of automated vehicles specifically, product-focused interventions include demonstrating that these vehicles can navigate critical situations (Gold et al. 2015), explaining how they work and providing real-time transparency into their processing via engaging user interfaces (Beller, Heesen, and Vollrath 2013; Koo et al. 2015; Kraus et al. 2020; Oliveira et al. 2020), and by anthropomorphizing them (Waytz, Heafner, and Epley 2014).

Psychological barriers due to biased self-perception

Another class of psychological barriers may stem, not from prejudiced judgments of algorithms and automated vehicles, but from biased perceptions of the self. Such biased perceptions may include self-serving comparative evaluations, as well as self-threat cued by algorithms that perform tasks considered identity-relevant, which can include driving (Leung, Paolacci, and Puntoni 2018). Consumers who strongly identify with driving are more likely to own cars with manual versus automated transmissions, for instance, after controlling for driving expertise and driving outcomes (Leung et al. 2018). This line of psychological resistance suggests reducing the identity-threat evoked by automated vehicles and increasing the objectivity of criteria used to evaluate the self and technology could reduce the ability of self-serving bias to influence evaluations (Morewedge 2022). We suggest that since comparisons between other

drivers and automated vehicles should be less personally threatening, consumers should theoretically be more accepting of others using automated vehicles than themselves.

Most consumers exhibit self-serving evaluations when comparing themselves to others (Alicke 2000; Kruger and Dunning 1999), and believe that they are above average drivers. Compared to other drivers, consumers believe they are slower, more skillful, and less risky (Horswill, Waylen, and Tofield 2004; Svenson 1981), less likely to be involved in accidents (DeJoy 1989), and better at navigating a range of concrete driving scenarios like parking, reversing, and driving under adverse weather conditions (McKenna, Stanier, and Lewis 1991).

We propose that self-servings assessment of driving skills lead consumers to be less accepting of automated vehicles for themselves than for others for two reasons. First, because consumers believe themselves to be better drivers than other consumers. Second, because consumers also believe themselves (but not others) to be better drivers than automated vehicles. We present evidence of this in a pre-registered experiment with a high-powered, nationally representative sample (Experiment 1), and directly replicate these findings in a convenience sample (Experiment 1b). Following up on these results (Experiment 2), we separately measure perceived capabilities of the self, others, and automated vehicles, and find that it is indeed self-serving assessments of driving abilities—not different assessments of automated vehicles as a technology—that leads to the asymmetry in acceptance of automated vehicles for self and others. We do not directly measure the purchase of automated vehicles, but consumer perceptions of the performance and safety gains provided by automated vehicles and the relevance of their adoption by other consumers for self should predict the diffusion of automated vehicles, just as perceived innovativeness and social influence strength predict the diffusion of other technological

innovations like personal computers, cellular telephones, microwave ovens, and color televisions (Bass, 1969; Meade and Islam, 2006).

Data, code and survey materials are publicly available in the following Github repository:
https://github.com/Ethical-Intelligence-Lab/av_perspective

EXPERIMENT 1a

We used quota sampling to recruit a nationally representative sample of Americans, matched to 2021 census data on age, ethnicity, gender, and region. Inattentive responses from participants have been on the rise across multiple survey platforms and have a large impact on data quality (Aronow et al. 2020). As a result, we included four attention checks at the beginning of the survey. Participants who failed these checks were excluded.

Each participant expressed their preferred level of automation for purchasing a theoretical automated vehicle. Critically, we randomly assigned half of the participants to assess the level of automation they prefer for themselves, and the other half to assess the level of automation they prefer for other drivers. They subsequently made comparative evaluations of the trustworthiness and safety of either the self, relative to automated vehicles, or of others, relative to automated vehicles. We hypothesized that participants in the ‘self’ condition would prefer a lower level of automation for themselves, but participants in the ‘others’ condition would prefer a higher level of automation for other drivers. We expected that this self-other difference in preferred level of automation would be mediated by the tendency to inflate the self’s driving abilities, relative to automated vehicles, compared to the abilities of other drivers, relative to automated vehicles. All procedures and analyses were pre-registered (<https://aspredicted.org/wc7vg.pdf>).

Method

Participants. One thousand and twenty participants who passed attention checks were recruited from Lucid Theorem, an online survey platform that facilitates data collection of nationally representative samples. It employs quota sampling techniques to balance participants across a range of demographics, such as age, gender, ethnicity, and geographic region using United States Census benchmarks (Coppock and McClellan 2019). Of the 1,020 participants recruited, 43.2% were excluded from the final analysis for failing the comprehension checks, which is a typical exclusion rate on Lucid for studies with challenging comprehension checks (Aronow et al. 2020). These comprehension checks were designed to ensure participants’ understanding of the different levels of automation, and their respective human-machine task distribution (see Web Appendix for verbatim comprehension check questions). We note that the results of this study and all others in the manuscript are qualitatively the same whether or not we perform these exclusions; in other words, results are statistically significant and in the same direction in all cases (see Web Appendix). After exclusions, we analyzed data from 579 participants ($M_{\text{age}} = 45.89$, 52.7% female) with 301 participants ($M_{\text{age}} = 45.69$, 53.8% female) in the ‘self’ condition and 278 participants ($M_{\text{age}} = 46.12$, 51.4% female) in the ‘other’ condition. Table 1 presents a comparison of demographic characteristics for participants from the Lucid study paired with demographic characteristics from United States Census data.

Variable	Variable sub-category	Lucid	US Census (2021)
Age (median)		45	38.70
Gender	Female	52.7%	51%
Race/ Ethnicity	White	77.4%	75.8%
	Black	7.3%	13.6%
	Asian	4.8%	6.1%
	American Indian or Alaska Native	3.5%	1.3%

Not Hispanic or Latino		90%	81.3%
Income	Under \$15,000	11.1%	9.3%
	\$15,000 to \$24,999	10.9%	8.1%
	\$25,000–\$34,999	11.2%	7.8%
	\$35,000–\$49,999	15.5%	10.9%
	\$50,000–\$74,999	18.7%	16.2%
	\$75,000–\$99,999	10.7%	11.9%
	\$100,000–\$149,999	10.7%	15.9%
	\$150,000–\$199,999	3.5%	8.3%
	\$200,000 or above	4.5%	11.6%
Education (Age 25 and older)	Less than High School	2%	8.9%
	Diploma		
	High School Graduate	15.4%	27.9%
	Some College, No Degree	18%	14.9%
	Bachelor’s Degree	32.8%	23.5%
	Advanced Degree	23.9%	14.4%
Population by Region	Northeast	19.5%	17.2%
	Midwest	20.4%	20.7%
	South	35.4%	38.4%
	West	24.7%	23.7%
Political Orientation	Democrats	34%	29%
	Republicans	20.4%	27%
	Independents	36.8%	42%

Table 1. Comparison of the demographics of participants in Experiment 1 and current population survey benchmarks (Census.gov 2022). Some categories do not sum to 100 as Lucid Theorem allows participants to select options like “other” or “prefer not disclose”.

Procedure. Initially, participants were given background information on the potential benefits of automated vehicles in making transportation safer and eliminating accidents caused by human error such as drunk driving and distractions, according to experts within the field. Next, participants were educated on the six possible levels of automation for a vehicle, based on the definition by the Society for Automotive Engineers, including the tasks that are controlled by

humans and machines at each level—Figure 1. After reading this information, participants randomly assigned to the ‘self’ condition rated their preferred level of automation for themselves on a 6-point scale, with Level 1 (not automated at all) and Level 6 (fully automated) as endpoints: “Imagine that automobile companies are selling vehicles of all types at the same price, and that you need to buy a vehicle. Which level would you buy?” Participants randomly assigned to the ‘others’ condition rated their preferred level of automation for other drivers on the same scale: “Imagine that automobile companies are selling vehicles of all types at the same price, and that other people need to buy a vehicle. Which level should other people buy?” Additionally, participants were asked to explain their response in a text box, “In one sentence, please explain why you chose this particular level.” A pretest ($N=150$; <https://aspredicted.org/py8sw.pdf>) confirmed that the majority of participants (88.1%) interprets “other people” as the average driver, i.e., “People other than you -- regardless of whether they are similar to you or different from you”, rather than as people who are very different from the participant (see Web Appendix).

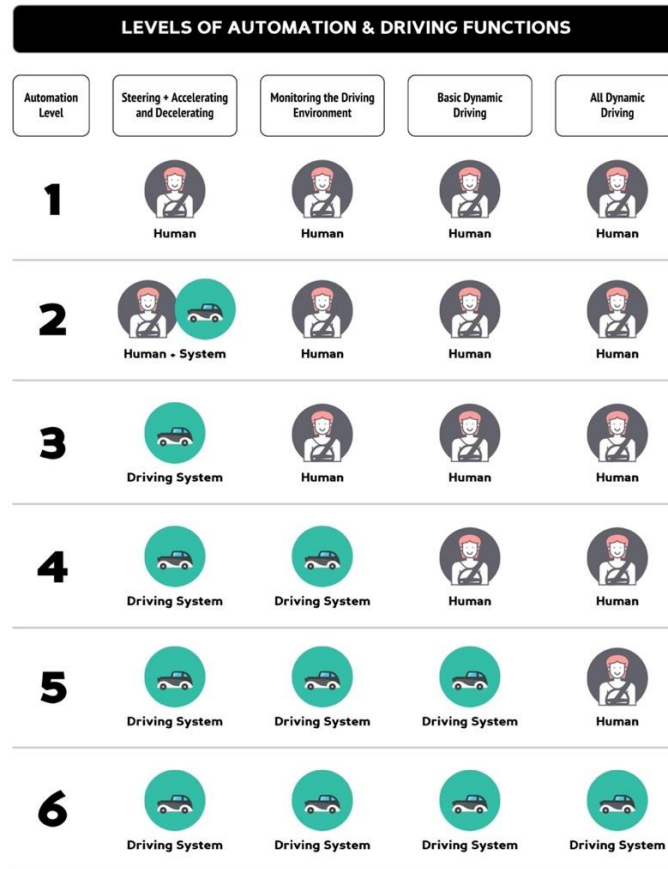


Figure 1. Levels of automation shown to participants.

Next, participants compared their or others' driving skills to automated vehicles. They indicated the extent to which they agreed with a statement about trust in driving skills: "I would be willing to trust my own driving ability [the driving ability of other drivers] more than an automated vehicle's driving abilities", in addition to a statement about driving safety: "I am definitely a safer driver than an automated vehicle [Other drivers are definitely safer drivers than an automated vehicle.]". They rated both items on 100-point scales with 0 (completely disagree) and 100 (completely agree) as endpoints. Finally, we measured participants' familiarity with automated vehicles, asked whether they had a driver's license, and collected basic demographic information.

Results

We first tested for differences in preferred levels of automation and driving skill judgments between the ‘self’ and ‘others’ conditions using a parametric, independent samples t-test, given that assumptions of normal distribution and homoscedasticity were satisfied. As predicted, participants preferred lower levels of automation for themselves than for other drivers ($M_{\text{Self}} = 3.25$ vs. $M_{\text{Others}} = 4.14$, $t(577) = -6.01$, $p < .001$, $d = -.50$)—Figure 2. Given the ordinal nature of the preferred automation variable, we also compared conditions using a non-parametric analysis (Wilcoxon test) and found similar results ($W = 30246$, $p < .001$).

Since the safety and trust measures were highly correlated ($\alpha = 0.86$), we averaged them into a single safety-trust construct for analysis purposes (although we find similar statistical results when analyzing the safety and trust measures separately; see Web Appendix). Relative to automated vehicles, participants indicated higher levels of safety-trust assessments in their own driving skills than in the driving skills of others ($M_{\text{Self}} = 65.35$ vs. $M_{\text{Others}} = 44.93$, $t(577) = 9.53$, $p < .001$, $d = .79$).

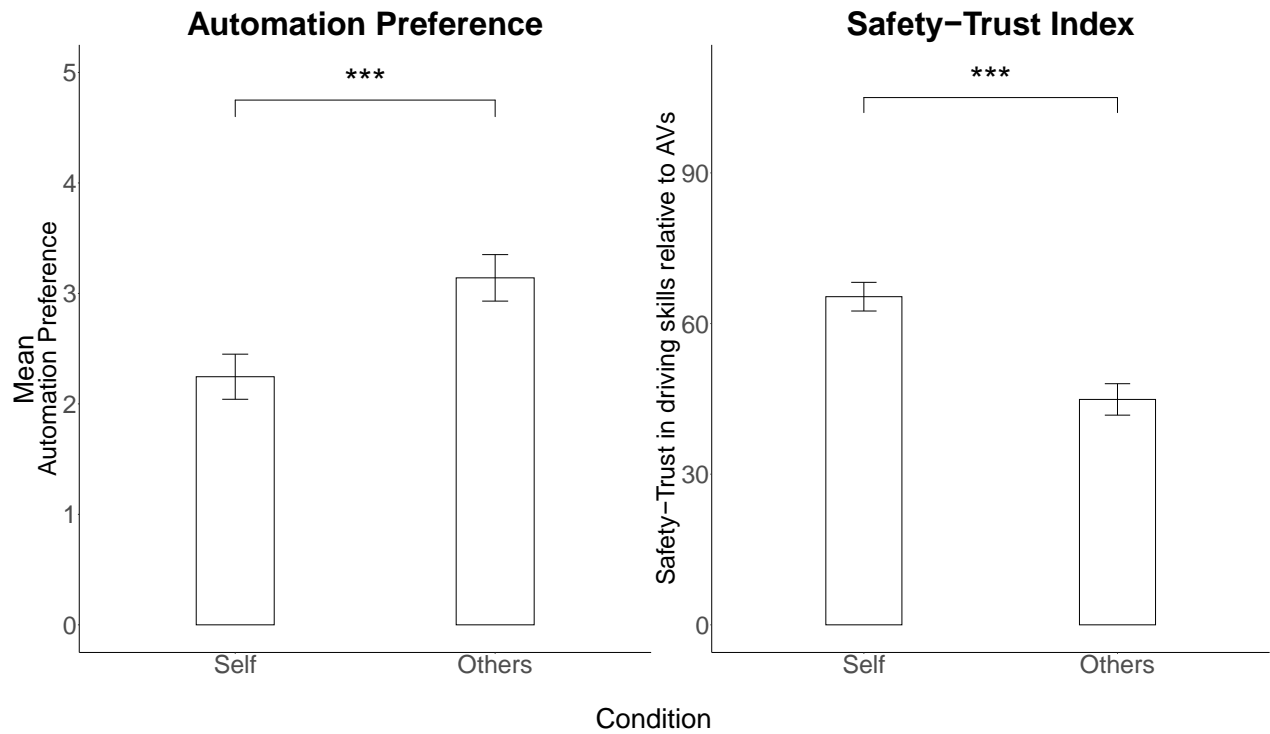


Figure 2. Participants preferred lower levels of automation for themselves than for other drivers. They also perceived themselves as safer and more trustworthy drivers, relative to automated vehicles, than other drivers, relative to automated vehicles. All comparisons were statistically significant at the $p < .001$ level (***). The y-axis for preferred level of automation has been transformed to a 0-5 scale, to correspond to the official Society for Automotive Engineers categorization of automation levels.

To test the psychological process underlying this response pattern, we conducted a parallel mediation analysis (PROCESS Model 4; Hayes 2012) with the treatment condition (‘self’ versus ‘others’) as the independent variable, automation preference as the dependent variable, and safety-trust judgments as mediator. We found that self-other differences in safety-trust assessments ($b = 0.82$, $SE = 0.10$, 95% CI [0.633, 1.021]) mediated the self-other difference in preferred level of automation—Figure 3. So, the higher automated driving preferences for

others (versus the self) can be explained by lower trust in other's driving skills relative to automated vehicles (versus in the self's driving skills relative to automated vehicles). That is, when participants make judgments about others (rather than the self), this is associated with a decrease in trust-safety assessments which, in turn, is associated with an increase in automation preferences. The main effects and mediation results were replicated when controlling for driver's license or familiarity with automated vehicles (see Web Appendix).

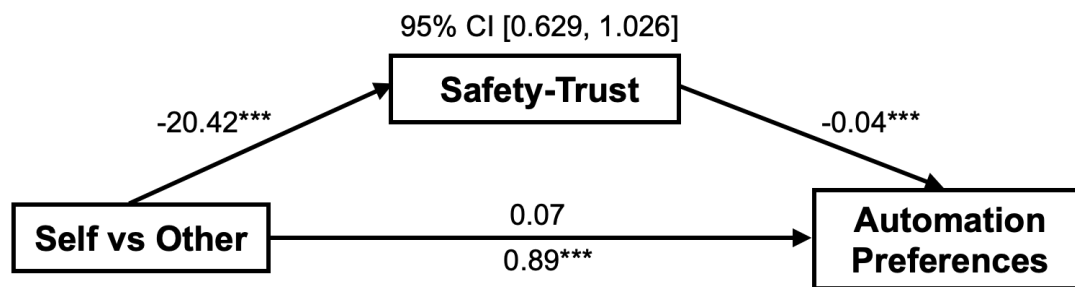


Figure 3. The difference in the preferred level of automation for the self and others was mediated by differences in the perceived trustworthiness and safety of self and others relative to automated vehicles. The total effect of treatment condition on the DV is reported below the line and the direct effect is reported above the line.

Discussion

Participants preferred lower levels of automation for themselves than for other drivers. Lower preferences for the self were statistically explained by self-enhancing assessments of driving ability. Relative to automated vehicles, participants believed themselves to be safer and more trustworthy drivers than other human drivers. These results have important implications for influencing strategies of automated vehicle adoption, suggesting that biased judgments of the self must be considered when estimating acceptance of automated vehicles.

EXPERIMENT 1b

Experiment 1b directly replicated Experiment 1a with a convenience sample.

Method

Participants. Two hundred and twenty-three participants who passed attention checks were recruited from Prolific. After excluding participants who failed comprehension checks, the remaining sample consisted of 192 participants ($M_{\text{age}} = 33.85$, 50.5% female), with 96 participants ($M_{\text{age}} = 34.45$, 49% female) in the ‘self’ condition and 96 participants ($M_{\text{age}} = 33.25$, 52.1% female) in the ‘others’ condition.

Results

As in Experiment 1a, participants preferred lower levels of automation for themselves than for other drivers (parametric independent samples t-test: $M_{\text{Self}} = 3.64$ vs. $M_{\text{Others}} = 4.31$, $t(190) = -2.95$, $p = 0.004$, $d = -.43$; non-parametric Wilcoxon test: $W = 3580.5$, $p = 0.006$). Relative to automated vehicles, they indicated higher levels of safety-trust ($\alpha = 0.79$) in their own driving skills than in the driving skills of others ($M_{\text{Self}} = 52.23$ vs. $M_{\text{Others}} = 38.02$, $t(190) = 4.32$, $p < 0.001$, $d = .62$). Self-other differences in safety-trust assessments mediated the self-other difference in preferred level of automation ($b = 0.66$, $SE = 0.16$, 95% CI [0.354, 0.965]).

Analogous to Experiment 1a, we found similar results when analyzing the safety and trust measures separately, and replicated all findings when controlling for driver’s license and familiarity with automated vehicles (see Web Appendix).

EXPERIMENT 2

Experiment 2 built on the first set of experiments in four ways. First, we unpacked evaluations of driving ability for self, other humans, and automated vehicles. One possibility is that consumers make different assessments of automated vehicles as a technology when assessing them for the self than others. The risks of the technology, for instance, could be more salient or important when making judgments for the self. By contrast, we suggest the difference is driven by self-enhancing assessments of human drivers. To test these accounts, we drew from Alicke & Govorun (2005) and had all participants independently rate the abilities of the human driver and of automated vehicles. We predicted that participants would exhibit self-enhancing assessments of their abilities, not different evaluations of automated vehicles when compared to self and others. Because many stakeholders are interested in understanding consumer preferences for fully autonomous vehicles (Level 6), we also added a dependent variable soliciting preferences for fully autonomous vehicles.

Second, we addressed alternative explanations of the self-other asymmetry in automated vehicle acceptance by testing competing mediators of the effect, including: (i) the relevance of driving to their identity (Leung et al. 2018); (ii) whether participants desire to maintain their driving skills over time (Cheng and Novick 1990; Oyserman 2009); and (iii) the need for control, given that people generally desire to exert control over their environments in order to achieve desired goals (Bandura, Freeman, and Lightsey 1999; Jb 1966; Leotti, Iyengar, and Ochsner 2010; Ryan and Deci 2006). These were chosen, in part, from our coding of the explanations that participants in Experiment 1b gave to explain their preferred automation level. Safety/trust (36.2%) and the need to maintain control of the vehicle (24.2%) were the most common

explanations (see Web Appendix). We predicted that self-enhancing assessments of human drivers would mediate differences in preferences for self and others even when including these other measures in the mediation analysis. All procedures and analyses were pre-registered (<https://aspredicted.org/ya5k8.pdf>).

Third, Experiments 1a-b included a potential confound in their preference elicitations. Participants in the self condition were asked what vehicle they “would” buy. Participants in the other condition were asked what vehicle others “should” buy. Differences could reflect different preferences for wants and shoulds, accordingly (Milkman, Rogers, and Bazerman 2008). In Experiment 2, we used the “would” formulation in both preference elicitations for self and other and predicted that consumers would prefer less automated vehicles for themselves than for others.

Fourth, whereas Experiments 1a-b asked participants their preferred level of automation, many stakeholders are most interested in understanding consumer preferences for fully autonomous (Level 6) vehicles. Thus, we add a dependent variable only asking about fully automated vehicles.

Method

Participants. Nine hundred and twenty-one participants who passed attention checks were recruited from Prolific. Of the 921 participants ($M_{\text{age}} = 44.09$, 49.9% female), 12.8% were excluded from the analysis for failing to clear the comprehension checks. Data were analyzed from the remaining 803 participants ($M_{\text{age}} = 41.91$, 49.2% female) with 415 participants ($M_{\text{age}} = 42.64$, 48% female) in the self and 388 participants ($M_{\text{age}} = 41.13$, 50.5% female) in the other conditions.

Procedure. The design was similar to Experiments 1a-1b, with the following changes. Our primary measure of automation preference used a more parallel structure across conditions “...Which level would **you** prefer to buy?” (self condition) and “Which level would you prefer **other people** buy?” (other condition). Participants also rated purchase preference for a fully autonomous vehicle for self and others on a 100-point scale, with 0 (Low preference) and 100 (High preference) as endpoints [Self condition: “Imagine that automobile companies are selling automated vehicles with Level 6 automation (fully automated) in compliance with road laws and regulations. How much would **you** prefer to buy a Level 6 (fully automated) vehicle?”; Other condition: “...How much would you prefer **other people** to buy a Level 6 (fully automated) vehicle?”].

Next, participants separately rated safety and trust in driving skills for themselves or other drivers, and for automated vehicles. They also rated items corresponding to the competing mediators (‘identity-relevance’, ‘need for control’, and ‘desire for skills’). All items were presented in randomized order—see Table 2. Finally, participants reported whether they had a driver’s license, how many years they had been driving for, their familiarity with automated vehicles, and basic demographic information.

Measure	Item
Trust, self [other]	“I would be willing to trust my own driving ability [the driving ability of other human drivers].”
Trust, automated vehicle	“I would be willing to trust an AV’s driving ability.”
Safety, self [other]	“I am a safe driver [Other drivers are safe drivers].”
Safety, automated vehicle	“Automated vehicles are safe drivers.”

Identity relevance	“Being a driver is relevant to my [other people’s] identity.”
Desire to maintain driving skills	“It is important to maintain my driving skills over time [It is important to other drivers that they maintain their driving skills over time].”
Need for control	“It is important for me to have complete control over the vehicle during driving [It is important to other drivers that they have complete control over their vehicle during driving].”

Table 2. Potential mediators measured in Experiment 2. Note: All items were rated on 100-point scales. The first four had endpoints 0 (Completely disagree) to 100 (Completely agree), whereas the last four had endpoints 0 (Not at all) to 100 (Very much).

Results

As in Experiments 1a-1b, participants preferred lower levels of automation levels for themselves than for other drivers (parametric t-test: $M_{\text{Self}} = 3.42$ vs. $M_{\text{Others}} = 3.81$, $t(801) = -3.02$, $p = .003$, $d = -.21$; Wilcox Test: $W = 70880$, $p = 0.003$). They also had lower purchase preferences for a fully automated vehicle for themselves than for other drivers (parametric t-test: $M_{\text{Self}} = 40.00$ vs. $M_{\text{Others}} = 51.58$, $t(801) = -4.40$, $p < .001$, $d = -.31$).

Trust and safety assessments for the self and others were averaged into a single safety-trust construct ($\alpha = 0.91$), as were trust and safety assessments for AVs ($\alpha = 0.92$). Notably, participants indicated higher levels of safety-trust in their own driving skills compared to that of other drivers ($M_{\text{Self}} = 84.17$ vs. $M_{\text{Others}} = 49.00$, $t(801) = 25.85$, $p < .001$, $d = 1.83$). There was no

difference in safety-trust assessments for automated vehicles between conditions ($M_{\text{Self}} = 56.32$ vs. $M_{\text{Others}} = 58.61$, $t(801) = -1.16$, $p = .245$, $d = -.08$; Figure 4).

To replicate the mediation analyses from Experiments 1a-1b, we created a *relative* index of safety-trust by subtracting these assessments for the human driver (self or others) from assessments for AVs. As in Experiment 1a-b, participants exhibited higher assessments of safety-trust in their own driving skills relative to AVs, as compared to in other drivers relative to AVs ($M_{\text{Self}} = 27.84$ vs. $M_{\text{Others}} = -9.62$, $t(801) = 14.31$, $p < .001$, $d = 1.01$). To test whether this relative index mediated the self-other differences in preferences for automation level and fully autonomous vehicles, we conducted a parallel mediation analysis (PROCESS Model 4; Hayes 2012) for each of the DVs, with the treatment (self vs. other) condition as the independent variable, and relative safety-trust index, identity-relevance, desire to maintain skills, and need for control as parallel mediators. For both preference elicitations, the relative safety-trust index was the only significant mediator (automation level preference: $b = 1.25$, $SE = 0.10$, 95% CI [1.063, 1.460]; full autonomy preference: $b = 25.84$, $SE = 2.06$, 95% CI [21.984, 30.014]; Figure 5).

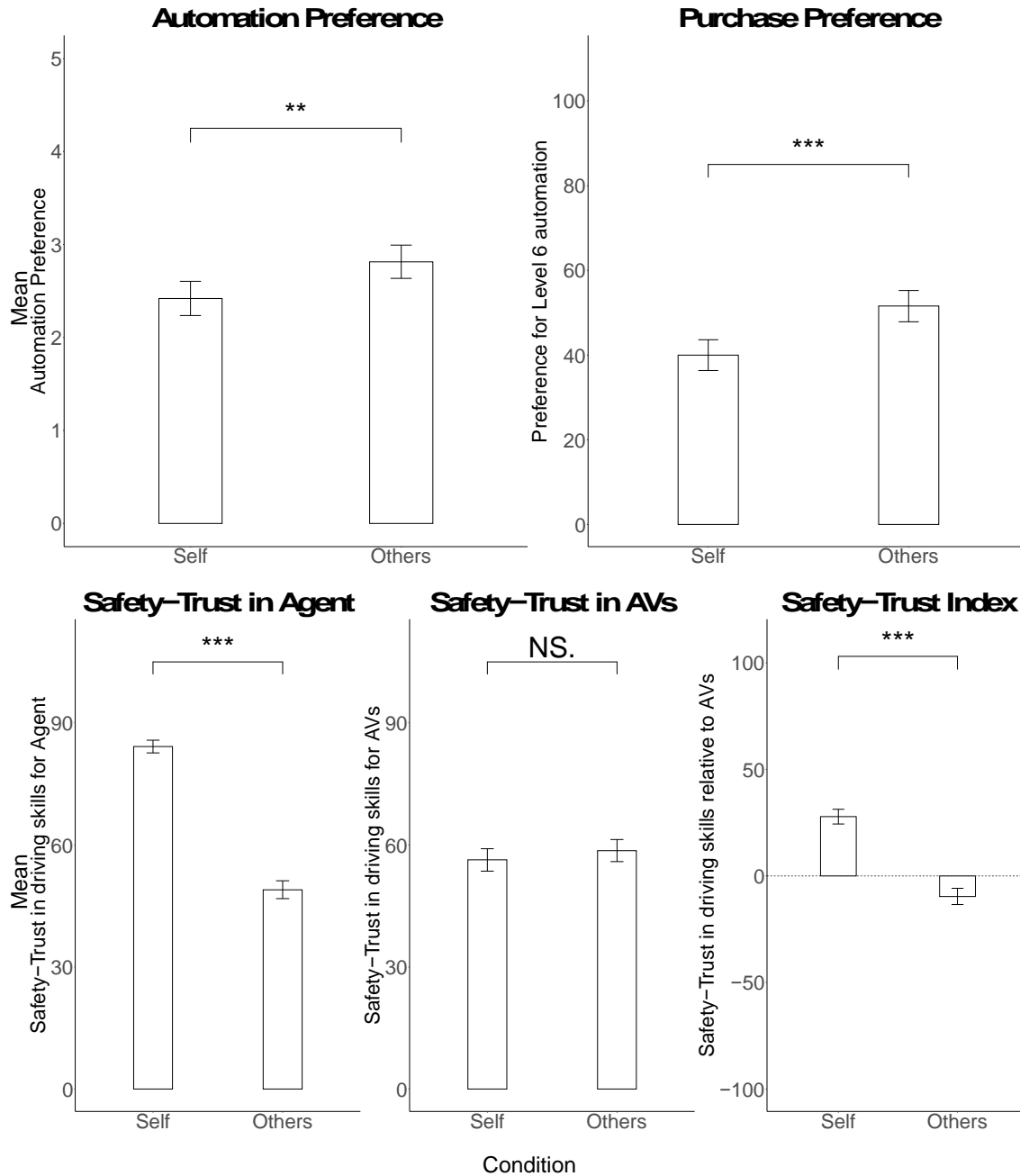


Figure 4. Participants preferred lower automation levels for themselves than for other drivers and preferred fully autonomous vehicles to be purchased more by others than themselves. These differences are explained by self-enhancing assessments of human drivers, not different assessments of automated vehicles. Subtracting assessments of autonomous vehicles from the

self [other] yields the same asymmetry in safety-trust found in Experiment 1. $p < .01$ (**), and $p < .001$ level (***).

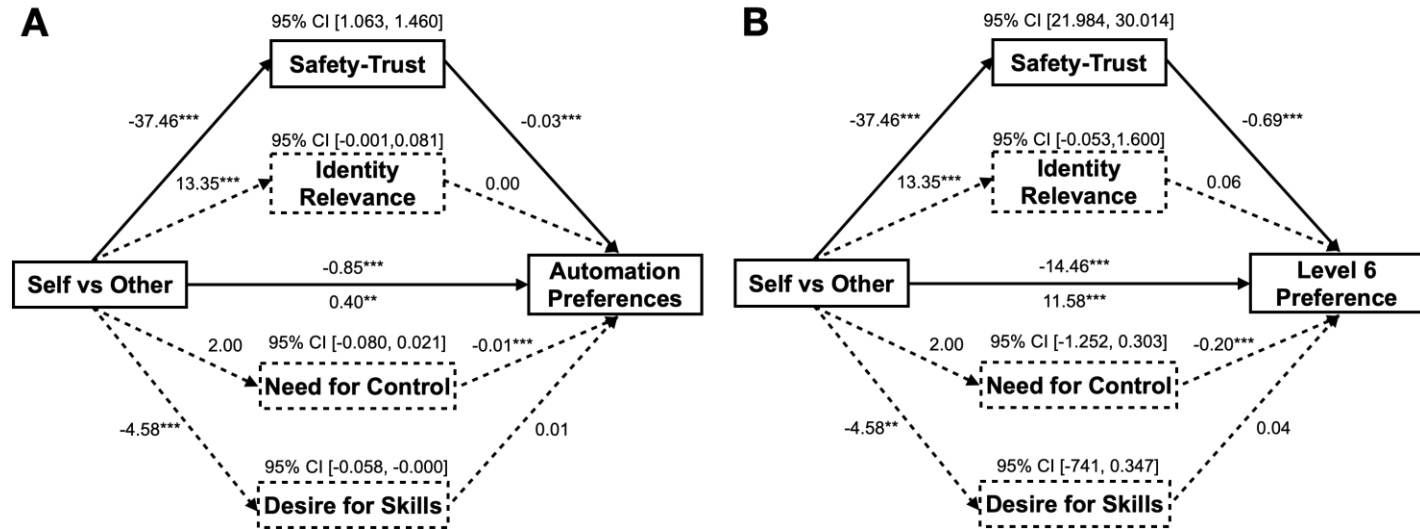


Figure 5. The differences in (A) the preferred level of automation for the self and other drivers as well as in (B) preferences for purchasing fully autonomous vehicles were selectively mediated by the safety-trust index, and not by other competing mediators. The total effect of treatment condition on DV is reported below the line and the direct effect is reported above the line.

Discussion

The results of Experiment 2 replicate and show the generalizability of the different preferences for self and others. With more conservatively aligned measures, participants again preferred to purchase less automated vehicles for themselves than they preferred for other consumers. In addition, participants were less likely to prefer a fully automated vehicle for themselves than for other consumers. The results of Experiment 2 also provide further evidence that these different preferences are driven by self-serving bias. When measuring the driving abilities of humans (self or other) and automated vehicles independently, participants exhibited self-enhancement in their assessment of the abilities of human drivers but not of automated

vehicles. Furthermore, these trust-safety assessments mediated the self-other difference preferences whereas plausible alternative factors (identity-relevance, desire to maintain skills, and need for control) did not.

GENERAL DISCUSSION

Consumers exhibit a self-other asymmetry in preferences for automated vehicles. They prefer vehicles with lower levels of automation for themselves and vehicles with higher levels of automation for other consumers; they also are less likely to prefer fully automated vehicles for themselves than for other consumers. This asymmetric preference is explained by self-enhancing assessments of their driving skills. Participants believed themselves to be more trustworthy and safe drivers relative to automated vehicles, and this pattern was selectively associated with lower levels of automation preferences for themselves. By contrast, participants believed others to be less trustworthy and safe drivers relative to automated vehicles, and this tendency was associated with higher levels of automation preferences for others. Critically, the differences in these assessments were driven by self-serving assessments of human drivers, not different assessments of automated vehicles.

Theoretical and Practical Contributions

Our findings make a theoretical contribution to the literature on predicting and explaining consumer acceptance and adoption of automation, algorithms, and artificial intelligence (for a review, see De Freitas et al. 2023a). Psychological barriers to adoption reside not only in the perceptions of algorithms, artificial intelligence, and automation, but also in the way consumers perceive themselves. Consumers harbor realistic and exaggerated concerns about the performance, safety, and abilities of automated vehicles and the algorithms that guide their

decision making (De Freitas and Cikara 2021; Dietvorst, Simmons, and Massey 2015; Reich et al. 2022). We find that the tendency to engage in self-enhancement may create an additional psychological barrier to consumer acceptance of automated vehicles, and perhaps automation more generally. In so doing, our work illustrates a novel way in which self-perceptions influence the adoption of technologies that may augment or replace human skills and abilities (Leung et al. 2018; Longoni et al. 2019; Polman et al. 2022).

We do not directly measure the purchase or use of automated vehicles, but the consumer perceptions we identify are likely to impede the diffusion of automated vehicles in the marketplace. The classic Bass model used widely to predict the diffusion of technological innovations (Bass 1969; Meade and Islam 2006) identifies two psychological factors that predict the rate and likelihood of the diffusion of technological innovations: their (i) perceived innovativeness and (ii) the propensity of consumers to imitate other consumers who adopt those innovations. With regards to the perceived innovativeness of automated vehicles, if consumers believe automated vehicles do not drive as well as they drive, this is a direct drag on the perceived innovativeness of automated vehicles that may not be observed if automated vehicles are compared in public surveys to other drivers (e.g., average drivers). With regards to imitativensness, descriptive norms could wield less influence on consumer adoption of automated vehicles if consumers believe that other consumers need automated vehicles more than they do (i.e., if consumer perceive themselves to be unique in their lack of need for automated vehicles). In these ways, our findings are connected to well validated psychological predictors of the diffusion of technological innovations ranging from personal computers to color televisions (Meade and Islam 2006).

Practically, the greater acceptance of automation for others than self suggests that framing automated vehicles as yielding benefits for fellow drivers (e.g., public safety) may be a more successful strategy for increasing their acceptance than appeals focused on the self (e.g., personal safety). For instance, Waymo's "Let's Talk About Autonomous Driving" campaign is largely centered on educating consumers on the benefits of automated vehicles for the public, especially for those with mobility and accessibility issues (Waymo 2023). However, one question is whether consumers will be sufficiently motivated to buy technologies for themselves just because they benefit society. Another potential marketing strategy could be to frame safety benefits around the consumer's loved ones (e.g., teenage drivers), whom consumers are motivated to protect but whose driving capabilities might remain unembellished. It is also important to note that these findings might be moderated by culture, as consumers from cultures with less tendency to engage in self-enhancement such as East Asian cultures (e.g., Maddux et al. 2010) may be less likely to view themselves as above-average drivers than do Americans.

Another set of strategies hinges on increasing the perceived objectivity of comparisons between consumers and automated vehicles (Castelo, Bos, and Lehmann 2019). This could be achieved by asking consumers to compare themselves to automated vehicles on concrete outcomes, like accident rates and deaths, as opposed to on subjective outcomes, like perceived driving ability. Of relevance, self-serving bias emerges only when it has latitude to influence judgments, as when evaluative criteria are ambiguous (Dunning, Meyerowitz, and Holzberg 1989). When evaluative criteria are objective or constrained it should be mitigated (Morewedge 2022). This suggests, for instance, that the benefits of automated vehicles should be listed concretely rather than abstractly. Another strategy would be to increase consumers' awareness of their biased perceptions, then use debiasing interventions to elicit more accurate judgements of

driving abilities, relative to automated vehicles. Educational videos on biases and observational learning have shown success in reducing the better-than-average effect for driving, as well as other cognitive biases like confirmation bias and blind spot bias (Morewedge et al. 2015; Scopelliti et al. 2015). At the same time, it may be very challenging to get such interventions to work, given the resilience of self-enhancement biases in driving ability (Shariff, Bonnefon, and Rahwan 2021; Sibley and Harré 2009; White, Cunningham, and Titchener 2011). A final set of strategies would be to introduce simple incentives such as insurance discounts or tax breaks for adopting automated vehicles. By giving consumers an economic motive with which to purchase automated vehicles, this may dilute the influence of the lack of a perceived gain in performance or safety when using an automated vehicle rather than driving oneself.

In closing, our findings show that self-enhancement can explain differences in the perceived value of automated vehicles for self and others, suggesting new paths through which to increase consumer acceptance. With one fatality occurring every 23 seconds (WHO 2023), any marketing strategies that accelerate the adoption of autonomous vehicles can literally be a matter of life and death.

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