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ARTICLE

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Who is to blame for crashes involving autonomous vehicles? Exploring blame attribution across the road transport system

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ABSTRACT

The introduction of fully autonomous vehicles is approaching. This warrants a re-consideration of road crash liability, given drivers will have diminished control. This study, underpinned by attribution theory, investigated blame attribution to different road transport system actors following crashes involving manually driven, semi-autonomous and fully autonomous vehicles. It also examined whether outcome severity alters blame ratings. 396 participants attributed blame to five actors (vehicle driver/user, pedestrian, vehicle, manufacturer, government) in vehicle–pedestrian crash scenarios. Different and unique patterns of blame were found across actors, according to the three vehicle types. In crashes involving fully autonomous vehicles, vehicle users received low blame, while vehicle manufacturers and government were highly blamed. There was no difference in the level of blame attributed between high and low severity crashes regarding vehicle type. However, the government received more blame in high severity crashes. The findings have implications for policy and legislation surrounding crash liability.

Practitioner summary: Public views relating to blame and liability in transport accidents is a vital consideration for the introduction of new technologies such as autonomous vehicles. This study demonstrates how a systems ergonomics framework can assist to identify the implications of changing public opinion on blame for future road transport systems.

Abbreviation: ANOVA: analysis of variance; DAT: defensive attribution theory; IV: independent variable

Introduction

Fully autonomous vehicles, where technology controls all aspects of driving, at least in some driving situations, are predicted to be available to the Australian public by 2020 (National Transport Commission 2018). Such vehicles already operate under test conditions in many countries. Semi-autonomous vehicles, where technology controls some aspects of driving, are already available. Various issues relating to these new technologies have been examined, including trust (Schaefer et al. 2016; Walker et al. 2019), automation transitions and takeovers (Favarò et al. 2019), and human–automation interactions (Deb, Strawderman, and Carruth 2018). Indeed, the topic of autonomous vehicles has inspired recent discussions within this journal amongst leading ergonomics researchers (Hancock 2019a; Hancock 2019b; Endsley 2019; Lee 2019; Salmon 2019; de Winter 2019; Waterson 2019; Emmenegger and Norman 2019). Such discussions have focussed on both human interactions with autonomous vehicle technologies, as well as the wider socio-technical implications of their introduction.

One area beginning to receive more attention is that of liability in the event of a crash involving an autonomous vehicle (Hancock 2019a; Bellet et al., 2019). Given that the human driver role is reduced to that of an automation supervisor, allocation of blame is less straightforward in crashes with autonomous vehicles, compared to manually driven vehicles. To a large extent, current legislation holds drivers responsible for vehicle crashes due to failures to obey traffic regulations (Hughes, Anund, and Falkmer 2015). This approach does not apply to autonomous vehicles, as vehicle users (i.e. the passenger) will have either restricted or no control over vehicles. Thus, government policy around liability will need to change in response to these new technologies (Bellet et al.,

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2019; Kyriakidis et al. 2019). If liability continues in its current form, Hancock (2019a) argues that this will create stress for users, as they are held responsible for crashes, but have no control to prevent these events.

Thus, the issue of responsibility and liability for crashes involving autonomous vehicles requires resolution. As policy response should be based on societal input (Bellet et al., 2019), understanding how the general public attributes blame to different actors in crashes involving autonomous vehicles is an area requiring exploration.

Aims

This study aimed to investigate how the Australian public attributes blame to actors across the road transport system in crashes involving manually driven, semi-autonomous, and fully autonomous vehicles, and whether outcome severity alters the level of blame attributed across the three vehicle types.

Blame attribution and attribution theory

Blame involves two components; causality and morality (Heider 1958). Causality assesses an actors' responsibility for outcomes through the relationship between their behaviours and outcomes (Harvey and Rule 1978). Morality refers to actors' obligations in certain situations, such as acting cautiously while driving to avoid injuring others (Harvey and Rule 1978). Throughout the literature, the blame is commonly substituted for other constructs such as responsibility and liability. While these terms convey slightly different meanings, they remain appropriate when exploring blame attribution, as they are at least moderately related to blame (Krulewitz and Nash 1979).

Blame attribution can be understood through attribution theory which explains how information is utilised to make causal attributions (Kelley 1973). The theory is based on three principles (Heider 1958); that human behaviour is intentional, resulting in attempts to understand underlying motives for behaviour; that causal attributions are attempts to control and predict the environment; and that there is a difference between internal and external attributions. When the causal link between actor behaviour and outcome decreases, so does attribution to internal or individual factors, as outcomes are perceived to be outside the individual's control. Instead, attributions are directed to external or environmental factors (Heider 1958).

Shaver's (1985) causality staircase depicts how a causal association between actors and outcomes increases together with actors' level of control and blameworthiness. The staircase has four steps; association (actors are connected to the outcome); causality (actors' behaviour is necessary for the outcome to occur); foreseeability (actors can anticipate outcomes); and intention (actors create the outcome on purpose; Shaver 1985).

Various influences and biases affecting blame attribution and related constructs have been identified such as personal similarity with the actors involved (Shaver 1970) and emotional states (Ask and Pina 2011; Feigenson and Park 2006). One of the key areas that have been explored in previous studies is outcome severity. For example, in scenarios that differ only on outcome severity, more blame is attributed in high severity compared to low severity scenarios (Walster 1966). Defensive attribution theory (DAT) states that high severity scenarios evoke protective defences against the randomness of accidents. This is expressed through increased blame as it provides a sense of control (Walster 1966). DAT has however received varied support and has been adapted over time to improve its predictability (Walster 1967, Shaver 1970).

Blame attribution in crashes involving autonomous vehicles

Several studies have investigated blame attribution in general accidents (Lagnado and Channon 2008; Remijn and Crombag 2007; Schroeder and Linder 1976) and road crashes (Arkkelin, Oakley, and Mynatt 1979; Stewart 2005; Walster 1966), including how blame attribution affects recovery from road crashes (Hickling et al. 1999; Thompson et al. 2015; Thompson, O'Donnell, et al. 2014).

The literature is largely congruent with attribution theory and its sub-theories, whereby control and severity are key variables used in assessing blame attribution. Research on blame attribution in autonomous vehicle crashes is however limited, given the technology is currently emerging and constantly evolving. The two available studies indicate that control is critical for blame attribution in autonomous vehicle crashes (Li et al. 2016; McManus and Rutchick 2018). McManus and Rutchick (2018) investigated blame attribution towards drivers/users in fatal vehicle crash scenarios. Less blame was attributed to users of manufacturer-programmed fully autonomous vehicles, compared to conditions where users pre-selected the programming of their vehicle's algorithms (to behave selfishly or selflessly), or manually drove the vehicle. The findings suggest that blame attributed to fully

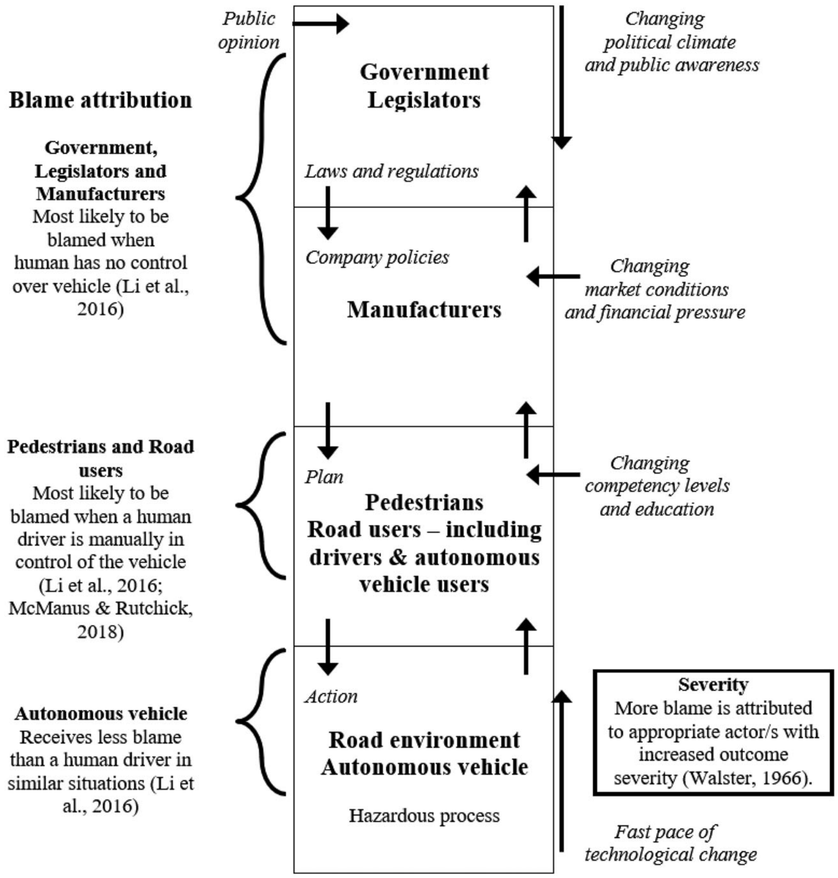

Figure 1. Rasmussen's (1997) risk management framework adapted to autonomous vehicles.

autonomous vehicle users is mitigated. Li et al. (2016) assessed how blame is attributed to actors in the wider road system including manufacturers, government agencies, the vehicle itself, drivers/users, and pedestrians. This study revealed that user blame decreased in crashes involving fully autonomous vehicles, while blame to manufacturers and government increased. The vehicle was not perceived to be equally to blame as drivers in manually driven vehicles, as it received less blame in matched crash scenarios. While studies in this area are beginning to emerge, none have assessed how blame is attributed in semi-autonomous vehicle crashes.

A systems approach to blame attribution

The research to date is thus suggesting that blame shifts from drivers/users to manufacturers and government in fully autonomous vehicle crashes. As a result, it has been recognised that whole-of-systems approaches are required to fully understand blame in autonomous vehicle crashes (Banks, Stanton, et al. 2018). A systems framework that has been applied in various road safety studies is Rasmussen's (1997) Risk Management Framework (Newnam and Goode 2015; Scott-Parker, Goode, and Salmon 2015; Young and Salmon 2015). The framework views the road transport system within which autonomous vehicles operate as both hierarchical and dynamic (see Figure 1). Within this framework, with the levels adapted from a generic workplace context to represent the road transport system, government and regulators reside at the system's highest hierarchical level, followed by vehicle manufacturers, and individual actors (drivers/users and pedestrians). At the lowest level is the driving environment, which incorporates autonomous vehicles themselves. All actors play a role in risk management associated with the operation of autonomous vehicles. For example, governments can minimise risk through appropriate legislation, and vehicle manufacturers can minimise risk through comprehensive design, testing and commissioning processes.

Importantly, the framework includes the role of public opinion and changing public awareness in influencing government decision-making. The current study responds to this by eliciting public opinion around blame to ensure that laws are reflective of societal expectations.

Causality of road system actors in crashes

According to attribution theory and Heider's (1958) prediction, that external forces are blamed when individuals lack control over outcomes, control is a key factor in blame attribution. Thus, less blame is likely to be attributed to autonomous vehicle users, who lack control over the vehicle, compared to drivers of manually driven vehicles. The findings of previous research into control and how this affects the attribution of blame to actors across the different system levels are shown on the left-hand side of Figure 1.

The connection between control and blame is further congruent with Shaver's (1985) causality staircase described earlier. Figure 2 provides a generalised overview of the changing positions of road system actors on the causality staircase, depending on whether the vehicle is manually driven, semi-autonomous or fully autonomous. The figure shows that moving from manually driven vehicles to semi and fully autonomous vehicles, causal links between drivers/users and crashes are weakened (reside lower on the staircase), while links are strengthened for manufacturers and government (reside higher on the staircase). Fully autonomous vehicle users are downgraded on the staircase from Foreseeability, which might be expected from drivers of manually driven vehicles, to Association, as users do not control the driving task. Manufacturers, government and vehicles, however, move up the staircase from Association to Foreseeability. These actors may be required to foresee crashes through road safety regulations, risk assessment, and technology, as suggested by Rasmussen's framework. For semi-autonomous vehicles, all four actors reside on the same level (Foreseeability), as they share vehicle control. It should be noted that the positions may change based on specific circumstances, for example, it is possible for drivers of manually driven vehicles to sit at the level of Intention, in cases of intentional self-harm or the use of vehicles in terrorist acts. Further, the manufacturer of a manually driven vehicle might be placed at the level of Causality or even Foreseeability in cases of product negligence which contributes to a crash.

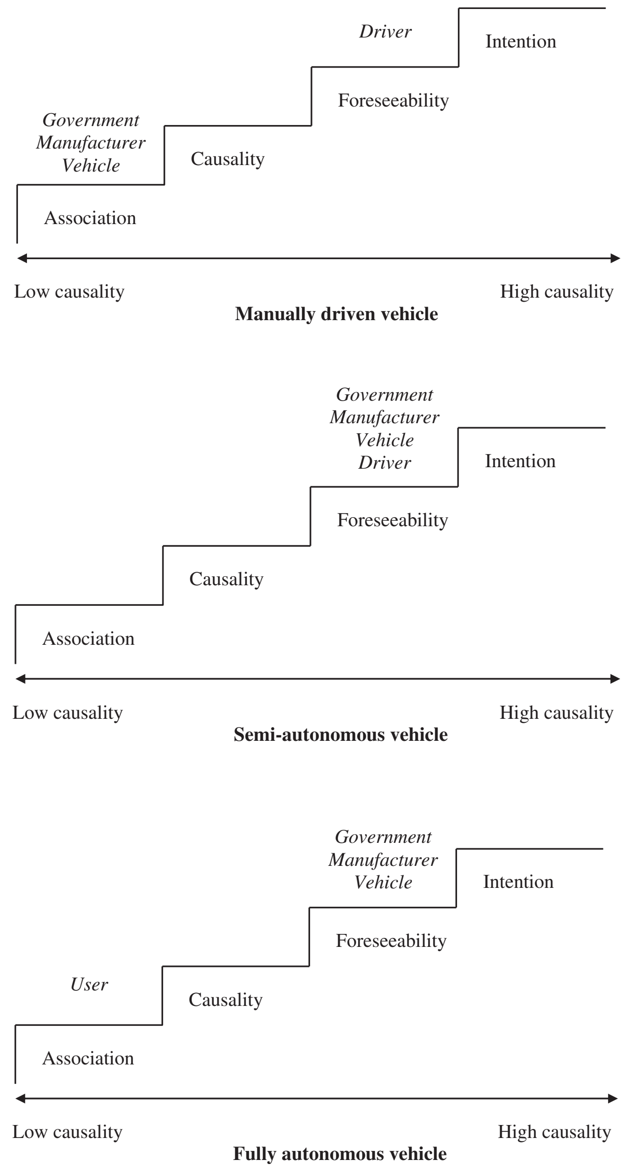

Figure 2. Shaver's (1985) causality staircase adapted to manually driven vehicles, semi-autonomous vehicles and fully autonomous vehicles.

Hypotheses

The current study was motivated by gaps in this emerging research area. Firstly, there is a lack of knowledge regarding blame attribution in crashes involving semi-autonomous vehicles and limited knowledge regarding how blame is attributed in crashes involving fully autonomous vehicles. Secondly, the role of severity in influencing blame attribution in autonomous vehicle crashes is currently unknown.

It was hypothesised that:

1: there will be differences in how blame is attributed across actors depending on the level of control that humans have over the vehicle (i.e. whether the crash involves a manually driven vehicle, semi-autonomous vehicle or fully autonomous vehicle).

2: Higher levels of blame will be attributed in high severity crashes compared to low severity crashes across manually driven vehicles, semi-autonomous vehicles, and fully autonomous vehicles.

Method

Participants

This research was approved by the Institutional Review Board at the University of the Sunshine Coast (approval S181187). Informed consent was obtained from each participant. All data were non-identifiable.

A snowball recruitment approach used social media, participant e-mail lists, and an undergraduate student pool. Participation was limited to Australian citizens aged 18 years or older, to control for variability in perceptions of blame and responsibility due to potential legislative and cultural differences.

A total of 396 participants completed the online survey. Participants' ages ranged from 18 to 81 years ($M = 38.48$, $SD = 13.82$) and 71% were female. The majority, 98%, held a driver's licence (91% full/open, 7% provisional, 1% learner, 1% other types of licenses). On average, participants had held a driver's licence for 20.35 years ($SD = 13.55$, range $= 63$). Eight participants (2%) reported involvement in vehicle crashes with pedestrians, of which four had been drivers, three had been pedestrians, and one had been a passenger.

Design

A $2 \times 3 \times 5$ mixed-design was employed. Two of the three independent variables (IVs) were between-subjects variables. The first IV was crash severity, with two levels: high and low. The second IV was vehicle type, with three levels: manually driven vehicle, semi-autonomous vehicle, and fully autonomous vehicle. These variables were manipulated through six vehicle crash scenarios. The within-subjects IV was actor, with five levels: vehicle driver/user, pedestrian, vehicle, manufacturer, and government. The selection of actors followed the study by Li et al. (2016). This included the inclusion of the vehicle itself to explore the extent to which the public view vehicles, especially autonomous vehicles, as moral agents (Li et al. 2016) who will be faced with moral dilemmas (Awad et al. 2018). The dependent variable was the level of blame. A 7-point Likert scale ranging from 1 *(no blame)* to 7 *(a lot of blame)* was used for blame attribution to each of the actors. Hypotheses were analysed through a $2 \times 3 \times 5$ mixed-design analysis of variance (ANOVA), and follow-up tests. An alpha level of .05 was adopted for hypothesis testing.

Materials

A survey was developed comprising fictitious vehicle crash scenarios adapted from vignettes utilised by Li et al. (2016). The survey incorporated demographic questions, crash scenarios, and a single open-ended question. Demographic questions included age, gender, postal code, driver's licence status, and prior crash involvement. The survey incorporated six crash scenarios. Each participant was exposed to one scenario only, to secure independent responses to each between-subjects variable. The base text for the six scenarios was the following:

> A person is [driving a car/in their semi-autonomous car which is driving/in their autonomous car which is driving] down a street in a suburb. At an intersection, a pedestrian crosses the street. The [car/semi-autonomous car/autonomous car] hits the pedestrian. The pedestrian [doesn't suffer any injuries/suffers severe injuries], and [walks away from the scene without medical attention/dies at the scene]. Similarly, [there is no damage to the car/the car is severely damaged].

An open-ended question asking for participants' motivation for their blame allocation ratings was also included as a validity check for spurious or random responding.

Procedure

Participants completed the study via an online survey, commencing with the demographic questions. They were then presented with one of the six vehicle crash scenarios. For semi-autonomous and fully autonomous vehicle scenarios, participants were provided with a definition of the vehicle. The following definition was utilised for semi-autonomous vehicles: 'In a semi-autonomous vehicle, an automatic system controls all aspects of driving while it is in autonomous mode, however, a human driver is expected to respond and take over control when there is a request from the vehicle to intervene'. The definition for fully autonomous vehicles was: 'In an autonomous vehicle, an automatic system controls all aspects of the driving, and humans have no ability to control the vehicle, as there is no steering wheel or pedals'. For fully autonomous vehicle scenarios participants were prompted to imagine that the scenario was occurring in the future. Participants were then asked to attribute blame to each of the five actors. The random allocation was determined by the online survey host. The completion of the survey took approximately 5 min.

Results

Allocation of blame in relation to actors, vehicle type and severity

As displayed in Table 1, there was no significant three-way interaction between actor, vehicle type, and

Table 1. Main effects and interactions of 2 × 3 × 5 mixed-design ANOVA between severity, vehicle types, and actors on blame attribution.

	df	*F*	η_p^2	*p*
Actors vs vehicle types vs severity[a]	6.95, 1354.58	1.23	.006	.283
Actors vs vehicle types[a]	6.95, 1354.58	77.26	.284	.001
Actors vs severity[a]	3.47, 1354.58	3.15	.008	.019
Vehicles types vs severity	2, 390	0.57	.003	.568
Actors[a]	3.47, 1354.58	61.21	.136	.001
Vehicle types	2, 390	37.04	.160	.001
Severity	1, 390	0.001	.000	.981

Note. [a]Adjusted with the Huynh–Feldt correction, due to violation of the assumption of sphericity.

severity. However, a significant interaction effect between actors and vehicle types was found, indicating that actors were blamed significantly differently depending on what type of vehicle was involved in the crash. The interaction between vehicle type and severity was non-significant, suggesting that there was no difference in the level of blame attributed in high severity crashes, compared to low severity crashes across the vehicle types. In contrast, there was a significant interaction between actors and severity, indicating that the level of blame attributed to actors was significantly different between high and low severity crashes. Main effects for actor and vehicle type were also significant, however, these are not further considered, as the effects are more meaningful to the research aims when interpreted with the significant interactions. The significant interactions are further explored in the following sections.

Actors and vehicle types interaction

To investigate the interaction between actor and vehicle type, one-way ANOVA tests were conducted with actors and vehicle types as IVs and blame as the dependent variable. The analysis, presented in Table 2, revealed that all actors were blamed significantly differently from one another across the three vehicle types. Post hoc t-tests were used to compare, for each actor, how blame attributed differed based on the vehicle type. Table 3 displays descriptive data and *p*-values for the post hoc test, while a visual comparison is provided in Figure 3. Vehicle drivers/users were blamed significantly more in crashes involving both semi-autonomous vehicles and manually driven vehicles compared to fully autonomous vehicles, while pedestrians were blamed significantly more in crashes involving manually driven vehicles compared to both semi-autonomous vehicles and fully autonomous vehicles. Vehicles were blamed significantly more in crashes involving a semi-autonomous vehicle and fully autonomous vehicles than in crashes involving

Table 2. One-way ANOVA of actor and vehicle type interaction.

	df	*F*	η_p^2	*p*
Vehicle driver/User[a]	2, 256.54	92.85	.348	.001
Pedestrian	2, 393	16.83	.026	.005
Vehicle [a]	2, 228.73	65.52	.206	.001
Manufacturer[a]	2, 230.41	176.88	.403	.001
Government[a]	2, 243.17	29.56	.120	.001

Note. [a]Corrected with Welch's *F*, due to violation of assumption of homogeneity of variance.

Table 3. ANOVA post hoc comparisons of actors and vehicle types interaction.

	M	*SD*	Manual	S-AV	F-AV
Vehicle driver/User					
Manual	5.28	1.68			
S-AV	5.43	1.73	1.000		
F-AV	2.54	2.01	.001	.001	
Pedestrian					
Manual	4.25	1.70			
S-AV	3.60	1.70	.008		
F-AV	3.71	1.88	.038	1.000	
Vehicle					
Manual	1.71	1.31			
S-AV	3.52	2.23	.001		
F-AV	4.07	2.45	.001	.098	
Manufacturer					
Manual	1.59	1.26			
S-AV	4.08	2.33	.001		
F-AV	5.30	2.08	.001	.001	
Government					
Manual	1.79	1.40			
S-AV	2.63	2.00	.001		
F-AV	3.43	2.08	.001	.002	

Note. All data are corrected with Bonferroni to control for multiple comparisons. Manual = manually driven vehicle; S-AV = semi-autonomous vehicle; F-AV = fully autonomous vehicle.

manually driven vehicles. The level of blame attributed to manufacturers was significantly different across all three vehicle types, with the lowest blame in crashes involving manually driven vehicles, then semi-autonomous vehicles, and the highest involving fully autonomous vehicles. The same pattern was found for blame attributed to the government, where the lowest blame was attributed in crashes involving manually driven vehicles, then semi-autonomous vehicles, and the highest when the crash involved fully autonomous vehicles. Lastly, overall, vehicles, manufacturers, and government were blamed more in semi-autonomous vehicle crashes and fully autonomous vehicle crashes, compared to manually driven vehicle crashes.

Actors and severity interaction

Figure 4 displays the means of the severity and actor interaction. Visual inspection suggests that the significant interaction was driven by higher levels of blame to the government when severity was high. This was explored through planned contrasts, shown in Table 4. Although effect sizes were small, significant differences

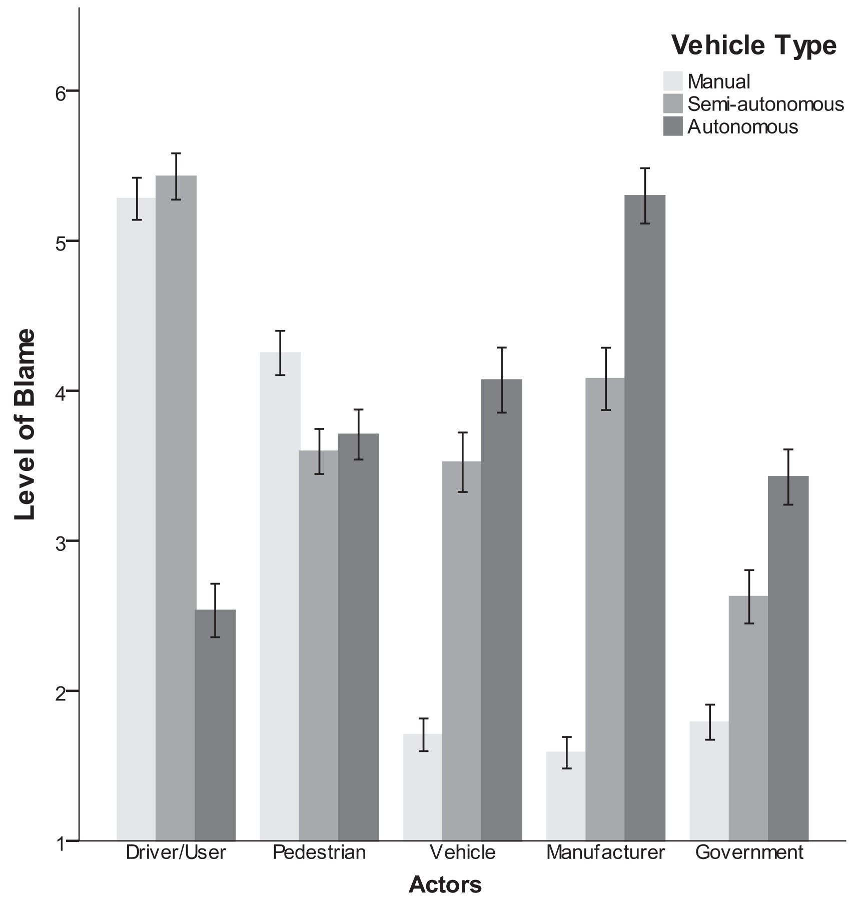

Figure 3. Mean level of blame attributed according to vehicle type and actor interaction. Error bars denote one standard error around the mean.

were found when comparing blame attribution in low and high severity crashes to government compared to drivers/users, pedestrians and vehicles but not manufacturers. In general, the government received the lowest levels of blame for both high and low severity crashes. However, a significant increase in blame to the government in high severity conditions compared to low severity conditions was detected, compared to the difference between the two conditions for drivers/users, pedestrians, and vehicles. These findings indicate that in crashes involving high severity outcomes, blame to government is augmented more than for the other actors.

Discussion

This study aimed to investigate how blame is attributed to different road transport system actors in crashes involving manually driven vehicles, semi-autonomous vehicles, and fully autonomous vehicles. In addition, the study examined whether outcome severity alters the level of blame attributed across the three vehicle types.

Role of control in blame attribution

The first hypothesis, that there will be differences in blame attribution across actors depending on control (i.e. whether crashes involve manually driven vehicles, semi-autonomous vehicles, or fully autonomous vehicles), was supported. In addition, each actor had unique patterns of blame attribution across the three vehicle types.

Specifically, less blame was attributed to vehicle drivers/users in crashes involving fully autonomous vehicles compared to manually driven vehicles. This finding was congruent with previous research (Li et al. 2016; McManus and Rutchick 2018). The findings of the current study are also consistent with Li et al. (2016), whereby more blame was attributed to manufacturers and government in scenarios involving fully autonomous vehicles than manually driven vehicles.

Another pattern of blame attribution of interest relates to vehicles being considered as liable actors. Li et al. (2016) found that in fully autonomous vehicle crashes, vehicles were not held as responsible as human drivers of manually driven vehicles, even though both actors were in control at the time of the

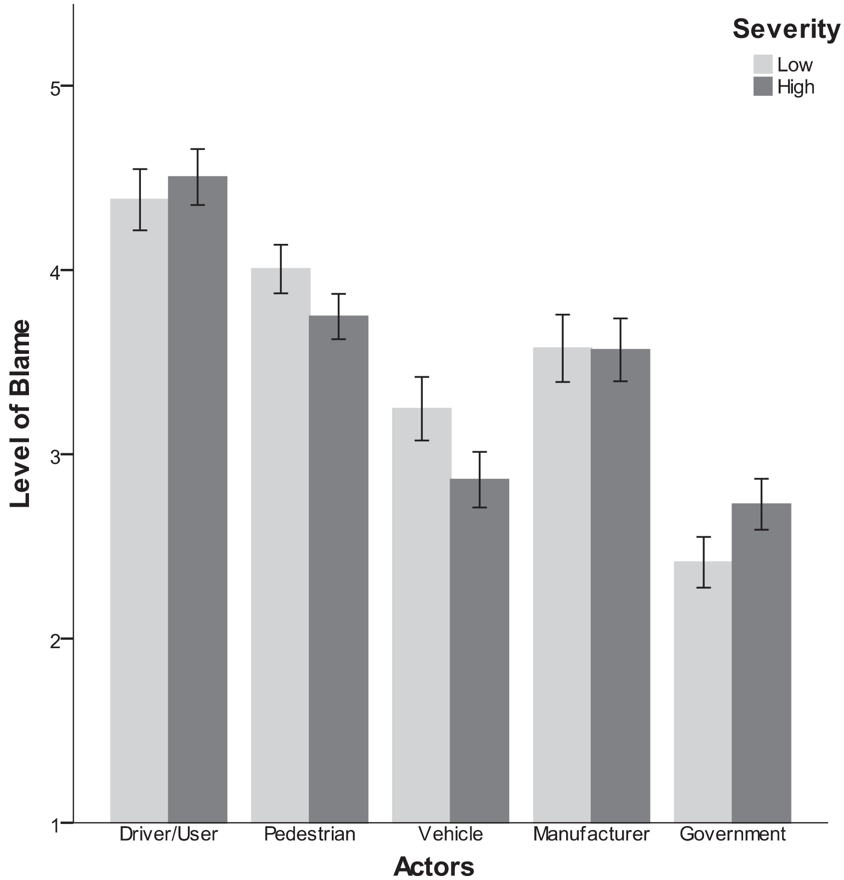

Figure 4. Mean level of blame attributed according to severity and actor interaction.

Table 4. Planned contrasts of actors and severity interaction.

	df	*F*	η_p^2	*p*
Government vs vehicle driver/user	1, 390	4.17	.011	.042
Government vs pedestrian	1, 390	8.03	.020	.005
Government vs vehicle	1, 390	10.11	.025	.002
Government vs manufacturer	1, 390	1.24	.003	.266

crashes. Building on this, the current study found that vehicles were blamed more in semi-autonomous and fully autonomous conditions than in manual conditions. Taken together these studies imply that vehicles may not be held as responsible as human drivers, but are still perceived as blameworthy actors in autonomous vehicle crashes.

Uniquely, the current study investigated patterns of blame attribution for semi-autonomous vehicles. While McManus and Rutchick (2018) found that utilising fully autonomous vehicles mitigated responsibility to drivers/users even when fully autonomous vehicles were pre-programmed by users, the current study found that the use of semi-autonomous vehicles did not have the same effect. Instead, drivers/users were blamed equally across the manually driven and semi-autonomous vehicle conditions. These findings may be explained by vehicle drivers/users residing on the same step, ('foreseeability') on the causality staircase for both manually driven and semi-autonomous vehicles.

It was also found that vehicles received similar levels of blame in crashes involving both semi-autonomous and fully autonomous vehicles. In contrast, less blame was attributed to manufacturers and government in semi-autonomous vehicle crashes compared to fully autonomous vehicle crashes. These differences may be due to humans still retaining some level of control in semi-autonomous vehicles.

Taken together, these patterns of blame attribution are likely to be due to the perceived control actors have over incidents, as predicted by the general blame attribution literature (Arkkelin, Oakley, and Mynatt 1979; Lagnado and Channon 2008; Schroeder and Linder 1976). The role of control is, as previously discussed, further supported by attribution theory, as in fully autonomous vehicle crashes, the causality between users and incidents is diminished by users' lack of control (Heider 1958). This results in indirect actors, such as manufacturers and government, receiving more blame.

The predictions made previously based on Shaver's (1985) causality staircase, also appear to be supported by these findings. For example, drivers of manually driven vehicles received the highest blame, potentially because participants perceived that drivers should be able to foresee, and thus prevent crashes. In contrast, users of the fully autonomous vehicle received low levels of blame, likely due to their inability to control the vehicle, meaning they were therefore perceived as merely associated with crashes. Instead, vehicles oversaw monitoring the road, which may have resulted in the increased blame attributed to those responsible for vehicle design and implementation (i.e. manufacturers and government). With semi-autonomous vehicles, the responsibility to foresee incidents is shared between drivers/users and vehicles. This could be why drivers/users in semi-autonomous vehicles were blamed equally as in the manually driven vehicle condition, and why vehicles, manufacturers, and government were blamed more than in the manually driven vehicle condition.

Role of severity in blame attribution

The second hypothesis, that more blame will be attributed in high severity crashes compared to low severity crashes across manually driven vehicles, semi-autonomous vehicles and fully autonomous vehicles, was rejected. There was no difference in levels of blame attributed across the three vehicle types in high and low severity crashes. These results contradict DAT, as well as the findings from previous studies by Schroeder and Linder (1976), Stewart (2005), Remijn and Crombag (2007), and Walster (1966). While these results could reflect that severity does not influence blame attribution with autonomous vehicle crashes, it is important to note that the literature on severity is not coherent, and amendments to the theory have been made (Walster 1967). One of these amendments is that of situational relevance, which suggests that situations must be applicable and important to individuals to activate defensive attributions (Shaver 1970). Our sample had limited exposure to semi-autonomous vehicles as they are relatively uncommon in Australia. They had no exposure to fully autonomous vehicles, as they are not yet legal, thus were generally unfamiliar with autonomous vehicles and their capabilities. The scenarios may have been perceived as foreign and futuristic, and thus inapplicable or unimportant to the participants' lives. A threat may therefore not have been perceived, resulting in an absence of defensive attributions, thus explaining the non-significant results for severity.

However, some differences between high and low severity crash across actors were found, as more blame was attributed to the government in high severity crashes. Thus, regarding the government, the findings are consistent with the DAT. That this pattern was only detected for the government could be explained by personal similarity, another modification to DAT. Personal similarity predicts that individuals that identify with certain actors in scenarios will direct their defensive attribution away from those actors towards other actors or factors (Shaver 1970). In the current study, participants may have identified with actors in the vehicle crashes, for example, as pedestrians, drivers, or users of vehicles. Personal defences may, therefore, have been activated, which, according to personal similarity, would result in blame being directed away from these three actors, and directed to other actors, such as government.

Implications for the road transport system

The findings have various implications for the road transport system and how Rasmussen's risk management framework is applied within road transport. In the current road system, the primary form of safety control is the enforcement of laws and regulations set by the government on road users (Salmon, Read, and Stevens 2016). With the coming advances in technology, we are likely to see the road transport system structure change to more closely emulate that of other safety-critical systems, such as aviation, rail or mining, whereby governments and regulators impose controls on companies (i.e. vehicle manufacturers), who then impose controls on the technology to promote its safe operation. This represents a step-change in how the road transport system operates and planning for how this will affect aspects of the road system such as government policy frameworks, safety regulation, data systems and injury and personal liability insurance schemes is needed soon to prepare for their introduction. As Hancock (2019a) notes, if current liability frameworks continue to operate without change, the 'dissociation between responsibility and control will not be welcomed by consumers' (Hancock 2019a, 485).

The findings from the present study suggest that public perceptions of blame will change as technologies become more advanced. This supports the Leveson's (2004) argument that, as technology progresses, responsibility shifts from the individual to the government. Governments will need to be cognisant of this shift – that it will no longer be acceptable to rely on explanations of 'driver error' for crashes and implement driver-centric safety initiatives such as education and enforcement. Instead, system-level initiatives will be required, as will accident investigation processes that consider crash contributory factors across the system (Stanton et al. 2019). This shift also has significant implications for road safety researchers, who will need to continue the paradigm shift in road safety research (e.g. Larsson, Dekker, and Tingvall 2010; Salmon, McClure, and Stanton 2012; Salmon, Read, and Stevens 2016; Salmon and Read 2019) towards systems approaches, in order to support governments to meet the new expectations of the public.

In relation to legislation for crash liability specifically, the current legislative scheme in Australia renders drivers responsible for the behaviour of their vehicles. This requirement does not differ between manually driven vehicles and semi-autonomous vehicles. However, our findings indicate that the general public perceives blame differently across the two vehicle types. This disconnect between public opinion and legislation will become more pressing as increasing numbers of semi-autonomous vehicles are introduced. As shown in Rasmussen's framework (Figure 1) government and legislatures are influenced by public opinion and changing public awareness. Our findings may assist in the revisions to liability legislation to better represent public opinion around blame in crashes involving semi-autonomous vehicles.

Regarding fully autonomous vehicles, legislation requires revision before they can be operated in Australia. This will need to be supported by policy decisions around crash liability. Our findings indicate that the general public would expect actors higher up in the road transport system, such as manufacturers and government, to take more responsibility in crashes involving fully autonomous vehicles than the current situation. Also, this study has implications for manufacturers, as expectations regarding blame and liability may influence decisions around programming of fully autonomous vehicle algorithms.

Lastly, the finding that less individual blame arises in crashes involving fully autonomous vehicles could have implications for survivor recovery. Research has found that those who perceived that they were not responsible for a crash (i.e. who attribute blame to another party), are at greater risk for experiencing poorer physical and mental health after injury (Thompson, Berk, et al. 2014; Thompson, O'Donnell, et al. 2014) and lower levels of satisfaction with the performance of no-fault injury compensation schemes (Thompson et al. 2015). This is hypothesised to be due to a perceived lack of control and concerns of being unable to prevent similar events in the future. Health services, therefore, need to be cognisant of potential negative impacts on recovery and the implications for maintaining high levels of system performance as fully autonomous vehicles enter the road system.

Limitations

As no psychometrically validated scale of blame was available, we adopted a Likert scale in this study, similar to that used in previous similar research. It is, however, possible that participants did not perceive blame as a distinct construct but may have incorporated responsibility, liability, or other related constructs when making attributions. An instrument assessing blame with higher validity may differentiate between these related constructs. Further, this study was conducted with Australian participants only. There may be contextual and cultural differences that limit the generalisability of the findings to other contexts.

Future research

To our knowledge, this study is the first to consider blame attribution in semi-autonomous vehicle crashes and also the first to consider the impact of outcome severity in relation to autonomous vehicle crashes. Further research in this area is thus warranted.

Regarding severity, future research should consider specifying whose perspective the participants should take in the scenarios (i.e. the participant might be the driver/owner of the vehicle or the pedestrian). This would control for the influence of personal similarity when making attributions.

Further, given that anger has been found to impact perceptions of intentionality (Ask and Pina 2011), and thus blame, it may be interesting to manipulate emotions in future studies. In the current study, scenarios were purposefully written in a factual and unemotive manner. Future studies could employ scenarios using more popularist media style, and look to invoke a sense of outrage or anger through including pedestrian victims likely to be considered more vulnerable such as young children, or pregnant women.

Another aspect that should be explored in future research is the reasons behind the attributions of blame. Methods such as interviews or focus groups may be useful to delve deeper into perceptions of blame and how attribution might shift depending on the circumstances of the crash.

Further, the exploration of the impact of other individual differences, such as attribution styles (with dimensions of internal versus external, stable versus unstable, and global versus specific causes; Peterson et al. 1982) or attachment styles (e.g. Whelan and Dawar 2016) on blame attribution in this context would be a useful area for future research.

Finally, similar studies should be conducted internationally to test the generalisability of the findings and inform local policy. Public opinion may be dependent on prevailing public experience of autonomous vehicles and existing and emerging legislative frameworks around crash liability. Factors such as national culture may play a role. For example, Hofstede's (1980) original conceptions of individualism-collectivism, power distance and uncertainty avoidance could be interesting to explore, based on either national culture or in relation to individual differences. Indeed, some cross-cultural differences in ethical autonomous vehicle decision-making were identified via the large-scale 'Moral Machine' experiment conducted at MIT (Awad et al. 2018).

Conclusions

This study has contributed to an important emerging research area regarding liability in crashes involving autonomous vehicles. Blame is attributed differently across actors in the road system depending on the vehicle's level of autonomy. Key findings were that more blame was attributed to manufacturers and government in crashes involving fully autonomous vehicles, and drivers/users, vehicles, manufacturers and government are perceived to share responsibility in crashes involving semi-autonomous vehicles. Thus, the pattern of blame attribution in crashes with semi-autonomous vehicles will not be applicable to crashes with fully autonomous vehicles. Further, regardless of the type of vehicle, the government receives more blame when crashes are severe. As semi-autonomous vehicles are already a reality, and fully autonomous vehicles are expected to be available in the near future, further research in this area is necessary as it has critical implications for decisions about road safety legislation and liability schemes.

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References

Arkkelin, D., T. Oakley, and C. Mynatt. 1979. "Effects of Controllable versus Uncontrollable Factors on Responsibility Attribution: A Single-Subject Approach." *Journal of Personality and Social Psychology* 37 (1): 110–115. doi:10.1037/0022-3514.37.1.110.

Ask, K., and A. Pina. 2011. "On Being Angry and Punitive: How Anger Alters Perception of Criminal Intent." *Social Psychological and Personality Science* 2 (5): 494–499. doi:10.1177/1948550611398415.

Awad, E., S. Dsouza, R. Kim, J. Schulz, J. Henrich, A. Shariff, J-F. Bonnefon, and I. Rahwan. 2018. "The Moral Machine Experiment." *Nature* 563 (7729): 59–64. doi:10.1038/s41586-018-0637-6.

Banks, V. A., N. A. Stanton, G. Burnett, and S. Hermawati. 2018. "Distributed Cognition on the Road: Using EAST to Explore Future Road Transportation Systems." *Applied Ergonomics* 68: 258–266. doi:10.1016/j.apergo.2017.11.013.

Bellet, T., M. Cunneen, M. Mullins, F. Murphy, F. Pütz, F. Spickermann, C. Braendle, and M. Felicitas Baumann. 2019. "From semi to fully autonomous vehicles: New emerging risks and ethico-legal challenges for human-machine interactions." *Transportation Research Part F: Traffic Psychology and Behaviour*, 63: 153–164. doi:10.1016/j.trf.2019.04.004.

Deb, S., L. J. Strawderman, and D. W. Carruth. 2018. "Investigating Pedestrian Suggestions for External Features on Fully Autonomous Vehicles: A Virtual Reality Experiment." *Transportation Research Part F: Traffic Psychology and Behaviour* 59 (A): 135–149. doi:10.1016/j.trf.2018.08.016.

de Winter, J. C. F. 2019. "Pitfalls of Automation: A Faulty Narrative?" *Ergonomics* 62 (4): 505–508. doi:10.1080/00140139.2019.1563334.

Emmenegger, C., and D. Norman. 2019. "The Challenges of Automation in the Automobile." *Ergonomics* 62 (4): 512–513. doi:10.1080/00140139.2019.1563336.

Endsley, M. R. 2019. "The Limits of Highly Autonomous Vehicles: An Uncertain Future." *Ergonomics* 62 (4): 496–499. doi:10.1080/00140139.2019.1563330.

Favarò, F. M., P. Seewald, M. Scholtes, and S. Eurich. 2019. "Quality of Control Takeover following Disengagements in Semi-Automated Vehicles." *Transportation Research Part F:*

Traffic Psychology and Behaviour 64: 196–212. doi:10.1016/j.trf.2019.05.004.

Feigenson, N., and J. Park. 2006. "Emotions and Attributions of Legal Responsibility and Blame: A Research Review." *Law and Human Behavior* 30 (2): 143–161. doi:10.1007/s10979-006-9026-z.

Hancock, P. A. 2019a. "Some Pitfalls in the Promises of Automated and Autonomous Vehicles." *Ergonomics* 62 (4): 479–495. doi:10.1080/00140139.2018.1498136.

Hancock, P. A. 2019b. "Some Promises in the Pitfalls of Automated and Autonomous Vehicles: A Response to Commentators." *Ergonomics* 62 (4): 514–520. doi:10.1080/00140139.2019.1586103.

Harvey, M. D., and B. G. Rule. 1978. "Moral Evaluations and Judgments of Responsibility." *Personality and Social Psychology Bulletin* 4 (4): 583–588. doi:10.1177/014616727800400418.

Heider, F. 1958. *The Psychology of Interpersonal Relations*. New York, NY: John Wiley & Sons.

Hickling, E. J., E. B. Blanchard, T. C. Buckley, and A. E. Taylor. 1999. "Effects of Attribution of Responsibility for Motor Vehicle Accidents on Severity of PTSD Symptoms, Ways of Coping, and Recovery over Six Months." *Journal of Traumatic Stress* 12 (2): 345–353. doi:10.1023/A:1024784711484.

Hofstede, G. 1980. *Culture's Consequences: International Differences in Work-Related Values*. Newbury Park, CA: SAGE.

Hughes, B. P., A. Anund, and T. Falkmer. 2015. "System Theory and Safety Models in Swedish, UK, Dutch and Australian Road Safety Strategies." *Accident Analysis & Prevention* 74: 271–278. doi:10.1016/j.aap.2014.07.017.

Kelley, H. H. 1973. "The Processes of Causal Attribution." *American Psychologist* 28 (2): 107–128. doi:10.1037/h0034225.

Krulewitz, J. E., and J. E. Nash. 1979. "Effects of Rape Victim Resistance, Assault Outcome, and Sex of Observer on Attribution of Rape." *Journal of Personality* 47 (4): 557–574. doi:10.1111/j.1467-6494.1979.tb00209.x.

Kyriakidis, M., J. C. F. de Winter, N. Stanton, T. Bellet, B. van Arem, K. Brookhuis, M. H. Martens, K. Bengler, J. Andersson, N. Merat, N. Reed, M. Flament, M. Hagenzieker, and R. Happee. 2019. "A Human Factors Perspective on Automated Driving." *Theoretical Issues in Ergonomics Science* 20 (3): 223–249. doi:10.1080/1463922X.2017.1293187.

Lagnado, D. A., and S. Channon. 2008. "Judgments of Cause and Blame: The Effects of Intentionality and Foreseeability." *Cognition* 108 (3): 754–770. doi:10.1016/j.cognition.2008.06.009.

Larsson, P., S. W. A. Dekker, and C. Tingvall. 2010. "The Need for a Systems Theory Approach to Road Safety." *Safety Science* 48 (9): 1167–1174. doi:10.1016/j.ssci.2009.10.006.

Lee, J. D. 2019. "Trust and the Teleology of Technology." *Ergonomics* 62 (4): 500–501. doi:10.1080/00140139.2019.1563332.

Leveson, N. 2004. "A new accident model for engineering safer systems." *Safety Science*, 42 (4): 38–53. doi:10.1016/j.trf.2019.04.004.

Li, J., X. Zhao, M. Cho, W. Ju, and B. Malle. 2016. "From Trolley to Autonomous Vehicle: Perceptions of Responsibility and Moral Norms in Traffic Incidents with Self-Driving Cars." Paper presented at the Society of Automotive Engineers World Congress, Detroit, MI, April 12–14.

McManus, R., and A. Rutchick. 2018. "Autonomous Vehicles and the Attribution of Moral Responsibility." *Social Psychological and Personality Science* 10 (3): 345–352. doi:101177/1948550618755875.

National Transport Commission. 2018. "Safety assurance for automated driving systems: Consultation regulation impact statement." www.ntc.gov.au/Media/Reports/(C07CE648-0FE8-5EA2-56DF-11520D103320).pdf

Newnam, S., and N. Goode. 2015. "Do Not Blame the Driver: A Systems Analysis of the Causes of Road Freight Crashes." *Accident Analysis & Prevention* 76: 141–151. doi:10.1016/j.aap.2015.01.016.

Peterson, C., A. Semmel, C. von Baeyer, L. T. Abramson, G. I. Metalsky, and M. E. P. Seligman. 1982. "The Attributional Style Questionnaire." *Cognitive Therapy and Research* 6 (3): 287–300. doi:10.1007/BF01173577.

Rasmussen, J. 1997. "Risk Management in a Dynamic Society: A Modelling Problem." *Safety Science* 27 (2–3): 183–213. doi:10.1016/S0925-7535(97)00052-0.

Remijn, C. A. C., and H. F. M. Crombag. 2007. "Heuristics in Causal Reasoning and Their Influence on Eyewitness Testimony." *Psychology, Crime & Law* 13: 201–211. doi:10.1080/10683160600711688.

Salmon, P. M. 2019. "The Horse Has Bolted! Why Human Factors and Ergonomics Has to Catch up with Autonomous Vehicles (and Other Advanced Forms of Automation)." *Ergonomics* 62 (4): 502–504. doi:10.1080/00140139.2018.1563333.

Salmon, P. M., R. McClure, and N. A. Stanton. 2012. "Road Transport in Drift? Applying Contemporary Systems Thinking to Road Safety." *Safety Science* 50 (9): 1829–1838. doi:10.1016/j.ssci.2012.04.011.

Salmon, P. M., and G. J. M. Read. 2019. "Many Model Thinking in Systems Ergonomics: A Case Study in Road Safety." *Ergonomics* 62 (5): 612–628. doi:10.1080/00140139.2018.1550214.

Salmon, P. M., G. J. M. Read, and N. Stevens. 2016. "Who is in Control of Road Safety? A STAMP Control Structure Analysis of the Road Transport System in Queensland, Australia." *Accident Analysis & Prevention* 96: 140–151. doi:10.1016/j.aap.2016.05.025.

Schroeder, D. A., and D. E. Linder. 1976. "Effects of Actor's Causal Role, Outcome Severity, and Knowledge of Prior Incidents upon Attribution of Responsibility." *Journal of Experimental Social Psychology* 12 (4): 340–356. doi:10.1016/S0022-1031(76)80003-0.

Schaefer, K., J. Chen, J. Szalma, and P. Hancock. 2016. "A Meta-Analysis of Factors Influencing the Development of Trust in Automation: Implications for Understanding Autonomy in Future Systems." *Human Factors: The Journal of the Human Factors and Ergonomics Society* 58 (3): 377–400. doi:10.1177/0018720816634228.

Scott-Parker, B., N. Goode, P. Salmon. 2015. "The Driver, the Road, the Rules … and the Rest? A Systems-Based Approach to Young Driver Road Safety." *Accident Analysis & Prevention* 74: 297–305. doi:10.1016/j.aap.2014.01.027.

Shaver, K. G. 1970. "Defensive Attribution: Effects of Severity and Relevance on the Responsibility Assigned for an

Incident." *Journal of Personality and Social Psychology* 14 (2): 101–113. doi:10.1037/h0028777.

Shaver, K. G. 1985. *The Attribution of Blame: Causality, Responsibility, and Blameworthiness*. New York, NY: Springer-Verlag.

Stanton, N. A., P. M. Salmon, G. Walker, and M. Stanton. 2019. "Models and Methods for Collision Analysis: A Comparison Study Based on the Uber Collision with a Pedestrian." *Safety Science* 120: 117–128. doi:10.1016/j.ssci.2019.06.008.

Stewart, A. 2005. "Attribution of Responsibility for Motor Vehicle Crashes." *Accident Analysis & Prevention* 37 (4): 681–688. doi:10.1016/j.aap.2005.03.010.

Thompson, J., M. Berk, M. O'Donnell, L. Stafford, and T. Nordfjaern. 2014. "Attributions of Responsibility and Recovery within a No-Fault Injury Compensation Scheme." *Rehabilitation Psychology* 59 (3): 247–255. doi:10.1037/a0036543.

Thompson, J., M. Berk, M. O'Donnell, L. Stafford, and T. Nordfjaern. 2015. "The Association between Attributions of Responsibility for Motor Vehicle Accidents and Patient Satisfaction: A Study within a No-Fault Injury Compensation System." *Clinical Rehabilitation* 29 (5): 500–508. doi:10.1177/0269215514546009.

Thompson, J., M. O'Donnell, L. Stafford, T. Nordfjaern, and M. Berk. 2014. "Association between Attributions of Responsibility for Motor Vehicle Crashes, Depressive Symptoms, and Return to Work." *Rehabilitation Psychology* 59 (4): 376–385. doi:10.1037/rep0000012.

Walker, F., J. Wang, M. H. Martens, and W. B. Verwey. 2019. "Gaze Behaviour and Electrodermal Activity: Objective Measures of Drivers' Trust in Automated Vehicles." *Transportation Research Part F: Traffic Psychology and Behaviour* 64: 401–412. doi:10.1016/j.trf.2019.05.021.

Walster, E. 1966. "Assignment of Responsibility for an Incident." *Journal of Personality and Social Psychology* 3 (1): 73–79. doi:10.1037/h0022733.

Walster, E. 1967. "Second Guessing" Important Events." *Human Relations* 20 (3): 239–249. doi:10.1177/001872676702000302.

Waterson, P. 2019. "Autonomous Vehicles and Human Factors/Ergonomics – A Challenge but Not a Threat." *Ergonomics* 62 (4): 509–511. doi:10.1080/00140139.2019.1563335.

Whelan, J., and N. Dawar. 2016. "Attributions of Blame following a Product-Harm Crisis Depend on Consumers' Attachment Styles." *Marketing Letters* 27 (2): 285–294. doi:10.1007/s11002-014-9340-z.

Young, K. L., and P. M. Salmon. 2015. "Sharing the Responsibility for Driver Distraction across Road Transport Systems: A Systems Approach to the Management of Distracted Driving." *Accident Analysis and Prevention* 74: 350–359. doi:10.1016/j.aap.2014.03.017.