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Autonomy bias: A deception experiment to isolate the effect of vehicle automation on perceptions of pedestrian comfort & safety

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ABSTRACT

Ensuring comfort and safety for pedestrians is essential to the responsible introduction of automated or self-driving vehicles (SDV). Few studies have attempted to isolate the effect of vehicle automation on perceptions of pedestrian interactions with SDV, separate from the potentially confounding effects of vehicle operation or appearance, and we still have limited understanding of the explicit and implicit attitudes mediating those perceptions. The objectives of this study are to determine 1) if there is an "Autonomy Bias" in the population of British Columbia, Canada (i.e., whether people perceive pedestrian-SDV interactions as inherently more or less comfortable and safe than otherwise equivalent interactions with human-driven vehicles or HDV), and if so, 2) which personal attributes influence Autonomy Bias. We isolate the effect of vehicle autonomy on perceptions using a novel deception-based experiment in which 1,133 participants rate 8 video clips of pedestrian interactions in a crosswalk; all clips show HDV, but a random half of the videos for each participant are described as SDV. Results show that Autonomy Bias varies widely across the population, with a small but significantly ($p < 0.05$) negative mean value (i.e., SDV interactions are perceived as less comfortable and safe). To ensure that an average person is as comfortable crossing with SDV as they currently are with HDV (i.e., to offset their Autonomy Bias), SDV must allow at least 0.4 s additional passing time at crosswalks; at least 3.7 s additional time is needed to ensure equivalent comfort for 85 % of the population. The implicit attitude of Autonomy Bias is strongly related to but distinct from explicit, self-reported attitudes toward technology and SDV, and may improve with SDV familiarity.

1. Introduction

Many public agencies around the world have programs and policies encouraging non-motorized, physically active modes of travel such as walking and cycling because of the associated sustainability, health, and well-being benefits (Mueller et al., 2015). In recent years, public agencies have also been increasingly focussed on the introduction of self-driving vehicles (SDVs).[1] Experts from

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[1] These vehicles have been called self-driving vehicles (Hőgye-Nagy et al., 2023), driverless vehicles (Nordhoff et al., 2018), autonomous vehicles (Nair & Bhat, 2021), and automated vehicles (Sanbonmatsu et al., 2018) in the literature. We use the term SDV to be consistent with our survey instrument (described later), which in turn used SDV because it was most easily understood by participants during pilot testing.

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academia, industry, and government expect the introduction of SDVs to align with the promotion of active modes of travel, on the presumption that SDVs will improve road safety for active mode users (Botello et al., 2019).

Considerable research has focused on the operation and technological reliability of SDVs: intersection navigation, collision avoidance, object/pedestrian detection, etc. (Badue et al., 2021). But ensuring SDVs to be technologically advanced is only one part of the process of responsible introduction and integration. Another crucial part is ensuring the comfort of other travellers interacting with SDV (Nair & Bhat, 2021), particularly avoiding degrading the walking experience for pedestrians (Spence et al., 2020).

Interactions with motor vehicles are a primary influence on walking experience (Gill et al., 2022; Merlino & Mondada, 2019; Zhuang & Wu, 2012). Interactions with SDV may be more or less challenging and uncomfortable than interactions with human-driven vehicles (HDV) for a range of reasons (Rothenbücher et al., 2016), and we still have limited understanding of public perceptions of pedestrian-SDV interactions (Rasouli & Tsotsos, 2020). The essential defining characteristic of SDVs is that vehicle control is ceded from a human to a computer, and yet no study has isolated the inherent effect of vehicle autonomy on perceptions, separate from vehicle appearance, operation, and other potentially confounding factors. Also, while past studies have investigated the role of explicit (self-reported) attitudes in mediating individual perceptions of interactions, the potential role of implicit attitudes has yet to be examined.

The goal of this paper is to improve understanding of pedestrian-SDV interactions by measuring the effect of vehicle autonomy, *ceteris paribus*, on perceptions of comfort and safety. We focus on the relatively challenging interactions that occur in unsignalized crosswalks, where pedestrians must quickly process information about the environment and communicate (nonverbally) with interacting road users to negotiate a safe crossing (Merlino & Mondada, 2019). Since perceptions of SDVs vary systematically in the population (Nair & Bhat, 2021), we also examine how a diverse and representative array of people perceive interactions between pedestrians and SDVs, in contrast to today's HDVs.

1.1. Literature review

General perceptions of SDV vary widely in the population, sometimes systematically with socio-demographic factors such as age and gender (Hulse et al., 2018). SDV perceptions have mostly been studied in the context of potential SDV users, but sometimes in the context of other road users sharing the road with SDVs, as summarised by Golbabaei et al. (2020). Since our paper focuses on SDV interactions, the scope of this literature review is limited to studies examining SDV perceptions in the context of SDV interactions with other road users.

Women have been reported to be less willing to interact with SDVs at crosswalks (Deb et al., 2017) and to perceive sharing the road with SDVs to be less safe (Deb et al., 2017; Pyrialakou et al., 2020), but Nair & Bhat (2021) did not find gender to be significantly related to perceptions of safety while sharing the road with SDVs. A few studies have observed no direct effect of age on perceived safety (Deb et al., 2017; Nair & Bhat, 2021), but Nair & Bhat (2021) noted that age indirectly influences perceived safety through people's attitudes about technology in general and about SDV technology specifically. Individuals who feel less safe sharing the road with SDVs are more likely to live in rural areas (Deb et al., 2017) and to have less educational attainment (Nair & Bhat, 2021).

Pyrialakou et al. (2020) compared pedestrian-SDV and cyclists-SDV interactions and found cyclist-SDV interactions to be perceived as less safe, but did not control for the travel habits of participants, which can significantly influence relative perceptions of safety by travel mode (A. Bigazzi et al., 2021). Hagenzieker et al. (2020) found that cyclists were less confident that an SDV (vs. HDV) would notice them and Ngwu et al. (2022) found that bicyclists prefer both visual and audible communication features on SDVs, and separate lanes, to improve their safety perception of SDV interactions. Other studies (Ferenchak, 2023; Parkin et al., 2022; Rahman et al., 2023) did not find any significant effect of travel mode of participants (driving, bicycling, and walking) on trust, comfort, and perceived safety of SDV interactions.

Beyond socio-demographics and travel habits, individuals' attitudes towards technology in general and towards SDV technology specifically are also important determinants of perceived safety of SDVs. Individuals who are more open to embracing new ideas or new technologies, or those who have a positive experience with anthropomorphized technologies (e.g., voice assistants on smartphones and computers) are more likely to perceive SDV interactions as safe (Deb et al., 2017; Nair & Bhat, 2021). This relationship between general tech-savviness and perceived safety also extends to SDV-specific tech-savviness; individuals who are relatively familiar with SDV technology (Nair & Bhat, 2021; Rahman et al., 2021) or those who have prior experience interacting with SDVs perceive SDVs to be safe (Das, 2021; Das et al., 2020; Penmetsa et al., 2019; Pyrialakou et al., 2020).

Affective response to SDVs has also been identified as a key component of perceived safety of SDVs (Liu et al., 2019; Liu & Xu, 2020; Nair & Bhat, 2021; Sanbonmatsu et al., 2018). Affects are evoked moods and emotions in response to SDVs and could be negative (anxiety, worry, fear) or positive (enthusiasm, satisfaction, relief). Studies have elicited affective responses by asking people to think about SDV development or SDV sharing. Positive affective response (i.e., feeling enthusiastic about SDV development) was found to increase the perceived safety of sharing the road with SDVs (Nair & Bhat, 2021). Beyond directly affecting SDV perceptions, affective response towards SDVs also mediates the relationships between socio-demographics and SDV perceptions. For example, women are found to be more likely to perceive SDV as less safe partially because they are more likely to feel anxious about SDV development (Nair & Bhat, 2021).

The studies investigating relationships between personal attributes and perceptions of pedestrian-SDV interactions have examined explicit attitudes using self-reported data (Das, 2021; Deb et al., 2017; Pyrialakou et al., 2020; Rahman et al., 2021, 2023). Self-reported attitudes can be vulnerable to response biases such as social desirability, and in other transportation literature implicit attitudes, measured indirectly through experimental observation, have been reported to be distinct determinants of travel behaviour (Tosi et al., 2021). Methods using both explicit and implicit attitudes (see the Dual-Process Model of Attitudes (Gawronski & Brannon, 2019)) can overcome response bias associated with self-reported attitudinal data, and help better explain attitudes affecting road safety behaviours (Tosi et al., 2021). To our knowledge no study has examined implicit attitudes toward SDV.

In addition to the individual determinants of perceived safety in pedestrian-SDV interactions summarized above, perceptions can also be determined by attributes of the SDVs. Most studies examining SDV attributes in the context of pedestrian-SDV interactions focus on communication features, as summarized by Rasouli & Tsotsos (2020) and Rouchitsas & Alm (2019). The presence of external communication features that provide clear visual and auditory cues (Mahadevan et al., 2018) improve perceived safety and comfort for crossing pedestrians, where the SDV could provide information regarding its awareness of the presence of pedestrians (Ackermann et al., 2019; Miguel et al., 2019) or its intentions (Chang et al., 2017; Deb et al., 2018; Mirnig et al., 2022). Operational attributes such as erratic driving behaviour (short stopping distance and abrupt acceleration) are perceived negatively by crossing pedestrians (Zimmermann & Wettach, 2017). Vehicle size (de Clercq et al., 2019) and appearance (aggressive or friendly) also affect willingness to cross (a substitute measure of perceived safety) but operational factors have been reported to be more dominant (Dey et al., 2019). Two studies (Dey et al., 2019; Rodríguez Palmeiro et al., 2018) report that vehicle type (SDV vs. HDV) has no significant effect on willingness to cross, but one (Rodríguez Palmeiro et al., 2018) found that a majority of the 20 participants felt less safe crossing in front of an SDV than an HDV.

Researchers have adopted various methods to investigate perceptions of pedestrian-SDV interactions (Rasouli & Tsotsos, 2020), necessitated by the rarity of SDVs operating in real-world or realistic settings. Some studies use survey questionnaires to ask participants how safe they would feel crossing the road in front of an SDV, without specific images or illustrations (Deb et al., 2017). Other studies use virtual reality technology to measure perceptions of participants interacting with SDVs in a virtual street environment, as summarized in Tran et al., (2021). A few studies rely on deception for experimental control to evaluate hypothetical technologies and situations. For example, in the "Wizard of Oz" experiment, a regular vehicle is fitted with a modified driver's seat to hide the driver and stickers stating "self-driving car" are installed on the car to give the impression of an SDV (Rothenbücher et al., 2016). Perceptions are obtained either through first-person evaluations (crossing pedestrians are presented with an intercept survey as in (Rodríguez Palmeiro et al., 2018)) or third-person evaluations (survey participant evaluate an observed event or interaction without being part of it) (Dey et al., 2019). More recent studies have used follow-up surveys to examine how people feel sharing the road with SDVs while walking, after they have experienced SDVs in real-world settings (Das, 2021; Pyrialakou et al., 2020; Rahman et al., 2021, 2023).

1.2. Summary and objectives

Most studies in the existing literature focus on potential SDV users (consumers), while fewer focus on the effects of SDV on other road users. Studies of pedestrian experience with SDV have mainly investigated the effects of SDV communication features on pedestrian crossing decisions and perceptions. Two studies are noteworthy in the context of the present study, as they investigated the effect of vehicle type (SDV vs. HDV) on pedestrian crossing decisions using deception-based experiments (Dey et al., 2019; Rodríguez Palmeiro et al., 2018). Relevant details and limitations of their experimental designs are that they varied other vehicle factors simultaneously with vehicle type (SDV vs. HDV), they examined willingness to cross rather than perceived safety or comfort, the samples were relatively small and not representative of the population (e.g., 24 young university students in Rodríguez Palmeiro et al. (2018)), Rodríguez Palmeiro et al. (2018) did not inform participants about vehicle type and only 40 % of participants self-reported distinguishing between SDV and HDV, and Dey et al. (2019) did inform participants about vehicle type but participants only evaluated either SDV or HDV so individual contrasts were not measured. In short, neither addressed the core aim of the present study, which is to determine the inherent effect of vehicle autonomy (separate from other vehicle attributes) on perceptions of pedestrian comfort and safety across the population. In addition, no study investigating perceptions of SDV interactions has yet investigated implicit attitudes toward SDV.

We have two main research questions: (RQ1) do individuals perceive pedestrian interactions with SDVs as more or less comfortable and safe than otherwise equivalent interactions with HDVs, controlling for all other differences (i.e., is there an "Autonomy Bias"?), and if so (RQ2) which individual perceiver attributes (e.g., age, gender, race, travel habits, familiarity with SDVs, affective response to SDV development) are systematically associated with their Autonomy Bias? We address these questions by implementing a novel deception-based experiment in which participants rate video clips of pedestrian interactions with SDVs and HDVs; all clips showed HDVs but half of the clips were described as SDVs, randomly for each participant. This deception-based experiment allows us to isolate the inherent effect of vehicle autonomy on perceptions while controlling for all other vehicle and interaction factors that could affect perceptions (speed, size, aggressiveness, etc.).

2. Methods

2.1. Overview of methods

We conceptualize the construct of Autonomy Bias to be a latent individual attribute, and we posit that Autonomy Bias can be inferred from three observed indicators: systematic differences in individual ratings of 1) yielding, 2) safety, and 3) comfort between otherwise similar interactions involving SDV versus HDV. For example, if a person has a positive Autonomy Bias (in favour of SDV), then they would perceive interacting SDV as more adequately yielding, and pedestrians as safer and more comfortable, than they would for the same interaction if they believed it involved an HDV. Perceived safety and comfort are strongly related yet distinct measures, and perception of yielding is crucial to understanding perceptions of crosswalk interactions (Gill et al., 2022). Our conceptualization of Autonomy Bias is an implicit attitude toward SDV, which could not be reliably self-reported (due to factors such as social desirability bias or being unconscious of one's own Autonomy Bias), so we developed a novel deception-based experiment to indirectly measure individual Autonomy Bias.

Fig. 1 illustrates the study framework. Data were collected using a web survey, which enabled participation by a large and geographically diverse sample. In the deception-based experiment, all survey participants watched the same 8 videos of pedestrian-vehicle interactions at unsignalized crosswalks, but those participants never interacted with the pedestrians or drivers from the videos. The videos were selected to include only plausible SDVs (dark-colored, late-model sedans), although all vehicles were (presumably) HDVs. A random half of the vehicles for each participant were described as SDVs, so that each video was rated by roughly half the participants as an SDV and the other half as an HDV. This deception-based approach allowed us to measure if each participant systematically evaluated their SDV interactions differently than their HDV interactions. We also collected participants' self-reported socio-demographic attributes, travel habits, comfort in taking risks, comfort in embracing new technology, and attitudes toward SDVs. video ratings from the survey were used in a statistical model to infer individual- and population-level Autonomy Bias (addressing RQ1), and then a second model was estimated to examine relationships between personal attributes and individual Autonomy Bias.

2.2. Data collection

The web survey was implemented in Qualtrics. Qualtrics was the preferred survey software as it allowed us the flexibility to design the deception-based experiment (i.e., randomization of videos) and it stored the confidential data from survey participants in Canada, in compliance with Provincial privacy laws and regulations. The survey was opened on October 22, 2021, and closed on December 12, 2021 (51 days). The survey was advertised on Facebook and Instagram throughout British Columbia (BC). We selected the study population as BC residents because that is the jurisdictional boundary for key SDV policy decisions (which are mostly made by the Provinces in Canada), and BC includes both a consistent transportation policy context and a wide variety of other contextual factors (population density, pedestrian facilities, transit services, etc.). The only inclusion criterion for the survey was experience travelling in BC. To minimize selection bias (i.e., not to disproportionately attract participants with strong opinions about SDVs), we did not mention SDVs on the survey advertisement (see Supplementary Material: Appendix A. Survey advertisement). Participants were incentivized with a chance to enter into a draw for one of ten gift cards of CA$25 each. The Behavioural Research Ethics Board at the University of British Columbia approved the study methods (#H21-02214). The full survey instrument is included in Supplementary Material: Appendix B. Survey instrument.

2.2.1. SDV questions

The survey began with a consent form describing the goal of the study, followed by a definition of SDVs for the survey: "Self-driving vehicles use advanced technology to scan the surrounding road environment and carry out all driving tasks, including steering, speed control, following traffic signs and lights, yielding at crosswalks, etc." Terminology for SDVs is evolving and inconsistent; we used the term "self-driving vehicles" (rather than alternatives like "driverless", "autonomous", or "automated") because that was the most easily understandable during pilot testing of the survey. We use the term "self-driving vehicles" throughout this paper to be consistent with the survey instrument.

The definition of SDVs was followed by prompts eliciting participants' attitudes towards SDVs: familiarity with SDVs ("Not familiar at all" to "Very familiar") and affective response to SDV development ("Very anxious" to "Very enthusiastic"). The prompts were selected based on consideration of the existing literature and this study's research questions, balanced against considerations of participant burden.

2.2.2. Deception-based experiment

Participants then entered the deception-based experiment (the experiment description as presented to participants is given in Supplementary Material: Appendix B. Survey instrument). Participants were shown 8 short (7–17 sec) video clips of pedestrian-vehicle interactions at unsignalized crosswalks, each on separate pages. The number of videos was selected based on consideration of the required time to complete the survey (targeting 15 min). Raw video data were collected from September to December 2018 at 11 marked and uncontrolled crosswalk locations in the City of Vancouver. All locations were two-lane collector streets with no directional dividing line and substantial pedestrian volumes. A total of 3176 pedestrian interactions with vehicles of all types (including scooters and bicycles) were identified in the video data during a previous study, based on post-encroachment time of < 4 sec (A. Y. Bigazzi et al., 2019). These interactions were manually reviewed to identify 36 interactions with plausible SDVs: dark-colored, late-model sedans. From these, we selected 8 videos for the survey using severity-based strata with passing time[2] thresholds of 3–4 sec ("low-risk"), 2–3 sec ("moderate-risk"), and < 2 sec ("high-risk"), informed by our recent research on this topic (Gill et al., 2022). To generate more observations of higher-severity interactions, we included 2 videos for the "low-risk" stratum and 3 videos from the other 2 strata.

The video strata are illustrated in Fig. 2. Four videos were identified as SDV for each participant, and the other four identified as HDV. The SDV group was drawn by selecting 1 video from each stratum, and a fourth from either the high- or moderate-risk stratum. The videos within each group were shown in random order, and the ordering of the groups was randomized as well (i.e., either the SDV or HDV group first).

Fig. 3 illustrates the video rating pages in the survey. The four severity prompts on yielding, comfort, and safety were designed after

[2] Passing time, also called post encroachment time (PET), is defined as the time gap between when the first road user exits the point at which their paths intersect and when the second road user enters it.

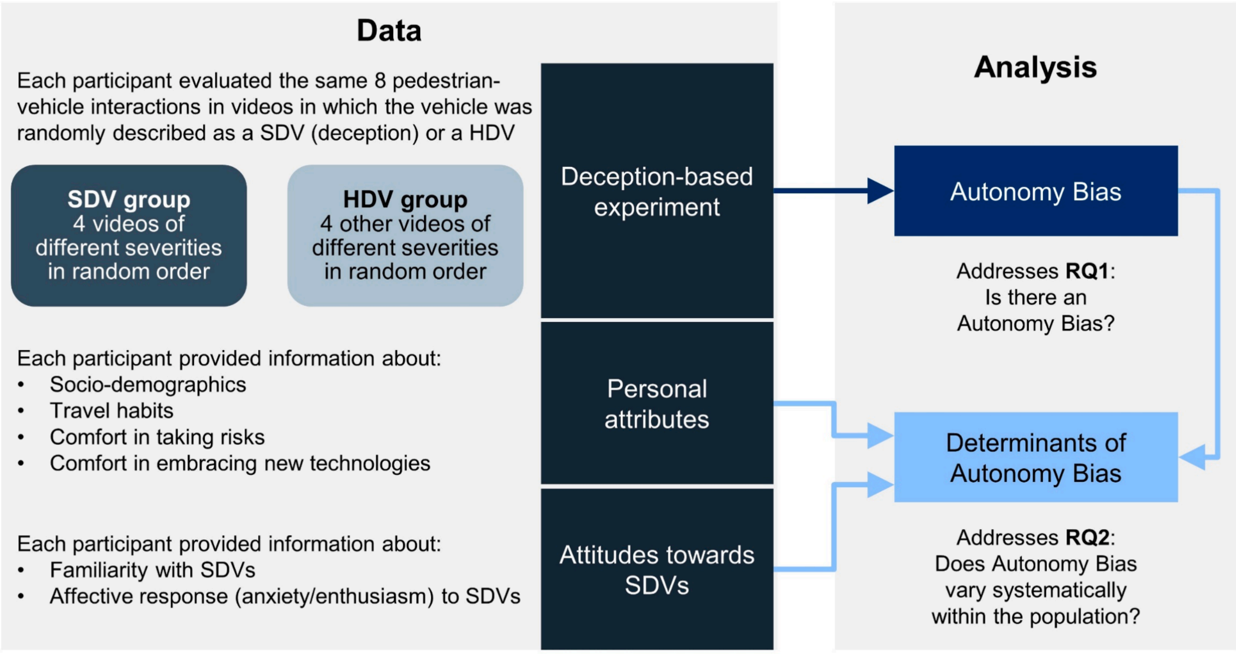

Fig. 1. Study framework.

a comprehensive review of the literature and pilot testing, and were also used in a previous study on perceptions of pedestrian comfort and safety (Gill et al., 2022). Fig. 3 shows the same video with different descriptions; the first is labelled "self-driving vehicle" (from the SDV group) while the second is labelled "regular vehicle" (from the HDV group). Each participant saw just one of these two screens. With no Autonomy Bias, a participant's ratings would have been the same if presented with either version. Negative Autonomy Bias would lead to ratings of less comfortable and less safe in the first video compared to the second video, and positive Autonomy Bias would lead to the opposite. Participants could not reliably rate both versions of the same video, but by having many people rate the same videos, we can measure an individual's systematic deviation for their set of SDV ratings using the statistical model described below.

2.2.3. Personal attributes and re-consent

After video ratings, participants answered questions about their socio-demographic attributes (age, gender, race, educational attainment, household income, and household location), travel habits (frequency of travel by automobile, bicycle, walking, and public transit), comfort in taking risks, and comfort in embracing technology.

The survey concluded with an evaluation and revelation of the deception. As a "soft" measure of deception effectiveness, participants were asked if they perceived any consistent differences between the SDVs and HDVs in the videos, with both closed-form rating and open text response options. Then, we revealed the deception (without the option to return and change their previous responses), explained the rationale for using deception, and asked for re-consent to use their responses in our study (in accordance with the ethics guidelines). Anyone who declined re-consent was not included in the analysis. Finally, as a "hard" measure of deception effectiveness, we asked if they had believed the vehicles were SDV when they rated the video interactions. Deception effectiveness is described in the next section.

2.3. Data processing

Analysis variables were created using the self-reported data collected from the survey. For gender, a binary variable of man (exclusive, vs. not man-exclusive) was created, for participants who only responded "man" to the prompt "What is your current gender?".[3] For racialization, a binary variable of person of colour (vs. white) was created, where white indicated participants who exclusively selected "white" in response to the prompt "Which of the following census categories best describes you?". We acknowledge that this colour-related terminology groups multiple cultural identities together that are disproportionately affected by racism. However, this terminology serves the purpose of this study since we are examining if people who experience racialization perceive SDVs differently and "person of colour" has been observed to be "a simpler and potentially better measure of racialization,

[3] This binary classification combined non-binary and women participants; it was necessary because our sample had only six non-binary responses, providing insufficient statistical power for multiple parameter estimates for gender variables.

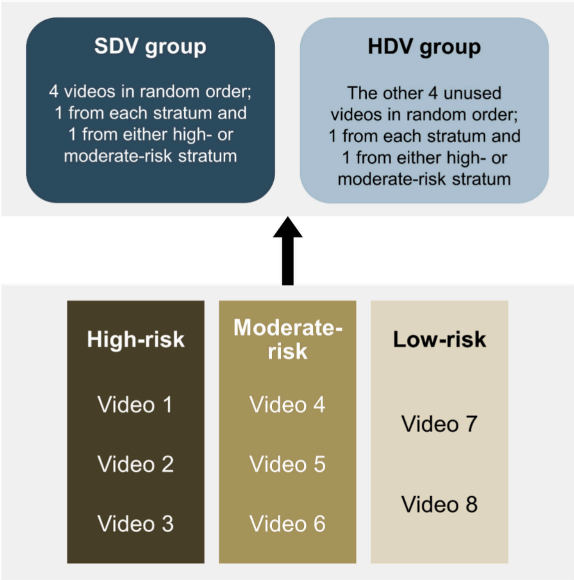

Fig. 2. Video clip groupings.

when that is the construct of interest" (Bauer et al., 2020). Two location-based binary variables were created using responses to the prompt "What are the first 3 digits of your home postal code? (or other location identifier, if you prefer)": rural (vs. urban) was indicated by "0" as the second character of postal code and metro Vancouver (vs. elsewhere in BC) was based on identifying the forward sortation areas (i.e., first 3 digits of postal code) representing the municipalities within metro Vancouver.

2.3.1. Filtering

The number of collected raw responses – individuals who gave consent – was 1557 (only 6 individuals declined initial consent). Participants who quit the survey before or at the re-consent page or declined re-consent were excluded from analysis, leading to 365 exclusions: 347 missing re-consent and 18 declined re-consent. Participants with self-reported home postal codes outside BC were excluded, leading to another 52 exclusions. Ratings were flagged as low timing if a participant spent less time on a video page than the length of that video. Entire responses were excluded if more than one of a participant's rated videos were flagged as low timing: this led to 7 exclusions (not highly sensitive to the low timing threshold). Only 1 participant had exactly 1 rating flagged as low timing, and data from that rating page was excluded while keeping the rest of their responses. The final sample after filtering was 1133 participants.

2.3.2. Deception effectiveness

Out of the filtered sample of 1133 participants, only 8 provided comments indicating that they were not deceived in response to our "soft" questions before the deception was revealed. But 102 reported not being deceived in response to the direct question after learning about the deception. Out of these 102 participants, 60 had previously reported observing behavioural differences between SDVs and HDVs in response to our "soft" deception questions (see Supplementary Material: Appendix C. "Observed" differences between SDVs and HDVs), suggesting they had actually been deceived but were loathe to acknowledge it after the deception was revealed. Data from these participants were retained for the analysis, and the other 42 were excluded. Thus, our final sample for statistical analysis included 1091 participants (who we believe were deceived), indicating 96 % success of the deception (and still 91 % success excluding all 102 who self-reported to be undeceived). The probable reasons for effectiveness of deception are summarized in Supplementary Material: Appendix D. Comments on deception.

2.4. Statistical analysis

In this section, we describe the primary steps taken in analyzing the data to answer the research questions. We start by describing the process of creating sampling weights to account for sampling bias in our data; those sampling weights were used for all statistical analyses. We then describe the process of extracting Autonomy Bias to answer RQ1 (is there an "Autonomy Bias"?). Finally, we describe the process of examining the determinants of Autonomy Bias to answer RQ2 (which individual perceiver attributes are systematically associated with their Autonomy Bias?).

2.4.1. Sample weights

To account for sampling bias as reflected in socio-demographic differences between the study sample and the BC population, sampling weights for each participant were created by iterative proportional fitting (Mercer et al., 2018) using the "survey" package in

Fig. 3. Video rating in the deception-based experiment with the same video presented as an SDV (left) or HDV (right).

R (Lumley, 2019; R Core Team, 2019). Target marginal distributions were taken from Census data (Statistics Canada, 2022) along three dimensions with substantive differences between the sample and population: person of colour (binary), educational attainment (five-level factor), and rural location (binary). Responses of "Prefer not to answer" (7 % for race, 4 % for educational attainment, and 0 % for rural location) were maintained as a synthetic marginal category in the comparison population data. Weights were trimmed (strictly) at lower and upper bounds of 0.3 and 3.0 times the median weight, respectively (0.222 and 2.22). This led to trimming of 57 (5 %) of the weights and a final median weight of 0.941. All statistical analyses used these sampling weights.

2.4.2. Autonomy bias indicators

We estimate 2 models: the first extracts Autonomy Bias indicators for each participant from their video ratings, and the second examines relationships between personal attributes and (latent) Autonomy Bias using the indicators from the first model. Fig. 4 illustrates the first model for extracting the three indicators of Autonomy Bias for each participant using ratings of Comfort, Safety, and Adequate Yield as dependent variables. Comfort was taken as the rating for "The pedestrian felt comfortable in this crossing," and Safety was taken as the rating for "The risk of injury for the pedestrian in this crossing was low." Adequate Yield was calculated from the two statements on yielding by subtracting the rating of "The [road user] should have yielded to the pedestrian" from the rating of "The [road user] yielded to the pedestrian" and then dividing by two to obtain a consistent scale range of −10 (severely inadequate yielding) to 10 (excessive yielding).

The independent variables were passing time (to represent varying interaction severity in the stratified videos), video fixed effects (to represent all other interaction attributes), participant fixed effects (to represent each person's overall rating tendency for all 8 videos), and an interaction term between participant fixed effects and a dummy variable for SDV video (to represent each person's idiosyncratic rating tendency for their set of SDV videos – i.e., the Autonomy Bias indicator). Besides representing interaction severity, the passing time was also included because it allows us to express the indicators of Autonomy Bias in terms of equivalent passing time (discussed later). The model framework in Fig. 4 was implemented using a weighted multivariate fixed effects regression model (Fox & Weisberg, 2018) in R (R Core Team, 2016). In addition to the person-level model, a similar model was estimated to measure the population-level Autonomy Bias by replacing the interaction term with a dummy variable for SDV video.

2.4.3. Determinants of autonomy bias

Fig. 5 illustrates the analysis framework for the second model, which examines the relationships between personal attributes (independent variables) and Autonomy Bias (latent dependent variable). Autonomy Bias has three indicators obtained from the results of the first model described above. The independent variables potentially influencing Autonomy Bias were the participant socio-demographics (age, gender, race, income, education, household income, household location), travel habits (frequency of travel by automobile, bicycle, walking, and public transit), familiarity with SDVs, comfort in taking risks, comfort in embracing technology, and affective response to SDV development (level of anxiety or enthusiasm). These variables were selected based on the literature review and our theoretical understanding of pedestrian-SDV interactions. We include a causal pathway for affective response to SDV to act as a potential mediator of the other personal attributes, based on past research (Nair & Bhat, 2021). For example, increasing familiarity with SDVs might have a positive direct effect on Autonomy Bias but also an indirect effect through a more enthusiastic affective response to SDV development.

The model framework in Fig. 5 was implemented using a structural equation model (SEM) in R estimated with the 'lavaan' package (Rosseel, 2012). Before model specification, independent variables were checked for multicollinearity; the control variable of intention to purchase an SDV was removed as it had a Pearson correlation coefficient of 0.7 with the variable of affective response. In other words, participants who were enthusiastic about SDV development were more likely to have an intention to purchase an SDV. We retained the affective response variable because it was more important for our conceptual framework. Since our focus was exploratory analysis of Autonomy Bias rather than creating a parsimonious prediction model, we retained all the independent variables (rather than step-wise addition or subtraction of independent variables).

3. Results

3.1. Data overview

Table 1 summarizes the socio-demographics and travel habits of the sample data, as well as comparison socio-demographic data for the BC population from 2021 Census data (Statistics Canada, 2022); comparison data on travel habits are not available. The sample differs in some ways from the socio-demographic characteristics of the province, possibly due to the online survey method and the survey topic. As described earlier, the statistical analysis used sampling weights (based on person of colour, education, and rural location) to account for socio-demographic differences between the sample and the BC population. Note that all variables summarized in the table are treated as binary for the sake of brevity, but all variables were coded as continuous (in line with the survey data) for statistical analysis, except gender, person of colour, living in a rural area, and living in metro Vancouver.

Other personal attributes are summarized in Fig. 6. Slightly more than half of the participants were comfortable taking risks and perceived themselves to be early adopters of technology. A majority of the participants had some level of familiarity with the development of SDVs, and slightly more participants were anxious than enthusiastic about the development of SDVs.

Fig. 7 shows the aggregate video ratings, separated between SDV and HDV (perceived) evaluations. Slightly fewer participants agreed that the vehicle yielded adequately, or that the pedestrian was comfortable or safe in the crossing, for SDV versus HDV ratings.

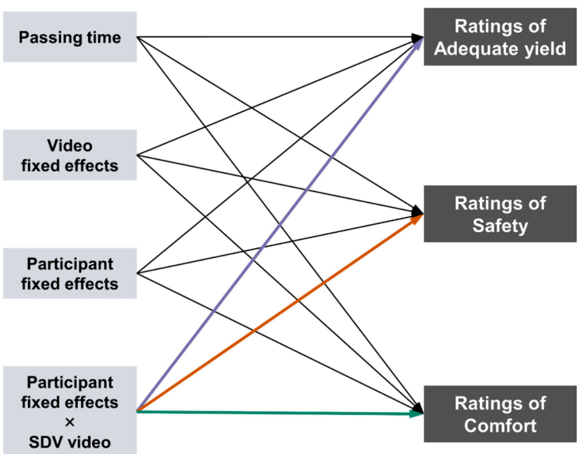

Fig. 4. Model framework to extract indicators of Autonomy Bias (indicated by colored lines) for each participant.

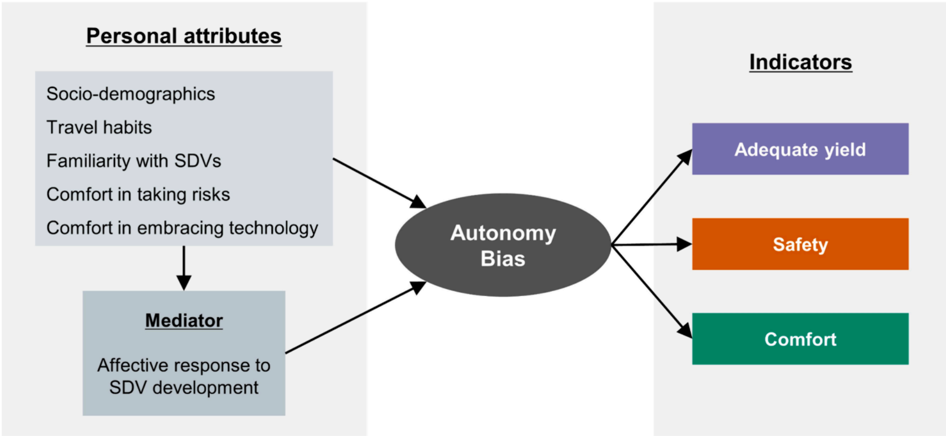

Fig. 5. Model framework to examine determinants of Autonomy Bias.

3.2. Is there an autonomy bias?

The first model results are given in Table 2. As expected, increasing passing time was positively related to ratings of adequate yield, safety, and comfort. In other words, for a given interaction, increasing passing time increases the perception that a vehicle yielded adequately and the pedestrian was safe and comfortable. The interaction terms (Participant fixed effect * SDV video) give the individual indicators of Autonomy Bias. Note that the effects estimates are summarized as mean (standard deviation) due to the number of participants. These results indicate a slightly negative mean Autonomy Bias for all three indicators, but varying widely across population.

To aid interpretability, passing time-equivalence was calculated for each of the three Autonomy Bias indicators, for each participant, by taking the ratio of the model-estimated coefficients for the interaction terms and passing time. The mean parameter values of −0.35, −0.20, and −0.45 for adequate yield, safety, and comfort Autonomy Bias indicators in Table 2 translate to −0.25, −0.11, and −0.40 s of passing time-equivalence. The slightly negative values indicate SDVs needing to give more passing time than HDVs to obtain the same level of perceived adequate yield, safety, or comfort for pedestrians. We also estimated a population-level model, which verified the presence of population-level Autonomy Bias that is slightly negative for all three indicators (significant at $p < 0.05$), with similar population means to the person-level model; full results are in Supplementary Material: Appendix E. Population-level Autonomy Bias model.

Fig. 8 illustrates the distribution of the three person-level Autonomy Bias indicators. The height of the violin plots represents the frequency of observations in a region, and the boxplots show the median, mean, interquartile values, and outliers. The vertical bar shows the 15th percentile value, included to show the extra passing time required from SDV for 85 % of the population to perceive SDV to be equally comfortable, safe, and yielding to HDV. The 85th percentile was selected as a common threshold in transportation engineering practice; other summary statistics are given in Supplementary Material: Appendix F. Summary statistics for person-level Autonomy Bias indicators.

The distribution of Autonomy Bias indicators shows a wide variety of SDV perceptions in the population, both positive and negative. The shapes of the violin plots reveal that the population is distributed around slightly negative SDV perceptions, rather than being divided into two factions with strong and opposite perceptions of SDV. The indicator of comfort had the largest magnitude and variability of Autonomy Bias, followed by safety and then adequate yield. SDVs need to give 3.7 s more passing time to pedestrians than HDVs for 85 % of the population to feel the same level of comfort.

Table 1
Summary statistics (unweighted) of the data used in analysis.

Variable	Study sample	BC population
Age (<40 years)	28 %	37 %
Gender (man exclusive)	45 %	49 %
Person of colour (vs. white)	19 %	40 %
Education (bachelor's degree or higher)	55 %	25 %
Household income (under CA$100,000)	69 %	68 %
Living in a rural area (vs. urban)	7 %	13 %
Living in metro Vancouver (vs. outside metro Vancouver)	55 %	47 %
Drive an automobile (several times a month of more)	78 %	Not available
Ride an automobile (several times a month of more)	62 %	Not available
Walk (several times a month of more)	69 %	Not available
Cycle (several times a month of more)	31 %	Not available
Take transit (several times a month of more)	37 %	Not available

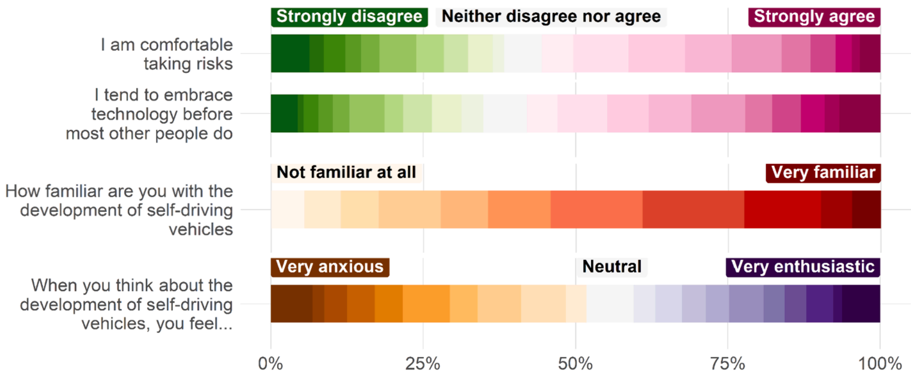

Fig. 6. Survey responses for other personal attributes.

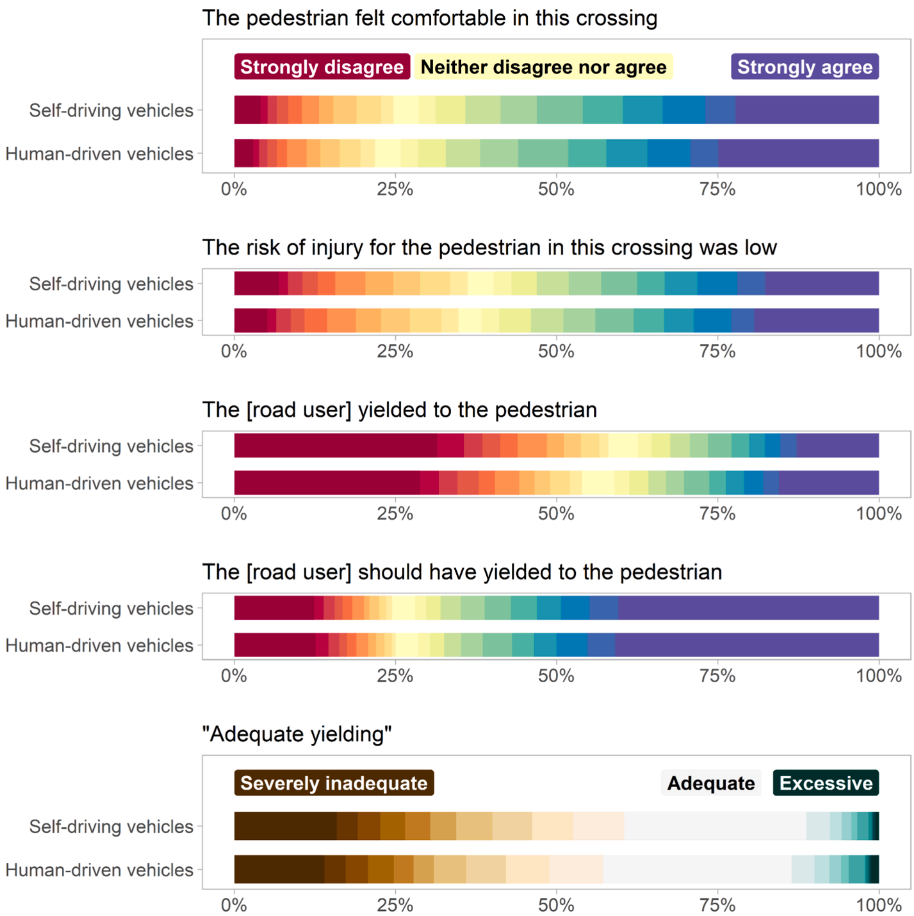

Fig. 7. Distribution of interaction ratings from the deception-based experiment.

Given the wide distribution of both positive and negative Autonomy Bias indicators, it can be illustrative to categorize the population into three groups:

- Skeptics: People who have a bias *against* SDVs (negative Autonomy Bias)
- Neutrals: People who have a small or no bias towards SDVs (no Autonomy Bias)
- Optimists: People who have a bias *in favour of* SDVs (positive Autonomy Bias)

Since the indicator of comfort had the largest variability, we used it to categorize the population based on equivalent passing time

Table 2
Estimates from the model specified in Fig. 4.

Dependent variable	Parameter	Estimate[1]	Standard error
Adequate yield	Passing time	1.40	0.08
	Video fixed effects	1.24 (0.15)	NA
	Participant fixed effects	−0.12 (2.35)	NA
	Participant fixed effect * SDV video (Autonomy Bias indicator)	−0.35 (2.71)	2.42 (0.64)
Safety	Passing time	1.75	0.12
	Video fixed effects	1.30 (0.22)	NA
	Participant fixed effects	−0.26 (3.54)	NA
	Participant fixed effect * SDV video (Autonomy Bias indicator)	−0.20 (4.24)	3.65 (0.96)
Comfort	Passing time	1.12	0.10
	Video fixed effects	0.37 (0.19)	NA
	Participant fixed effects	0.24 (3.06)	NA
	Participant fixed effect * SDV video (Autonomy Bias indicator)	−0.45 (3.84)	3.16 (0.83)

[1] Mean (standard deviation).

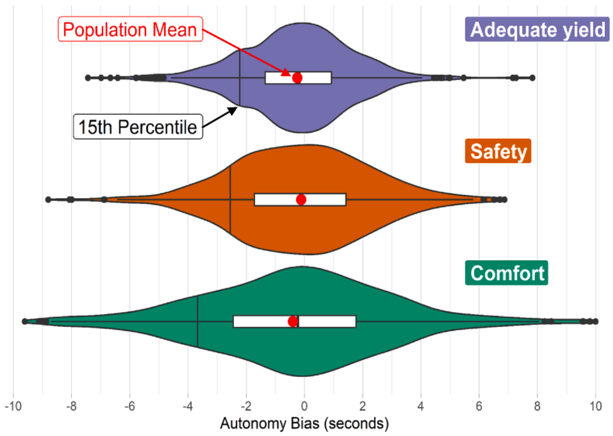

Fig. 8. Distribution of the three indicators of Autonomy Bias in the population.

thresholds of +/- 1 s. This threshold was selected based on past research on passing time effects on both perceived pedestrian comfort and safety (Gill et al., 2022) and critical conflicts for safety evaluations of unsignalized intersections (Paul & Ghosh, 2020). The 1-second threshold is a perceptually meaningful quantity, and 2.5 to 9.1 times larger than the population mean Autonomy Bias. This threshold also aligns with the risk-based stratification of videos in our experiment, for which the highest-risk stratum included interactions with passing times of 1–2 s.

Table 3 shows the proportion of population within the three groups, with the largest proportion (41 %) being Skeptics (people having a negative Autonomy Bias), followed by 34 % Optimists (people having a positive Autonomy Bias) and the remaining 25 % grouped as Neutrals (for whom Autonomy Bias is small or non-existent).

Note that we selected a practical, meaningful threshold to identify Autonomy Bias groups rather than using person-level p-value thresholds for several reasons. Firstly, p-values do not indicate the size of the bias, but rather the precision of our estimate. Secondly, our model provides low statistical power for a hypothesis test on person-level Autonomy Bias indicators in the multi-level model with 8 rating observations per person. The proportion of participants whose individual indicators of Autonomy Bias were significantly different from zero at $p < 0.05$ were 10.6 % for adequate yield, 10.8 % for safety, and 13.5 % for comfort. High p-values for these estimates are indicative of type II error (“false negatives”); a post-hoc power test indicates a power of just around 3 % for a difference of at least 0.1 s in individual Autonomy Bias estimates. At 80 % power (a common threshold) our model would yield significant differences for Autonomy Biases over 1.9 to 3.4 s (across different outcomes).

Table 3
Three groups of the population based on Autonomy Bias (comfort indicator).

Group	Description	Autonomy Bias in equivalent passing time	Percent in the population
Skeptics	People who have a bias *against* SDVs (Negative Autonomy Bias)	−1 s or less	41 %
Neutrals	People who have no bias towards SDVs	between −1 and 1 s	25 %
Optimists	People who have a bias *in favour of* SDVs (Positive Autonomy Bias)	1 s or more	34 %

3.3. Which personal attributes determine autonomy bias?

The estimated SEM to examine relationships between personal attributes and individual Autonomy Bias had a good fit to the data: Standardized Root Mean Squared Residual (SRMR) of 0.01, Root Mean Square Error of Approximation (RMSEA) of 0.03, Comparative Fit Index (CFI) of 0.96, and Tucker–Lewis Index (TLI) of 0.94. Cronbach's alpha for the latent variable Autonomy Bias was 0.70, which indicates reliable indicators for Autonomy Bias. The standardized loadings for the indicators were 0.52 for adequate yield, 0.77 for safety, and 0.67 for comfort.

Fig. 9 illustrates the standardized direct, indirect (affective response-mediated), and total (direct + indirect) effects of personal attributes on Autonomy Bias, as well as the standardized parameter estimates for the mediating variable (affective response). The variables in the figure are ordered based on decreasing magnitude of total effect on Autonomy Bias. Five independent variables had a significant effect (at $p < 0.05$) on affective response: comfort embracing technology, familiarity with SDV, man, age, and frequency of automobile riding; three independent variables had a significant direct effect on Autonomy Bias: affective response, comfort embracing technology, and man. Full model results are given in Supplementary Material: Appendix G. Estimated affective response and Autonomy Bias model parameters.

Being more comfortable embracing technology and increasing familiarity with SDVs had the largest effects on increasing enthusiasm for SDV development (Fig. 9). Men were more likely to be enthusiastic while older participants were more likely to be anxious about SDV development. Participants who rode automobiles or walked more frequently were more likely to be enthusiastic about SDV while those who drove more frequently were more likely to be anxious. Participants living in metro Vancouver (an area with higher active mode usage) were more likely to be anxious. Four other personal attributes had negligible effects on affective response: being a person of colour, living in a rural area, biking frequency, and level of educational attainment.

Fig. 9 shows that being enthusiastic about SDV development and being comfortable embracing technology had the largest direct effects on increasing Autonomy Bias (i.e., more favourable perceptions of SDV interactions). Another technology-related variable – familiarity with SDVs – also had a substantial positive direct effect on Autonomy Bias. Among socio-demographic factors, being a man, living in metro Vancouver, and higher educational attainment were associated with decreasing Autonomy Bias; being a person of colour had a negligible effect on Autonomy Bias. Two travel habit variables had substantial but opposing effects on Autonomy Bias: participants who drive automobiles more frequently were more likely to have a negative Autonomy bias while those who bike more frequently were more likely to have a positive Autonomy Bias.

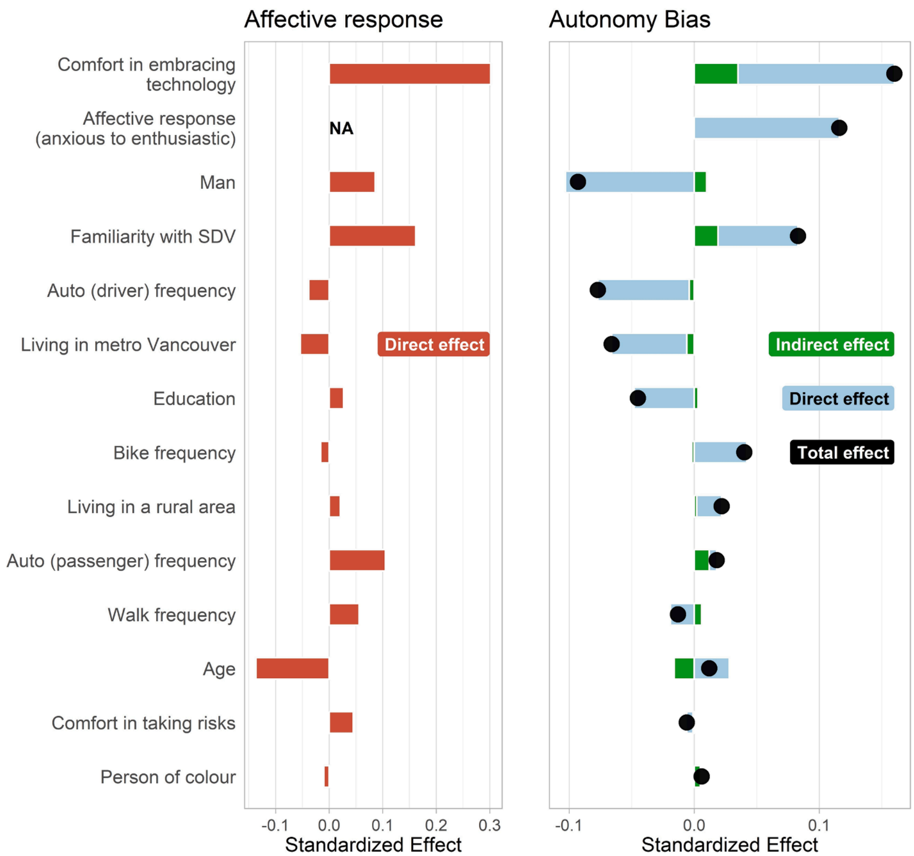

Fig. 9. Determinants of affective response and Autonomy Bias.

The mediation analysis reveals the indirect effects on Autonomy Bias through affective response to SDV – sometimes compounding and sometimes offsetting the direct effects of personal attributes on Autonomy Bias. The positive direct effects of being comfortable embracing technology, familiar with SDV, and higher auto passenger frequency on Autonomy Bias were compounded by positive indirect effects through affective response, as these personal attributes were associated with increasing enthusiasm about SDVs. Conversely, the direct effects of three personal attributes on Autonomy Bias – gender, age, and walking frequency – were offset by opposing indirect effects, as these personal attributes had the opposite relationships with affective response to SDV. For example, being a man was associated with less favourable perceptions of pedestrian-SDV interactions (i.e., more negative Autonomy Bias) but men had more enthusiasm towards SDVs. The sizes of the offsetting indirect effects did not outweigh the direct effects of these variables. Some personal attributes were not substantially mediated by affective response: auto driver frequency, biking frequency, educational attainment, living in metro Vancouver, and living in a rural area.

4. Findings and conclusion

Finding 1: Autonomy Bias exists and varies widely across individuals, with a negative mean population value.

The average Autonomy Bias in the BC population is slightly but significantly negative: −0.4 sec equivalent passing time, based on comfort. To contextualize this value, our previous research comparing pedestrian interactions with HDV versus bicycles in the same locations found that HDV need to give 1.2 sec more passing time than bicycles to achieve the same average level of perceived comfort for pedestrians (Gill et al., 2022). This comfort difference between HDV and bicycles is approximately three times larger than the comfort difference between SDV and HDV (although the previous study did not as completely control for differences in vehicle appearance and operation). The two studies together also show a broader trend of decreasing pedestrian comfort for otherwise similar interactions from bicycles to HDV to SDV.

Large portions of the BC population have a relatively strong Autonomy Bias (larger than 1 sec equivalent passing time) in both positive (34 %) and negative (41 %) directions. Those people perceive pedestrian interactions with SDVs as substantially more or less comfortable and safe than otherwise equivalent interactions involving HDVs. The Autonomy Bias is strongest for perceptions of comfort, followed by perceptions of safety and adequate yielding. Previous studies with varying contexts and methods have also observed both positive and negative self-reported perceptions of safety in sharing the road with SDV in comparison to HDV (Das et al., 2020; Nair & Bhat, 2021; Penmetsa et al., 2019; Pyrialakou et al., 2020); our findings show that the heterogeneity of explicit attitudes extends to implicit attitudes as well, and suggest that the BC population is somewhat more skeptical of SDV than the USA samples in previous research.

Finding 2: The implicit attitude of Autonomy Bias is strongly related to, but distinct from, the explicit attitude of affective orientation toward SDVs.

People who are anxious about SDVs are more likely to perceive SDV interactions negatively, as expected. But affective orientation does not completely explain Autonomy Bias, and some personal attributes have opposite relationships with explicit (affective orientation) versus implicit (Autonomy Bias) SDV attitudes. Men and younger participants, in particular, expressed more enthusiasm toward SDV and yet evaluated the SDV interactions significantly more negatively. There were 20 % more people with negative than positive Autonomy Bias in the population, but 30 % more people with anxiety than enthusiasm toward SDV, so explicit attitudes skew more negative in the population than implicit attitudes, although both indicate SDV skepticism, on average. At the individual level, the correlation between affective response and all three indicators of Autonomy Bias was 0.1. This result is in line with the broader transportation literature, for which implicit and explicit attitudes have been reported to have correlations ranging from 0 to 0.5, with a mean across studies of 0.1 (Tosi et al., 2021). The misalignments of self-reported, explicit attitudes to observation-based, implicit attitudes may be related to response biases in self-reported attitudes, as described by Tosi et al. (2021). For example, men may be inclined to overstate their enthusiasm toward SDV due to social desirability bias. In addition, the measures of implicit versus explicit attitudes in this study are not perfect analogs (emotion vs. safety perception and abstract vs. specific), which might also moderate the relationships.

Finding 3: Autonomy Bias is more systematically related to technological orientation than socio-demographics or travel habits.

People who are not comfortable embracing technology are more likely to perceive SDV interactions less favourably (i.e., more negative Autonomy Bias). This result is similar to a past study (Deb et al., 2017) that found personal innovativeness (attitude to try new things) to improve SDV receptivity. The effect of comfort with technology on Autonomy Bias may be explained by algorithm aversion (Dietvorst et al., 2015), which has been thought to explain some biases in perceptions of riding in an SDV (Shariff et al., 2021) and SDV crashes (Hong et al., 2020; Shariff et al., 2017). Increasing familiarity with SDV is also associated with more positive Autonomy Bias. This result is similar to past studies on road users' perception of safety while imagining sharing the road with SDVs (Nair & Bhat, 2021) as well as after experiencing interactions with SDVs in the real world as pedestrians (Rahman et al., 2021, 2023).

Controlling for other factors, being a man is associated with decreasing (i.e., less favourable) Autonomy Bias. This result was contrary to our expectations because men are generally more comfortable embracing technology and have more familiarity with and positive attitudes toward SDVs, as observed in our study (see Supplementary Material: Appendix H. Relationships between gender and explicit SDV attitudes) and the literature (Deb et al., 2017; Hulse et al., 2018; Nair & Bhat, 2021). Due to their greater trust in SDV technology in general, men may have held SDVs to a higher standard and so judged the observed SDVs more harshly – a form of betrayal aversion, as suggested in a past study of potential SDV riders (Shariff et al., 2021).

We did not observe any significant negative relationship between Autonomy Bias and certain equity factors in the context of transportation such as older people, people of colour, or people with less auto mobility (i.e., who rarely drive an automobile). Some similar results were also found in past studies that observed no effect of age (Deb et al., 2017) or travel habits (Ferenchak, 2023; Parkin et al., 2022; Rahman et al., 2023) on trust, comfort, or perceived safety of SDVs.

4.1. Limitations

We weighted our sample to represent the BC population over dimensions of education, race, and rural location, but that only partially offsets the potential sample bias of conducting an online survey. A more technology-orientated sample than the population might have led to underestimation of the strength of the negative Autonomy Bias in the population. Due to the nature of perception-based research, there is uncertainty about the generalizability of the findings outside of British Columbia. Similar studies in other geographic regions could reveal the extent to which traffic culture influences perceptions of pedestrian safety and comfort – particularly in regions with different pedestrian volumes or yielding norms. Perceptions of SDVs are modified by exposure, and we expect Autonomy Bias to improve with familiarity in locations with on-road SDV testing.

Another limitation is that the data were collected during the COVID-19 pandemic, and people's attitudes and travel behaviour were affected during that period (Javadinasr et al., 2022). We tried to minimize the effect of COVID-19 with the prompt in the survey: "While answering the following questions, consider a world where the risks of COVID are eliminated and social distancing measures are fully removed", but it is unknown how effective that was. Future studies could repeat our experiment to examine the post-COVID-19 perceptions towards SDV.

Finally, our study used a third-person evaluation method (in contrast to first-person) because it allowed us to collect data from a large and representative sample of the population and examine the effects of vehicle autonomation on perceptions of real-world interactions while controlling for other vehicle, pedestrian, and contextual variables. Our novel method contributes to the socio-technical research on SDV by providing a complementary method to the existing methods of virtual reality and "Wizard of Oz". Specifically, virtual reality provides the flexibility to design controlled experiments but suffers from lack of realism while "Wizard of Oz" examines real-world interactions but presents limitations for controlling variables, and both methods are impractical for collecting data from a large and representative sample of the population. However, future research should use those methods to extract Autonomy Bias through first-person evaluation and examine the transferability of our findings to first-person traveller perceptions.

4.2. Implications

The findings of this study have several important implications for researchers, policymakers, and SDV developers. To ensure the comfort of a large proportion of the population, SDVs should be programmed to operate more conservatively than HDVs around pedestrians and other vulnerable road users. Specifically, to ensure that the average person is as comfortable crossing with SDV as they currently are with HDV (i.e., to offset their Autonomy Bias), SDV must allow at least 0.4 s additional passing time at crosswalks; at least 3.7 s additional passing time is needed to ensure that 85 % of the population is equally comfortable. Unfortunately, a recent study reported that the mean passing time for pedestrian-SDV interactions in on-road testing in two USA cities and Singapore was 0.02 to 0.13 s *shorter* than in pedestrian-HDV interactions (Lanzaro et al., 2023) – which is the opposite of how pedestrian-friendly SDV would operate. Our recommendation of conservative SDV operation would probably also help alleviate the increased burden on crossing pedestrians, who have been observed to be more cautious and waiting longer to cross in front of SDV (vs. HDVs) (Kalatian & Farooq, 2021). Conversely, the users of SDVs and the drivers operating near SDVs might be less accepting of conservative SDV operation because of potentially increased travel time. However, we found that Autonomy Bias improves with SDV familiarity, and so the needed buffer for pedestrian comfort could decrease over time – as long as exposure to SDV corresponds to increasingly positive affective response (enthusiasm).

Our findings also show that perceptions of SDV as measured by Autonomy Bias are distinct from and not always aligned with explicit attitudes (i.e., self-reported affective orientation) toward SDV. More research is needed to further explore relationships between implicit and explicit attitudes toward SDV, and to better understand the conscious and unconscious pathways through which the introduction of self-driving vehicles will affect the human travel experience, particularly for vulnerable road users. Additionally, researchers should be cognizant that self-reported, explicit attitudes toward SDV provide useful but incomplete information about the perceptual impacts of vehicle automation.

CRediT authorship contribution statement

Gurdiljot Gill: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Alexander Bigazzi:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Jordi Honey-Rosés:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Emily Bardutz:** Writing – review & editing, Methodology.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2024.05.020.

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