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Machines versus humans: People's biased responses to traffic accidents involving self-driving vehicles

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ABSTRACT

Although self-driving vehicles (SDVs) bring with them the promise of improved traffic safety, they cannot eliminate all crashes. Little is known about whether people respond crashes involving SDVs and human drivers differently and why. Across five vignette-based experiments in two studies (total $N = 1267$), for the first time, we witnessed that participants had a tendency to perceive traffic crashes involving SDVs to be more severe than those involving conventionally human-driven vehicles (HDVs) regardless of their severity (injury or fatality) or cause (SDVs/HDVs or others). Furthermore, we found that this biased response could be a result of people's reliance on the affect heuristic. More specifically, higher prior negative affect tagged with an SDV (vs. an HDV) intensifies people's negative affect evoked by crashes involving the SDV (vs. those involving the HDV), which subsequently results in higher perceived severity and lower acceptability of the crash. Our results imply that people's over-reaction to crashes involving SDVs may be a psychological barrier to their adoption and that we may need to forestall a less stringent introduction policy that allows SDVs on public roads as it may lead to more crashes that could possibly deter people from adopting SDVs. We discuss other theoretical and practical implications of our results and suggest potential approaches to de-biasing people's responses to crashes involving SDVs.

1. Introduction

Automation refers to the complete or partial replacement of a function previously performed by an individual (Parasuraman et al., 2000). Accordingly, automated vehicles (AVs) are vehicles in which at least some aspects of safety-critical control functions (e.g., steering and braking) are conducted by an automated system that does not require a human driver's input (NHTSA, 2013). Vehicles with conditional automation (Level 3), high automation (Level 4), and full automation (Level 5) can work in the "self-driving" (i.e., "automated driving" or "driverless") mode, according to the Society of Automotive Engineers' (SAE) taxonomy for vehicle automation (SAE, 2014). SAE Level 5 AVs are also known as self-driving vehicles (SDVs), wherein an automated system performs all driving tasks under all conditions that are conventionally managed by a human driver. SDVs promise to substantially reduce traffic accidents, traffic congestion, and air pollution and increase fuel efficiency, space utilization, human mobility, and productivity (Fagnant and Kockelman, 2015; Anderson et al., 2016; Bansal et al., 2016; NHTSA, 2016). There is extensive ongoing research to understand public perceptions on, attitudes toward, and acceptance of, SDVs and other automation levels of AVs (Kyriakidis et al., 2015; Buckley et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018, Liu et al., in press, Liu et al., 2019b).

Not all accidents can be eliminated by SDVs (Kalra and Paddock, 2016; Awad et al., 2018a). Existing safety assessments (Schoettle and Sivak, 2015; Favarò et al., 2017; Banerjee et al., 2018) show that currently, AVs in the self-driving mode are not safer than human-driven vehicles (HDVs). There are few studies related to people's responses to SDVs in traffic accidents, which offered conflicting insights. Two studies observed that people treat machine drivers and human drivers equally: the severity of the same driving errors committed by them was judged equally (Kohn et al., 2018), and the same accident caused by them was blamed at the same level (Awad et al., 2018b). Thus, Awad et al. (2018b) asserted that people do not overreact to traffic accidents caused by SDVs. Contrary to the observations from the vignette-based surveys (Awad et al., 2018b; Kohn et al., 2018), the first fatality involving Tesla's Autopilot in May 2016 (Kohl et al., 2018) and the first fatality involving a pedestrian caused by an Uber AV in March 2018 (Associated Press, 2018) attracted wide media and public attention and aroused major concerns regarding traffic accidents caused by AVs. This

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indicates the possibility that people could overreact to traffic accidents caused by AVs. Awad et al.'s assertion (2018b) is also challenged by Waytz et al.'s (2014) experimental study, which reports that an AV was blamed more than a conventional HDV when such vehicles were hit by others.

We aim to test whether and why people have more negative responses to traffic crashes involving SDVs than they have to similar ones involving HDVs. Its practical contribution lies in the insights it provides into how the public responds to SDVs and HDVs, which, therefore, can influence how we approach the public and the introduction policy of SDVs during the deployment of SDVs. Its theoretical contribution lies in the better understanding it provides regarding the psychological mechanism underlying people's different responses to negative outcomes involving humans and machines.

2. Literature review and hypothesis development

In this section, we first review similarities and differences in people's responses to humans and machines (not limited to the AV context) and provide our first hypothesis, that is, people judge a traffic crash involving an SDV more severely than one involving an HDV. Then, we propose that people's reliance on the affect heuristic could lead to an overreaction to traffic crashes involving an SDV and subsequently, we provide three hypotheses for testing. Finally, we give an overview of five experiments in two studies, which serve the purpose of our research.

2.1. Humans versus machines

The distinction between humans and machines has been blurred because of rapid developments in computation, automation, artificial intelligence, and robotics (de Visser et al., 2016). In our daily lives, our communication with nonhuman agents (note: "nonhuman agents" and "machines" are interchangeable here), which are displaying more intelligence, sociability, and other humanlike characteristics and behaviors, is becoming increasingly necessary. Such nonhuman agents include, for example, artificial companions (Walter et al., 2014) and social robots (Breazeal, 2003). In the transportation sector, driver–vehicle interfaces will likely be personalized virtual companions to adjust settings, communication style, and other features according to the driver's preference (Wiese et al., 2017), and SDVs will be trained to behave more like humans ("humanized driving") (Newcomb, 2014). People have a natural propensity to mindlessly apply social rules and expectations to nonhuman agents and therefore show the same social reactions in their interaction with nonhuman agents (Nass and Moon, 2000). Human–automation interaction (Lewandowsky et al., 2000; Madhavan and Wiegmann, 2007) and human–robot interaction (Broadbent, 2017) share many qualitative similarities with human–human interaction.

However, subtle differences exist in the ways that people perceive and treat machines and humans, for example, in terms of accountability, responsibility, and blame attribution on the occurrence of negative outcomes. The tendency to blame technology for mistakes and errors is prevalent, and humans are abdicating more and more responsibility for negative outcomes to machines (Moon and Nass, 1998; Kim and Hinds, 2006). Humans are known to be inherently fallible, and therefore, they may be penalized less than nonhuman agents when both make mistakes (Madhavan and Wiegmann, 2007). They tend to be more sensitive to machine errors (Dzindolet et al., 2002); lose trust in it faster after an error has been made (Madhavan and Wiegmann, 2007; Prahl and Van Swol, 2017); and express less tolerance for algorithm errors than human ones (Dietvorst et al., 2015). Waytz et al. (2014) found that an AV received more blame than a conventional vehicle in an accident caused by other vehicles and explained that higher-level agency perception (e.g., rational thought) of an AV when compared with an HDV accounts for the AV being held to a higher level of responsibility. Contrary to the evidence and arguments, Kahn et al. (2012) found that when a robot causes harm, participants held less accountable than it would be a human.

In this study, we focus on one component of risk appraisals of traffic crashes: perceived severity. Perceived severity is associated with protective intentions and behavior (Sheeran et al., 2014). We assume that the vehicle type (HDV vs. SDV) affects people's perceived severity of traffic accidents and propose the following hypothesis (Note: in the other three hypotheses, we also consider the acceptability of traffic crashes):

H1. A traffic crash involving an SDV is perceived to be more severe than one involving an HDV (the SDV and the HDV are assumed to have the same safety performance).

2.2. Affect heuristic

People rely on heuristics (e.g., the availability heuristic) to guide their judgments and decisions (Tversky and Kahneman, 1974). These heuristics could impact people's risk perception, leading to biased estimates (Pachur et al., 2012). In particular, the affect heuristic proposed by Slovic and colleagues (Finucane et al., 2000; Slovic et al., 2004, 2007) suggests that people would rely on affect in the process of making an evaluation or a decision. Affective responses to an object (e.g., technology, behavior, and outcome) can provide diagnostic information regarding the object for a related evaluation or decision (Schwarz and Clore, 1996). People may use their affective response to a risk (e.g., "How do I feel about the traffic crash?") to infer the magnitude of the risk (e.g., "How severe do I perceive this traffic crash to be?"). According to the family of dual-process models in psychology (Epstein, 1994; Chaiken and Trope, 1999; Kahneman and Frederick, 2002), the affect heuristic reflects the experiential system that is labeled intuitive and automatic in information processing and decision-making (the other is an analytical system that is labeled deliberative, logical, cognitive, and rational). Hazards, risks, and unwanted outcomes may evoke images, representations, and associations tagged with positive or negative feelings, which, in turn, influence people's judgments of these hazards, risks, and unwanted outcomes.

In line with the affect heuristic, convergent evidence shows that affect and emotions guide risk judgments and behaviors (Loewenstein et al., 2001; Slovic and Peters, 2006; Pachur et al., 2012; Siegrist and Sütterlin, 2014). For example, Siegrist and Sütterlin (2014) reported that higher negative affect associated with human-caused hazards (vs. nature-caused hazards) accounts for a more negative evaluation of the outcomes subsequent to human-caused hazards. Rhodes and Pivik (2011) found that male drivers' higher positive affect toward risky driving behavior can explain why they engage more in these behaviors than do female drivers.

The affect heuristic could influence people's responses and decisions toward traffic crashes involving SDVs in two ways. People may depend on the affect they experience from the crashes to evaluate its severity and acceptability, which is labeled "affect heuristic I" (Siegrist and Sütterlin, 2014). People's mental images and representations of technologies are affectively tagged (Keller et al., 2012). This prior affect, tagged with a technology, may influence people's evaluations and decisions related to the technology, which is labeled "affect heuristic II" (Siegrist and Sütterlin, 2014). Affect heuristic I (situational affect works) and affect heuristic II (prior affect works) are not competitive but complementary models (Siegrist and Sütterlin, 2014). The prior affect evoked by a technology and the cognitive processes related to the interpretation of the new information about the technology could possibly jointly produce the experienced affect that subsequently influences people's judgments and decisions related to the technology (Siegrist and Sütterlin, 2014).

According to the affect heuristic (Finucane et al., 2000) and the two models of the affect heuristic (Siegrist and Sütterlin, 2014), there are

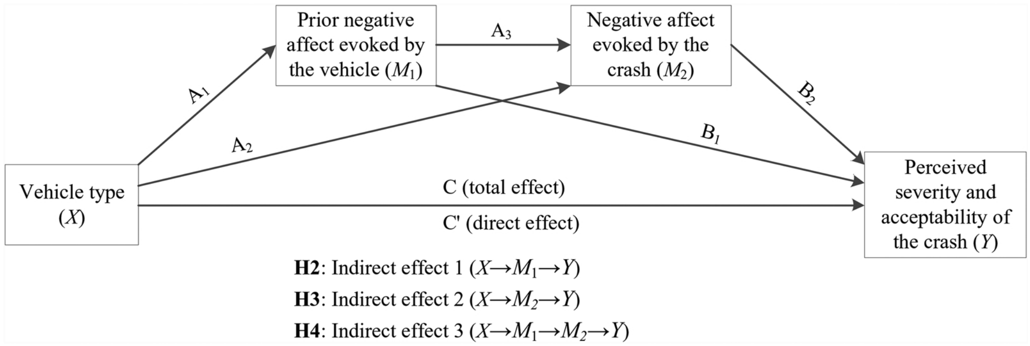

Fig. 1. A hypothetical model used for describing the relationships among vehicle type (X), prior negative affect evoked by the vehicle (M_1), negative affect evoked by the crash (M_2), and perceived severity and acceptability of the crash (Y). Perceived severity and acceptability are two separate dependent variables.

three potential accounts for **H1**. The prior affect tagged with its vehicle (affect heuristic II works) or the situational affect evoked by the crash information (affect heuristic I works) influences the perceived severity and acceptability of the crash, or the prior affect tagged with the vehicle influences the situational affect evoked by its crash information, which, in turn, influences the perceived severity and acceptability of the crash (both models work). Thus, we generate the following three hypotheses:

H2. Higher negative affect tagged with an SDV (vs. an HDV) results in higher perceived severity (a) and lower acceptability of the crash involving the SDV (b).

H3. Higher negative affect evoked by a traffic crash involving an SDV (vs. an HDV) results in higher perceived severity (a) and lower acceptability of the crash involving the SDV (b).

H4. Higher negative affect tagged with an SDV (vs. an HDV) results in higher negative affect evoked by a crash involving the SDV that subsequently results in higher perceived severity (a) and lower acceptability of the crash involving the SDV (b).

Fig. 1 shows the hypothetical model with which to describe the relationships among vehicle type (X), prior negative affect evoked by the vehicle (M_1), negative affect evoked by the crash involving the vehicle (M_2), and perceived severity and acceptability of the crash (Y). We need to examine the significance of three indirect effects: indirect effect 1 ($X \rightarrow M_1 \rightarrow Y$); indirect effect 2 ($X \rightarrow M_2 \rightarrow Y$); and indirect effect 3 ($X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$), which correspond to **H2**, **H3**, and **H4**, respectively.

2.3. Overview of studies

In the following sections, we present two studies. Study 1 demonstrates that a traffic crash involving an SDV is perceived to be more severe than one involving an HDV through four vignette-based online experiments that vary in the cause and severity of the crash. In Experiment 1a, a crash is caused by the HDV or the SDV (self-caused) and leads to an injury; in Experiment 1b, a crash is caused by others (others-caused) and leads to an injury; in Experiment 1c, a self-caused crash leads to a fatality. Unlike Experiments 1a/1b/1c that rely on student samples, Experiment 1d replicates Experiment 1c with a more diverse sample. All experiments support **H1** and provide convergent evidence that people have biased responses to traffic crashes involving SDVs (vs. HDVs).

Study 2 provides an account for this biased response through the affect heuristic and describes the potential psychological processes that induce people's biased responses. A 2 (cause: self-caused vs. others-caused) × 2 (vehicle: SDV vs. HDV) between-subjects design is conducted in a vignette-based offline experiment. The central finding on the biased response in Study 1 is replicated. Several serial multiple mediation analyses reveal that the higher prior negative affect associated with an SDV (vs. an HDV) reinforces the negative affect evoked by its crash, which, subsequently, results in higher perceived severity and lower acceptability of its crash. Thus, **H4** provides a more precise account for **H1** than **H2** and **H3**. People could possibly be led to have biased responses to traffic crashes involving SDVs by their reliance on the affect heuristic.

3. Study 1

3.1. Methodology

All four experiments employed a 2 (vehicle: HDV vs. SDV) between-subjects design. Considering that they were different in the cause or severity of the crash, only Experiment 1a is detailed for demonstration. In Experiment 1a, 159 students (100 females) were recruited from a university, representing a convenience sample. They were instructed to randomly choose one of two questionnaires (representing the HDV and SDV scenarios) that were unknown to them; 92 of them chose the HDV questionnaire and the rest chose the SDV questionnaire. The crash information read (translated from the Chinese original): "Assuming a driver [a self-driving vehicle] has an average driving safety performance of all human drivers. On an urban road, this driver [the self-driving vehicle] drove a passenger to a specific destination. However, due to mistakes made by the driver [the self-driving vehicle], a sudden traffic crash occurred and injured the passenger" (the text in [] is presented in the SDV questionnaire). To isolate the influence of vehicle type from the influences of participants' potential higher expectation of the safety of SDVs or their knowledge about the current safety of SDVs, we have to assume that the HDV and the SDV have the same driving performance. Before reading the crash information, participants in the SDV scenario were given an introduction of SDVs (see Appendix). The participants then judged the severity of the crash: "How severe do you consider this crash is?" (1 = *very low* and 10 = *very high*). We adopted a general single-item design for measuring perceived severity and other constructs to furnish a parsimonious focus with which to test the hypotheses (Kahan et al., 2012). Finally, the participants submitted their demographic information (sex, age, and driving experience). Age was evaluated on the basis of four levels: "< 20″ (n = 27); "20–25″ (n = 124); "26–30″ (n = 7); and "> 30″ (n = 1). Driving experience was evaluated on the basis of four levels: "0 year" (n = 105); "1–3 years" (n = 46); "4–7 years" (n = 7); and "> 7 years" (n = 1).

Experiment 1b was similar to Experiment 1a. In Experiment 1b, the crash was caused by others; thus, the HDV and SDV have no responsibility for the passenger's injury. The crash information, at the end, conveyed that "Accident investigation revealed that this crash was unrelated to the human driver [the self-driving vehicle]." A total of 167 college students (59 females) were recruited, 102 of whom randomly chose the HDV questionnaire and the rest chose the SDV questionnaire. Similarly, age was evaluated on the basis of four levels: "< 20″ (n = 108); "20–25″ (n = 59); "26–30″ (n = 0); and "> 30″ (n = 0). Driving experience was evaluated on the basis of four levels: "0 year" (n = 62); "1–3 years" (n = 100); "4–7 years" (n = 3); and "> 7 years"

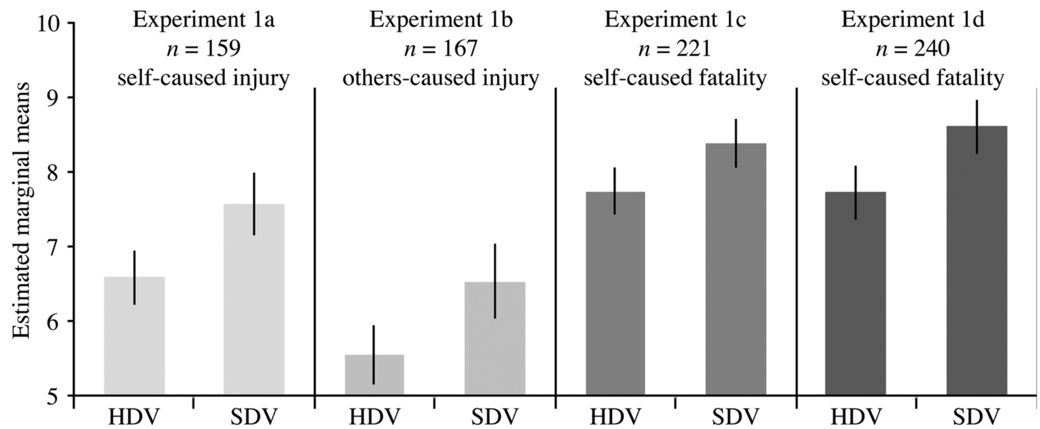

Fig. 2. Estimated marginal means of perceived severity of traffic crashes involving the HDV and SDV across the four experiments in Study 1. Error bars indicate 95% confidence intervals (CIs). HDV, human-driven vehicle; SDV, self-driving vehicle.

($n = 2$).

The key difference between Experiments 1a and 1c is that in the latter crash resulted in the death of the passenger. A total of 221 college students (128 females; 88 driving license holders; age: mean = 20.4, SD = 2.1, min = 17, and max = 31) were recruited and instructed to choose either the HDV scenario ($n = 110$) or the SDV scenario ($n = 111$) according to the odevity of the last digit of their cell phone number. Participants reported their sex, exact age, and whether they held a valid driving license.

Experiment 1d replicated Experiment 1c with a more diverse sample. A total of 240 participants were recruited online (122 females; 160 driving license holders; age: mean = 29.6, SD = 7.6, min = 20, and max = 59), 118 of whom responded to the HDV scenario and 122 responded to the SDV scenario.

3.2. Results

The estimated marginal means (EMMs) of perceived severity in the two scenarios across the four experiments are illustrated in Fig. 2. Analyses of covariance (ANCOVA) tests were conducted with perceived severity as the dependent variable; vehicle type as the independent variable (HDV = 0, SDV = 1); and sex, age, and driving experience in Experiments 1a/1b and sex, age, and driving license holder in Experiments 1c/1d as the covariates. In Experiment 1a, the injury crash caused by the SDV was perceived to be more severe than the injury crash caused by the HDV ($EMM_{SDV} = 7.57$, $EMM_{HDV} = 6.59$, $b = 0.98$, $F_{(1,154)} = 12.05$, $P < 0.001$). In Experiment 1b, the injury crash caused by others but involving the SDV was also perceived to be more severe than the one involving the HDV ($EMM_{SDV} = 6.53$, $EMM_{HDV} = 5.55$, $b = 0.98$, $F_{(1,162)} = 9.02$, $P = 0.003$). In Experiment 1c, the perceived severity of the fatality crash caused by the SDV was higher than that of the fatality crash caused by the HDV ($EMM_{SDV} = 8.37$, $EMM_{HDV} = 7.75$, $b = 0.62$, $F_{(1,216)} = 7.32$, $P = 0.007$). Experiment 1d replicated the finding in Experiment 1c with a more diverse sample ($EMM_{SDV} = 8.61$, $EMM_{HDV} = 7.72$, $b = 0.89$, $F_{(1,223)} = 11.65$, $P < 0.001$). Therefore, although the consequences of the crashes involving an SDV and an HDV were identical, the crash involving the SDV was assessed more harshly regardless of whether it was caused by the SDV or by others (see Experiments 1a and 1b) and whether it resulted in an injury or a fatality (see Experiments 1a and 1c/1d). The three covariates did not exert significant influence on perceived severity in all experiments; thus, their results were not reported.

3.3. Discussion

Assuming that a traffic crash involving an SDV is judged more negatively than one involving an HDV, **H1** was supported by all experiments with varying contexts of the traffic crash (cause and severity) in Study 1. Even more strikingly, although the SDV and the HDV were not liable for the traffic crash, participants still judged the crash involving the SDV more harshly. Our finding reveals people's overreaction to traffic crashes involving driverless vehicles, although previous studies (Awad et al., 2018b; Kohn et al., 2018) claimed that people treat errors of human drivers and machine drivers similarly.

4. Study 2

4.1. Methodology

In the between-subjects design (vehicle: SDV vs. HDV; cause: self-caused vs. others-caused), 480 students (274 females; 295 driving license holders; age: mean = 22.3, SD = 1.7, min = 17, and max = 28) in a university provided their responses to traffic crashes and were randomly assigned to one of the four groups (120 for each group).

In all groups, to illustrate the prior negative affect associated with the vehicle, participants were first required to read a piece of text about an HDV/ SDV (translated from the Chinese original): "Assuming a human driver [a self-driving vehicle] has an average driving safety performance of all human drivers. You are a passenger who is planning to take the driver's vehicle [the self-driving vehicle] to your destination." Then, they were asked to rate their levels of fear and anxiety in two items (1 = *very low*; 10 = *very high*) if they were required to ride in the driver's vehicle (the SDV). Fear and anxiety, adapted from Midden and Huijts (2009), measured the prior negative affect (Cronbach's alpha = 0.95). In the two SDV groups, participants additionally read an introduction regarding SDVs (see Experiment 1a) before this text. Then, participants turned to a new page on which information about a traffic crash was displayed. The description of the crash was similar to that in Study 1. In the two self-caused groups, the crash information read: "On an urban road, the driver [the self-driving vehicle] drove one passenger to a specific destination. However, due to mistakes made by the driver [the self-driving vehicle], a sudden traffic crash occurred and resulted in the passenger's death." In the two others-caused groups, the crash information read: "On urban roads, the driver [the self-driving vehicle] drove one passenger to a specific destination. However, a sudden traffic crash occurred and resulted in the passenger's death. Accident investigation revealed that this crash was unrelated to the human driver [the self-driving vehicle]." After reading about the crash, participants responded to questions: "What negative feeling do you experience because of this crash?"; "How severe do you consider this crash to be?"; and "How acceptable do you consider this kind of crash to be?" (1 = *very low*, 10 = *very high*). These questions for measuring negative affect evoked by the crash and the acceptability of this crash were adapted from Siegrist and Sütterlin (2014). Participants also provided their trust ratings in the HDV/SDV scenarios before and after reading the crash information, and their ratings of fear and anxiety after reading the crash information. These responses were unrelated to the current research and have not been reported here. Finally, participants reported their sex, exact age, and whether they held a valid driving license.

4.2. Results

The prior negative affect evoked by the vehicle, the negative affect evoked by the crash, and the perceived severity and acceptability of the crash were measured. A multivariate analysis of covariance (MANCOVA) was conducted with the three demographic factors as the covariates, which showed the significant main effects of vehicle ($F_{(4,470)} = 65.88$, $P < 0.001$, Wilks' $\Lambda = 0.641$, $\eta_p^2 = 0.359$) and cause ($F_{(4,470)} = 7.15$, $P < 0.001$, Wilks' $\Lambda = 0.943$, $\eta_p^2 = 0.057$). The interaction effect of vehicle and cause was not significant ($F_{(4,470)} = 1.68$, $P = 0.153$, Wilks' $\Lambda = 0.986$, $\eta_p^2 = 0.014$).

Separate *post hoc* univariate ANCOVAs were conducted. Vehicle type had significant main effects on the prior negative affect evoked by the vehicle ($F_{(1,473)} = 252.19$, $P < 0.001$, $\eta_p^2 = 0.348$), negative affect evoked by the crash ($F_{(1,473)} = 26.33$, $P < 0.001$, $\eta_p^2 = 0.053$), perceived severity ($F_{(1,473)} = 13.19$, $P < 0.001$, $\eta_p^2 = 0.027$), and acceptability of the crash ($F_{(1,473)} = 35.55$, $P < 0.001$, $\eta_p^2 = 0.070$). When compared with the HDV scenario, the SDV scenario was associated with higher prior negative affect, higher negative affect evoked by the crash, higher perceived severity, and lower acceptability (see Fig. 3) when the crash was caused by the SDV or by others. Cause had a significant main effect not on the prior negative affect ($F_{(1,473)} = 0.04$, $P = 0.851$, $\eta_p^2 < 0.001$) but on the negative affect evoked by the crash ($F_{(1,473)} = 17.05$, $P < 0.001$, $\eta_p^2 = 0.035$), perceived severity of the crash ($F_{(1,473)} = 25.28$, $P < 0.001$, $\eta_p^2 = 0.051$), and acceptability of the crash ($F_{(1,473)} = 9.16$, $P = 0.003$, $\eta_p^2 = 0.019$). When compared with the crash caused by others, the crash caused by the HDV/SDV was associated with higher negative affect evoked by the crash and perceived severity and lower acceptability (see Fig. 3). No significant interaction effects of vehicle and cause ($Ps > 0.05$) were found on the prior negative affect ($F_{(1,473)} = 1.99$, $P = 0.159$, $\eta_p^2 = 0.004$), negative affect evoked by the crash ($F_{(1,473)} = 0.30$, $P = 0.583$, $\eta_p^2 = 0.001$), perceived severity of the crash ($F_{(1,473)} = 0.26$, $P = 0.607$, $\eta_p^2 = 0.001$), and acceptability of the crash ($F_{(1,473)} = 2.33$, $P = 0.128$, $\eta_p^2 = 0.005$).

To examine **H2–H4** simultaneously, four serial multiple mediator (SMM) models (four models by two causes and two dependent variables) were run using a bootstrapping procedure (Hayes, 2013) with 5000 bootstrapped samples. For the SMM analysis, Hayes's PROCESS Macro (model 6) was used. Vehicle (HDV = 0, SDV = 1) acted as the independent variable (X); the prior negative affect evoked by the vehicle (M_1) and the negative affect evoked by the crash (M_2) acted as the serial mediators; the perceived severity and acceptability (Y) of the crash acted as separate dependent variables; and sex, age, and driving license holder acted as the covariates. As shown in Fig. 4, the bias-corrected 95% bootstrap CIs of the indirect effect 1 ($X \rightarrow M_1 \rightarrow Y$) and indirect effect 2 ($X \rightarrow M_2 \rightarrow Y$) included zero in all four models while controlling for the demographic variables; however, the indirect effect 3 ($X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$) did not include zero and its direction was as expected in all four models. Thus, **H4**, but not **H2** and **H3**, was supported by the SMM analysis, independent of the crash cause and the dependent variable. When the crash was self-caused, the indirect effect 3 ($X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$) was 0.56 on the perceived severity of the crash (95% CI [0.21, 0.99]) and −0.32 on the acceptability of the crash (95% CI [−0.63, −0.10]), respectively; when the crash was others-caused, it was 0.30 on the perceived severity of the crash (95% CI [0.13, 0.52]) and −0.29 on the acceptability of the crash (95% CI [−0.51, −0.12]).

The total effects of vehicle type on the perceived severity and acceptability of the crash were significant when the crash was self- or others-caused. In line with the findings of the four experiments in Study 1, the SDV was associated with higher perceived severity of the crash (self-caused: $b = 0.57$, 95% CI [0.10, 1.03]; others-caused: $b = 0.75$, 95% CI [0.22, 1.29]) and lower acceptability of the crash (self-caused: $b = -1.46$, 95% CI [−2.01, −0.91]; others-caused: $b = -0.85$, 95% CI [−1.41, −0.29]) (see Fig. 4). Vehicle lost the significant direct effect on the two dependent variables in three out of four models. It still exerted a direct effect on the acceptability of the self-caused crash ($b = -0.88$, 95% CI [−1.57, −0.19]).

4.3. Discussion

A fatality crash involving an SDV was perceived to be more severe

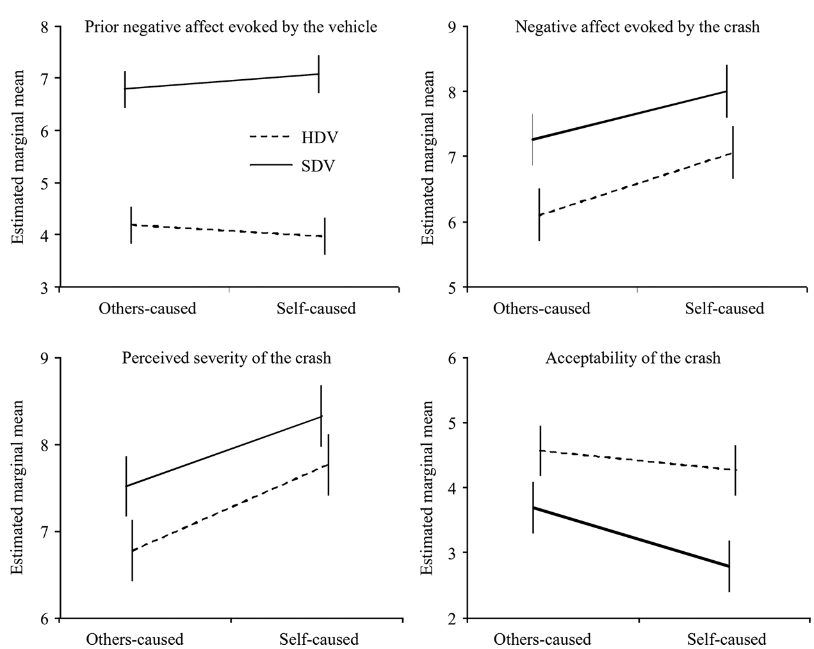

Fig. 3. Estimated marginal means of the four responses by vehicle and cause (n = 480). Error bars indicate 95% CIs. HDV, human-driven vehicle; SDV, self-driving vehicle.

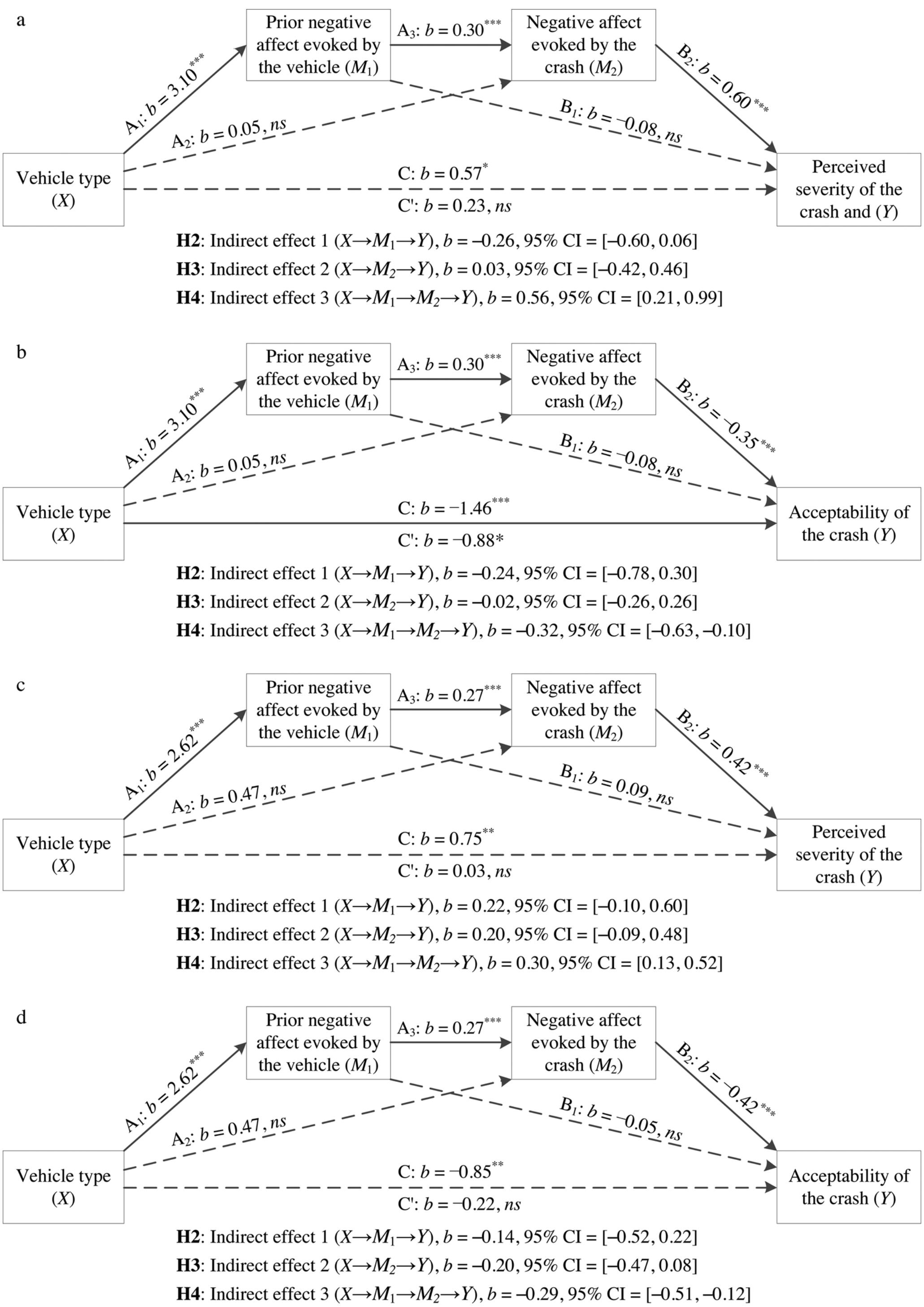

Fig. 4. Results of serial multiple mediator models. (a) and (b) show results on the self-caused crash; and (c) and (d) show results on the others-caused crash. Non-standardized coefficients are shown. Non-significant paths are shown as dotted lines. Vehicle type: HDV = 0, SDV = 1. $^{*}P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.001$; *ns*, not significant.

than one involving an HDV in both cases—whether the SDV/HDV was liable or not liable for the fatality in Study 2. Thus, Study 1 and Study 2 unanimously corroborated **H1**. In addition, in line with the findings on the severity judgment, the crash involving the SDV was less acceptable. We do not believe that it is irrational or rational to more concern traffic crashes involving SDVs when compared with those involving HDVs. However, identical negative outcomes (injury or death) were differently evaluated depending on the vehicle technology involved (even though the negative outcomes did not result from the vehicle technology *per se*; see Experiment 1b and the others-caused scenarios in Study 2), which indicates biased responses. Although previous studies indicate that participants had similar responses on human drivers and machine drivers with regard to the attribution of blame in their traffic crashes (Awad et al., 2018b) and the severity evaluation of their driving errors (Kohn et al., 2018), our finding is largely supported by public responses to real fatal accidents related to AVs (Shariff et al., 2017; Kohl et al., 2018).

We explain the biased response through the theory of the affect heuristic (Finucane et al., 2000), which suggests that people rely on affect to guide their decision and behavior. According to affect heuristic II (Siegrist and Sütterlin, 2014), the prior affect tagged with vehicle technology influences people's responses to the technology, including the vehicle's crash (see **H2**). According to affect heuristic I (Siegrist and Sütterlin, 2014), the cognitive interpretation of the crash information of the vehicle technology produces the affect, which, in turn, influences people's responses to the vehicle's crash (see **H3**). In line with affect heuristic II and affect heuristic I, **H2** and **H3** assumed that the prior negative affect tagged with the vehicle and the negative affect evoked by the crash information mediate the relationship between vehicle technology and the perceived severity and acceptability of the vehicle's crash, respectively. However, **H2** and **H3** were not supported by the SMM models; instead, **H4** was supported, suggesting that both types of negative affect mediate this relationship in serial order (see Fig. 4).

We do not suggest that affect heuristic I or II alone cannot explain people's responses to crashes. We indeed found the mediating effect of each negative affect in the mediation analysis, suggesting that both kinds of affect can explain **H1** (the results are not presented here but could be made available on reasonable request). We believe that the SMM model in which affect heuristics I and II jointly work can provide a more precise explanation than one in which either one of them works alone. As prior attitudes influence how new information is interpreted (Cvetkovich et al., 2002; Siegrist and Sütterlin, 2014), we explain that participants' prior negative affect associated with vehicle technology influences how participants interpret new crash information (affect heuristic II works), both of which jointly determine the negative affect evoked by the crash that finally influences the severity judgment and acceptability of the crash (affect heuristic I works). We concur with Siegrist and Sütterlin's statement (2014) that the prior affect associated with a technology and the cognitive processing of new information regarding the technology produce the situational affect, which subsequently influences the risk acceptability of the technology.

It should be noted that our experiments used simple vignettes, which may have been unlikely to trigger very strong negative emotions. In the future, crashes involving SDVs in real-life situations may elicit stronger affective reactions that would subsequently introduce stronger bias toward these crashes and SDVs.

The two models with perceived severity as the dependent variable shared the same significance of their paths (see Fig. 4a and c). Vehicle exerted a direct effect on the acceptability of the self-caused crash but not on the acceptability of the others-caused crash (see Fig. 4b and d). We are currently unaware as to whether this is a contingency or whether we missed other mediators in this significant direct effect of vehicle type.

5. General discussion

Our participants assessed traffic crashes involving SDVs more negatively and had less acceptance of these crashes than ones involving HDVs, which persisted even when SDVs were not causally responsible for these crashes. This indicated people's biased responses to traffic crashes involving SDVs. We explain that people intuitively have higher negative affect toward SDVs than they do toward HDVs. This intensifies their negative affect evoked by crashes involving SDVs (vs. those involving HDVs), which subsequently leads people to judge crashes involving SDVs more severely and be less willing to accept these crashes. We should pay close attention to people's overreaction to unavoidable crashes involving SDVs, which could derail its wide adoption.

5.1. Theoretical implications

Our result is in line with previous work on different aversion behaviors associated with various machines (e.g., autonomous machines), in making moral decisions (Bigman and Gray, 2018) and algorithms in forecasting tasks (Dietvorst et al., 2015). However, our result contradicts the evidence from recent studies that participants give similar responses to human and machine errors (Awad et al., 2018b; Gogoll and Uhl, 2018; Kohn et al., 2018). Certain studies (Awad et al., 2018b; Logg et al., 2019) even presented that, at times, people respond more positively to machines than they do to humans. For instance, Awad et al. (2018b) found that in cases where a human and an automated system share control of AVs, less blame is attributed to the machine when both make errors. With regard to these conflicting results, an integrative understanding of public responses to machines and humans across machine types (e.g., robot, automation, and algorithm), applications (e.g., driving, forecasting, and medical diagnosis), and responses (e.g., outcome evaluation and blame and responsibility attribution) is highly necessary.

Participants were less willing to accept traffic crashes involving SDVs (even when SDVs *per se* are a victim) than those involving HDVs. This result seems to be consistent with a previous observation on the difference between SDVs and HDVs in terms of acceptable risk: SDVs were implicitly required to be four to five times as safe as HDVs (Liu et al., 2019a). Thus, people who have to take their hands off the steering wheel and entrust their lives to SDVs have a higher safety requirement from SDVs and are less likely to tolerate traffic crashes involving SDVs.

The role of affect and emotions has been acknowledged in guiding people's decision-making and behavior (Loewenstein et al., 2001; Slovic et al., 2004; Kahneman, 2011; Lerner et al., 2015), including driving behaviors (Rhodes and Pivik, 2011). Their importance in shaping public acceptance of AVs was recognized in limited studies (Hohenberger et al., 2016, 2017, Winter et al., 2018). The affect heuristic (Finucane et al., 2000) was applied by us to explain people's biased responses to traffic crashes involving SDVs. The affect-induced bias is not rare in decision-making and behavior research (Gigerenzer, 2004; Siegrist and Sütterlin, 2014; Lerner et al., 2015), and we suggest using this affect heuristic to explain people's heterogeneous responses to humans and machines in the broader literature on people's responses to humans and machines, which mainly focuses on whether machines have similar human characteristics but seldom concerns different affect and emotions tagged with humans and machines.

5.2. Practical implications

Understanding public responses to human and machine drivers may determine how we treat the public during the deployment process of SDVs. Awad et al. (2018b) reported that in single-driver cases (a machine or a human), people blame them at the same level for their errors and that in dual-driver cases (a machine and a human sharing control of AVs), people blame the machine less for their errors. Thus, Awad et al. (2018b) asserted that people do not exhibit an overreaction but an under-reaction to faults of machines, and accordingly, suggested focusing on the impact of top-down regulation and not on the impact of public pressure on manufacturers' improvement in AV design. Contrary to Awad et al.'s assertion, our central finding clearly suggests that people exhibit an overreaction to traffic crashes involving SDVs even when the crashes are not by the SDVs' fault. As a higher level of perceived severity can lead to more protective intentions and behavior (Sheeran et al., 2014), people's overreactions to traffic crashes involving SDVs would lead them to be more averse to riding in SDVs. It could be costly for society at large in terms of reducing the opportunity to improve the safety of these vehicles and to save more human lives as accumulating real-world driving experience is necessary to improve the safety performance of SDVs and other AVs. For example, Gigerenzer (2004) found that the number of Americans who lost their lives on the road in trying to avoid the risk of flying in the three months following the attack on September 11, 2001, was higher than the total number of passengers killed on the four fatal flights in the attack. Thus, psychological and behavioral outcomes resulting from traffic crashes involving SDVs should be strongly emphasized.

Certain policymakers (Kalra and Groves, 2017) support less stringent introduction policies allowing SDVs on public roads when they are marginally safer than an average human driver. From a utilitarian perspective, such policies could save more lives than more stringent ones. Our results, however, indirectly suggest that such policies may backfire as the SDVs allowed on public roads under such policies would cause more crashes on roads, which may deter more people from adopting SDVs. Safety benefits of SDVs can be achieved only when people are willing to accept their risks and use them. While setting the introduction policy of SDVs, policymakers should be aware of people's biased responses to crashes resulting from the policy.

Our research suggests that to reduce the psychologically motivated toll of aversion to SDVs, mitigating the affect-induced bias would be critical. Reducing negative emotions, facilitating positive emotions, and increasing risk tolerability of SDVs can be achieved through, for example, highlighting the benefits of SDVs. In addition, as suggested by Gigerenzer (2004), it could be easy and inexpensive to make the public aware of their psychological reactions to traffic crashes involving SDVs and the potential risk of being averse to SDVs.

5.3. Limitations and future directions

Several weaknesses are noted. First, we used unrepresentative samples from only one country in the four online experiments (Study 1) and the offline experiment (Study 2), which could constrain the generalizability of our results. Second, our participants did not have real experience of an AV and thus could hold inaccurate mental models of SDVs. Third, various affect and emotions could influence people's decisions and behaviors (Lewandowsky et al., 2000); however, we focused on negative affect to explain people's different evaluations, which could be a narrow perspective.

We, therefore, suggest several research avenues. First, other researchers can replicate the present one in other countries. Considering that participants from developed countries (e.g., the USA and the UK) might hold a less positive attitude toward SDVs than those from developing countries (e.g., China) (Schoettle and Sivak, 2014), participants from developed countries could exhibit a higher level of overreaction to crashes involving SDVs. Second, it is necessary to check whether people are biased against a semi-AV in which a machine and a human share control over the vehicle. Third, locating which specific affect and emotions guide people's evaluations of traffic crashes would be necessary for a more precise explanation of the observed biased responses. Fourth, future research can consider whether the biased responses to traffic crashes involving SDVs can be reduced after people have direct experience of SDVs. Fifth, future studies can examine whether people's higher expectation regarding the safety of SDVs (vs. HDVs) could explain their more negative responses to crashes involving SDVs. Sixth, future research can also examine whether people are more averse to a superior SDV than an HDV in cases where both are involved in crashes. If that were to be the case, the bias will be even more problematic as it will deter consumers from adopting the superior vehicles.

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Appendix

The introduction of the SDVs used in all experiments is as below (adapted from Kyriakidis et al., 2015):

The automated driving system takes over speed and steering control completely and permanently on all roads and in all situations. The driver or passenger sets a destination via a touch screen. The driver or passenger cannot drive manually or perform interventions because the vehicle does not have a steering wheel.

Self-driving vehicles allow drivers (passengers) to perform non-driving activities, such as reading a book, watching a film, surfing the Internet, playing games on their phones, dealing with their working affairs, sleeping, and so on.

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