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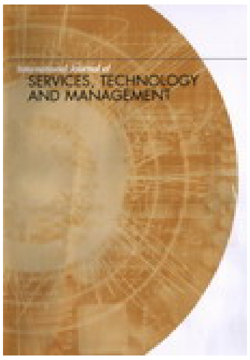

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Decision support or decision making? The critical decision roles of IS in autonomous vehicles

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Abstract: The era of autonomous vehicles has arrived. However, the relationship between information systems (IS) and the driving decisions of autonomous vehicles remains unclear. What decision roles do IS serve in driving autonomous vehicles? How do these roles influence the driving-decision quality of autonomous vehicles? To address this gap, we profile three major decision roles of IS in autonomous vehicles: decision maker, decision supporter and decision operator. Our profiling is based on a process-oriented viewpoint that integrates several classical decision theories. We utilise a computational simulation and experiment approach to explore and compare the possible effects of IS roles on the decision quality of autonomous vehicles. Our main findings suggest that each IS role has its distinctive strengths and weaknesses because no single role can consistently dominate the others in generating the best decision quality.

Keywords: autonomous vehicles; driving decision; information systems; decision quality.

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1 Introduction

Several leading research and advisory organisations, including Gartner and McKinsey, predicted that autonomous vehicles will bring about tremendous changes in the world. Information and technology firms, such as Google and Tesla, have either announced or already rolled out their state-of-the-art driverless or self-driving vehicles. Moreover, regardless of their brand or type, autonomous vehicles are largely reliant on information systems (IS) to handle their driving tasks. For example, an automatic emergency braking system alerts an autonomous vehicle to impending forward collisions. If the vehicle does not take any corresponding action to prevent the collision, the system may automatically control the brake to reduce the severity of a possible crash. An adaptive cruise control system adjusts the driving speed of an autonomous vehicle to maintain a safe distance from other vehicles ahead. An automatic parking system can move an autonomous vehicle to a particular parking lot. A collision avoidance warning system provides an alert when an autonomous vehicle is about to hit an object on the road. A lane departure warning system provides an alert when an autonomous vehicle is about to move out of its lane and a lane centring system maintains the vehicle in the centre of its lane. Mapping and navigation systems provide autonomous vehicles with map-dependent functions, including logistic planning. A speed limit warning system provides an alert when an autonomous vehicle is about to exceed the driving limit. A brief summary of some common IS utilised in autonomous vehicles is given in Table 1.

Table 1 Conventional IS in autonomous vehicles

IS	*Main functions*
Mapping and navigation system	• Positioning • Determining travel destination • Selecting the suitable path
Automatic emergency braking system	• Detecting an impending forward collision • Braking
Speed limit warning system	• Speed control • Safe distance maintenance
Collision avoidance warning system	• Dodging obstacles • Obstacle detection

Table 1 Conventional IS in autonomous vehicles (continued)

IS	*Main functions*
Adaptive cruise control system	• Adjusting driving speed • Vehicle detection
Lane departure warning or lane centring system	• Provides alert when changing lanes/centres the vehicle on the correct lane
Automatic parking system	• Reversing • Braking • Pulling over • Parking

However, increasing attention has been paid to the driving-decision quality of autonomous vehicles due to the frequent occurrence of related traffic incidents in recent years (Table 2).

Table 2 Summary of recent traffic accidents related to autonomous vehicles

Date	*Incident*
7.1.2015	A Google autonomous vehicle that tended to repeatedly stop was struck in the rear by a traditional vehicle when approaching an intersection. This is the first time that a Google autonomous vehicle was involved in an injury-causing event.
5.7.2016	A Tesla autonomous vehicle overlooked a truck and struck it when the truck made a left turn. Prior to this incident, no autonomous vehicle had ever been involved in a fatal event.
3.24.2017	An Uber autonomous vehicle collided with a traditional vehicle while making a turn. This is the first time that an Uber autonomous vehicle was involved in an injury-causing event.
3.18.2018	An Uber autonomous vehicle hit a pedestrian who was walking a bicycle east, across the road. This was the first time that an Uber autonomous vehicle was involved in a fatal event.
3.23.2018	A Tesla autonomous vehicle moving at a speed of about 70 mph directly hit a median barrier on a highway. This was a fatal incident. It also caused a fire and shut down highway lanes for hours.
3.1.2019	A Tesla autonomous vehicle struck a truck-tractor in combination with a semitrailer in a highway, when the vehicle's autopilot system was in use at the time of the accident.

While all these accidents may have had diverse causes, these causes were significantly associated with the driving decision taken in each case. Furthermore, since IS are one of the main components of autonomous vehicles, it is important to investigate the possible decision roles of IS in autonomous vehicles (Shang and Tsai, 2017; Uden and He, 2017; Kaiser et al., 2018). However, prior studies have scarcely investigated the impact of such roles on the decision quality of autonomous vehicles. Similarly, although IS-enabled individual task performance has been a very important research area (Serrano and Karahanna, 2016), most prior studies implicitly assumed that IS support people in decision making, rather than make decisions for people to follow (Davenport and Short, 1990; Hammer, 1990; Silver et al., 1995; Rifkin, 1998; Hoch et al., 2004; Kroenke, 2015; Brauner et al., 2019; Favarò et al., 2019; Hegner et al., 2019; Biondi et al., 2019).

Additionally, humans are conventionally viewed as having bounded rationality and tend to repeatedly make avoidable mistakes such as drunk driving. This would no longer be a problem when IS completely replace humans in driving autonomous vehicles. However, it is a fact that autonomous vehicles, even with state-of-the-art IS, have been involved in fatal accidents. To the best of our understanding, in recent years, the topic of whether IS should replace humans in the driver's seat have been a highly debated and challenging global issue. Therefore, to obtain further insights into this complicated issue, we address the following research questions in this study:

RQ1 What decision roles do IS play in driving autonomous vehicles?

RQ2 How do these roles influence the driving-decision quality of autonomous vehicles?

In the following section, we present our research background, methodological approach, and findings. Section 2 illustrates the general characteristics and associated IS of autonomous vehicles. In Section 3, from a process-oriented viewpoint based on classical decision theories, we identify the major decision roles of IS in autonomous vehicles and apply them to a number of real-world business cases. In Section 4, we explore the possible impact of the identified IS roles on the driving-decision quality of autonomous vehicles and summarise our findings. Next, we summarise our results and discuss their implications in Section 5. Then, we conclude this study by highlighting its main contributions and future research directions in Section 6 and Section 7.

2 Research background

An autonomous vehicle refers to a car that is elaborately operated using internal systems for driving, mainly pertaining to sensing, action (or control), and decision making (Narla, 2013; Lutin et al., 2013; Santo, 2016; Wang, 2016). Sensing systems are conventionally responsible for observing road conditions. For example, autonomous vehicles may be equipped with light detection and ranging (LIDAR) to indicate the distance to an object or map the shape of its surroundings. Action systems handle the steering, accelerating, decelerating, braking, etc. of autonomous vehicles (Tettamanti et al., 2016; Paden et al., 2016). Decision systems are essentially IS or their applications and are focused on using the sensing data to manage, improve, or even optimise, driving actions.

Table 3 Summary of recent studies on decision-related topics regarding autonomous vehicles

Extant studies	*Methodology*	*Main research focus*
Galceran et al. (2015)	Computational experiment	Proposed integrating behavioural inference and closed-loop policies to solve a specific driving-decision problem
Bonnefon et al. (2016)	Survey	Proposed that regulating utilitarian decision algorithms for autonomous vehicles may paradoxically postpone their adoption
Nasri et al. (2018)	Computational experiment	Proposed using a two-stage stochastic program to solve a driving-decision problem
Schwarting et al. (2018)	Review	A report on the state-of-the-art, emerging trends and challenges related to using IT to improve autonomous decision making

In recent years, although several investigations of autonomous vehicles associated with driving-decision algorithms, policies, etc. (Table 3) have been conducted, studies that examine the decision roles that IS may play in driving autonomous vehicles have been insufficient. For example, some studies proposed certain algorithms or rules to handle highly complicated autonomous driving situations under uncertainty (Galceran et al., 2015; Nasri et al., 2018), while others highlighted the challenges in normalising autonomous driving dilemmas such as optimisation decision problems, programmable formulas, etc. (Bonnefon et al., 2016; Schwarting et al., 2018).

These previous works provided important insights into certain IS opportunities and difficulties related to solving autonomous driving-decision problems. However, whether IS in autonomous vehicles serve in the role of driving-decision supporter or maker, or any other role, has yet to be explored and clarified further. As such, the identification or profiling of IS roles is a very important research area in IS literature (Premkumar and King, 1992; Street and Meister, 2004; Fichman et al., 2011); however, this study is the first one that focuses on IS decision roles and the decision quality of autonomous vehicles. Thus, in the next section, we explore several classical decision theories to examine the decision roles of IS in autonomous vehicles.

3 The process-oriented view and IS decision roles in autonomous vehicles

The process-oriented view generally defines a 'decision' as a process that comprises a set of step-wise components. For example, Drucker (1968) defined the decision process as analysing a problem, developing alternative solutions, finding the best solution, and implementing the decision. Adair (1973) defined the decision process as setting-up an objective, collecting relevant information, generating feasible options, making the decision, implementing the decision, and evaluating it. Simon (1976) defined the decision process as a sequential mechanism that pertains to design, choice, implementation and review. Robbins (2002) defined the decision process as identifying a problem, identifying decision criteria, allocating weights to the criteria, developing alternatives, analysing these alternatives, selecting the best alternative, implementing the alternative, and evaluating decision effectiveness. Overall, although these definitions of a decision vary slightly due to their unique research context, they mostly include the following decision-process components: definition (e.g., defining the decision goal, objective, or problem), analysis (e.g., analysing the problem, developing alternatives or options), prioritisation (e.g., making a choice, selecting an alternative, or making the decision), and implementation (e.g., implementing the alternative or decision).

Thus, it is evident that IS play multiple decision roles in autonomous vehicles based on the identified decision-process components above. First, IS may serve the role of decision maker (DM) if it dominates all three decision components. In this situation, the IS, rather than humans, are responsible for solving driving-decision problems, collecting driving information, generating driving options, selecting the best driving option, and transforming the selected driving option into actions such as steering, braking, or accelerating/decelerating. For example, Google Waymo tested its chauffeur system on a Chrysler Pacifica Hybrid minivan and a Toyota Lexus for millions of miles (Cunningham, 2016; Google, 2016). In a self-generated report, Google introduced the concept of 'driverless' in developing its autonomous chauffeur system; to this end, Google removed the steering wheel, brake pedal, gas pedal, etc. in its autonomous vehicle prototype (Chang, 2016; Etherington and Kolodny, 2016).

In the second IS role of a decision supporter (DS), IS do not define driving-decision problems or implement driving decisions in autonomous vehicles. Instead, IS are only responsible for providing humans with analysed or prioritised information to suggest the best driving option. In this situation, human drivers of autonomous vehicles solve their own driving-decision problems, such as whether to pass a vehicle ahead, and then refer to IS-provided suggestions, e.g., a speed limit warning, to make their own decisions. Next, human drivers transform their decisions into actions such as stepping further on their gas pedals or not; in other words, in their DS role, IS do not make decisions in the same way as they do in their DM role. Therefore, several autonomous vehicles are equipped with blind spot warning, lane departure warning, speed limit warning, collision avoidance warning, and other systems, to guide the decisions of human drivers.

Lastly, IS plays the role of a decision operator (DO). To a certain degree, this role is analogous to the other IS roles of DS and DM. Similar to the DS role, in the DO role, IS do not define or formulate the driving-decision problem for human drivers. Instead, IS are mainly responsible for analysing and prioritising driving options. However, in this role, IS may also actively take action to implement a driving decision; this characteristic is identical to the IS role of DM in autonomous vehicles. For example, although Tesla S or Tesla X still needs a human driver, it can achieve some driving tasks on its own without human involvement. Their autopilot systems would offer the services of autonomous lane centring, cruise control, lane changing, traffic-aware navigation, self-parking, summoning the vehicle from parking lot, etc. In other words, if an autonomous vehicle is equipped with certain IS, a human driver is not necessary for controlling the steering wheel, brake pedal, and gas pedal at all times for implementing driving decisions (Ayre, 2017; Lambert, 2017a, 2017b).

Table 4 Profiles of IS decision roles in autonomous vehicles

The decision component (DC)	*IS as decision maker (DM)*	*IS as decision supporter (DS)*	*IS as decision operator (DO)*
DC1 – define driving-decision objective (e.g., design or formulate driving-decision problem)	Dominated or mainly controlled by IS (e.g., chauffeur system)	Dominated or mainly controlled by human driver	
DC2 – analyse and prioritise driving options (e.g., collect driving information, generate driving option and suggest the best option)		Dominated or mainly controlled by IS (e.g., mapping and navigation system, blind spot warning system, lane departure warning system, speed limit warning system, or collision avoidance warning system)	
DC3 – driving-decision implementation (e.g., transforming driving decision into driving actions, including steering, braking, and accelerating/decelerating)		Dominated or mainly controlled by human driver	Dominated or mainly controlled by IS (e.g., adaptive cruise control system, automatic parking system, automatic braking system, or automatic lane centring system)

The profiles of the various IS decision roles in autonomous vehicles are summarised in Table 4. We used DC1, DC2, and DC3 to represent the three major driving-decision process components. DC1 represents defining the driving-decision objective, DC2 represents analysing and prioritise driving options, and DC3 represents driving-decision implementation. By mapping these components, we identified the first decision role of IS, i.e., DM, in which IS dominate all driving-decision components, including DC1, DC2 and DC3. In the DS role, IS dominate only DC2, while human (drivers) dominate DC1 and DC3. In the DO role, IS dominate DC2 and DC3, while human (drivers) dominate DC1.

In the next section, we further investigate the possible impact of each identified IS decision role on the decision quality of autonomous vehicles. Decision quality is an important topic in IS literature, although prior related studies scarcely focused on driving decisions (Barron and Barrett, 1996; Mennecke and Valacich, 1998; Raghunathan, 1999). Generally, decision quality is defined as the degree of generating excellent decisions. A high-quality decision typically results from a decision process that extracts maximum accuracy or minimum errors in a selection scenario or context. Thus, the decision quality of an autonomous vehicle is certainly related to the driving scenario, driving-decision process, and driving-decision accuracy. Moreover, our methodological approach for investigating the decision quality of autonomous vehicles is based on computational simulation and experiment. Several studies have adopted a similar approach across disciplines and obtained valuable findings (Galceran et al., 2015; Nasri et al., 2018).

4 Experiment model and design

Following the profiles of identified IS decision roles in autonomous vehicles (Table 4), we initialised our experiment using the following settings. First, the DM role was represented by our simulated decision process wherein all the decision components (DC1, DC2 and DC3) were fully controlled by IS. The DS role was represented by the simulated decision process wherein DC1 and DC3 were controlled by a human driver, while DC2 was controlled by IS. The DO role was represented by the simulated process wherein DC1 was controlled by a human driver while DC2 and DC3 were controlled by IS. Moreover, either the human driver or the IS would make mistakes. This was because human drivers may have natural decision limits such as bounded rationality. The state-of-the-art IS in autonomous vehicles are imperfect as well, although IS-made mistakes are generally more predictable than human-made mistakes. In our settings, the human error-free rates randomly varied between 95% and 99%, whereas the IS error-free rates were deterministically set at 95%, 97% and 99%. Specifically, the settings for human error-free rate emanates from the human error probability. It was found that the probability may vary between 1% and 5% (Di Pasquale et al., 2015), so we use 95%–99% as human error-free rate. Relatedly, the settings for IS error-free rate is based on the component malfunction rates (i.e., failure rates) of the new vehicles. The new vehicles refer to those of age 0, those of 0.5 age and those of age 1. It was found that their failure rates are near 1%, 2.5% and 5%, respectively. Thus, we use 99%, 97%, and 95% as IS error free rates.

Next, we designed and arranged different sets of driving-decision scenarios to test the impact of the DM, DS, and DO roles on decision quality. These scenarios were all binary, representing fundamental decision situations. For example, in DC1, there would be two decision objectives, such as 'to-stop' and 'to-move', to choose from in the DM, DS, or DO scenarios. One objective was correct and the other was incorrect. Similarly, there were only two decision analysis options to select in DC2 and only one option was correct. The same conditions applied to the options in DC3.

Subsequently, we modelled driving-decision quality based on the sequentially multiplied error-free rates across DC1, DC2 and DC3. In our experiment, if there was any error in the former decision-process component, it could not be corrected in any later process component. For example, if a decision error occurred in DC1, the error could not be corrected in DC2 and DC3. If there was any error in DC2, it could not be corrected in DC3. This kind of situation is common in the real world. For example, if a decision objective is wrongly defined as 'to-stop' rather than 'to-move' in the beginning of driving-decision process (DC1), such a problem can barely be fixed in the either of the decision analysis and implementation processes (DC2 and DC3).

In detail, we developed model (1) to estimate the driving-decision quality of autonomous vehicles based on each identified IS decision role in our experiment. We used model (2) to simulate the decision responses of IS in terms of their DM, DS, and DO roles for each scenario (e.g., 'to-stop' or 'to-move'). For example, the probability that IS in the DO role can correctly generate driving decisions at DC2 varied between 95% and 99% because, when IS play a DO role, DC2 is still controlled by a human driver. Regarding the IS role in DC1, the error-free rate was fixed at 95%, 97%, etc. since DC1 is controlled by IS rather than a human driver.

$$Q(r) = \frac{1}{m}\sum_{s=1}^{m}\left(\prod_{dc=1}^{n} Mah\left[A(r)_{s\_dc}, X_{s\_dc}\right]\right) \tag{1}$$

$$A(r)_{dc} = \left\{X_{dc}\,|_{p=Ef(r)}\right\} \tag{2}$$

Table 5 Description of model notations

- $Q(r)$: driving-decision quality of autonomous vehicles when IS serves in the role of r
- r: the identified role of IS as DM, DS or DO
- m: total number of experimental iterations
- n: total number of driving-decision process components of autonomous vehicles
- $Mah[A, X]$: comparison function that returns 1 when A matches X; otherwise, it returns 0
- $A(r)_{s\_dc}$: actual driving decision (e.g., 'to-stop' or not) for the identified role of r during the experimental iteration of s for the decision component of dc
- X_{s_dc}: correct driving decision as expected (e.g., 'to-stop' or not) for the role of r during the experimental iteration of s for the decision component of dc
- $X_{dc}|_{p=Ef(r)}$: generation of correct driving decision as expected, X, at the probability p that equals to the error-free rate $Ef(\ )$, for each of the identified roles r in association with the specific decision-process component dc

We implemented the model and experiment using computerised simulation programs. These programs iteratively generated 1000 decision results, according to each identified IS role of DM, DS, and DO for each decision-process component, i.e., DC1, DC2, and DC3 (i.e., 3 × 3 × 1,000). In total, we collected 9,000 results for further analysis.

5 Analysis of experiment results

The results pertain to the driving decision in each experimental scenario of 'to-stop' or 'to-move'. Thus, there are four types of results, such as correct move decision, correct stop decision, incorrect move decision and incorrect stop decision. Additionally, the results were based on experimental conditions where the error-free rate of IS in autonomous vehicles were at 95%, 97% and 99%. Tables 6, 7 and 8 show the final results obtained during each decision process, i.e., DC1, DC2, and DC3, when IS serve as the DM, DS, and DO at different IS error-free rates. Each number in Tables 6–8 represent the frequency of the different types of decisions generated for each IS role in the experiment.

Table 6 Experiment results at the 95% IS error-free rate

		DM	*DS*	*DO*
Correct move	DC1	481	486	486
	DC2	477	477	470
	DC3	476	487	480
Correct stop	DC1	474	489	487
	DC2	480	475	473
	DC3	472	490	476
Incorrect move	DC1	19	14	14
	DC2	23	23	30
	DC3	24	13	20
Incorrect stop	DC1	26	11	13
	DC2	20	25	27
	DC3	28	10	24

Table 7 Experiment results at the 97% IS error-free rate

		DM	*DS*	*DO*
Correct move	DC1	482	477	488
	DC2	486	490	487
	DC3	487	484	487
Correct stop	DC1	478	484	484
	DC2	494	493	485
	DC3	485	481	484
Incorrect move	DC1	18	23	12
	DC2	14	10	13
	DC3	13	16	13
Incorrect stop	DC1	22	16	16
	DC2	6	7	15
	DC3	15	19	16

Table 8 Experiment results at the 99% IS error-free rate

		DM	*DS*	*DO*
Correct move	DC1	496	480	486
	DC2	496	494	490
	DC3	499	484	496
Correct stop	DC1	493	481	483
	DC2	496	493	498
	DC3	497	488	490
Incorrect move	DC1	4	20	14
	DC2	4	6	10
	DC3	1	16	4
Incorrect stop	DC1	7	19	17
	DC2	4	7	2
	DC3	3	12	10

Next, we specifically visualised these results in sets of figures for pattern comparison. Figures 1, 2, 3 and 4 are associated with the 95% IS error-free rate. Figure 1 shows the comparison between incorrect move decisions caused by each IS role during each decision-process component, while Figure 2 shows the comparison between the correct move decisions caused by each role.

Figure 1 Results of incorrect move decisions at the 95% IS error-free rate (see online version for colours)

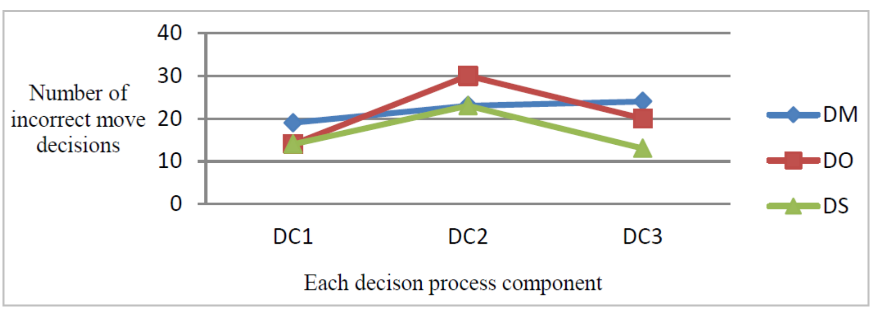


Figure 2 Results of correct move decisions at the 95% IS error-free rate (see online version for colours)

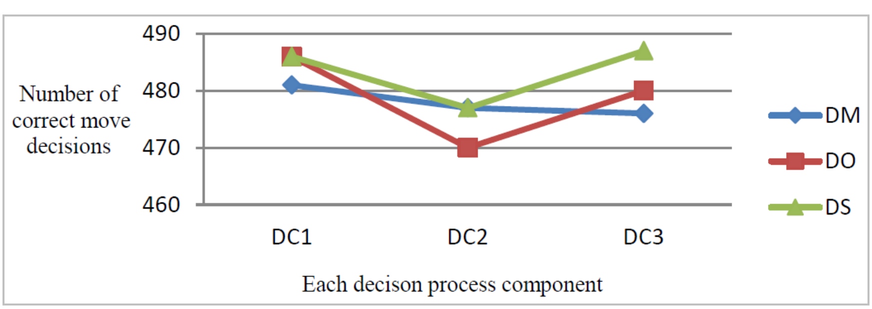


Figure 3 shows the comparison between incorrect stop decisions caused by each IS role during each decision-process component, while Figure 4 shows the comparison between the correct stop decisions caused by each role.

Figure 3 Results of incorrect stop decisions at the 95% IS error-free rate (see online version for colours)

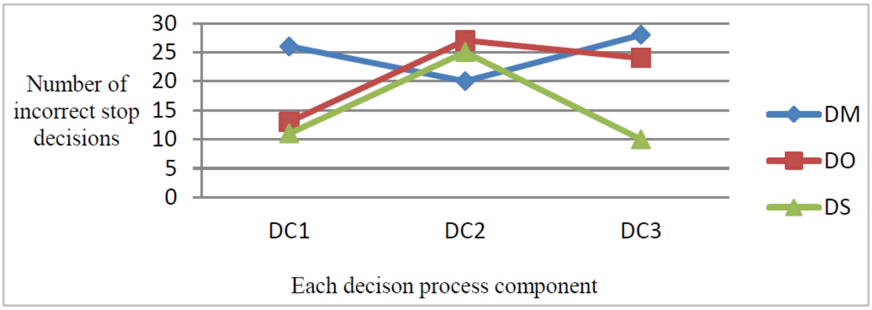
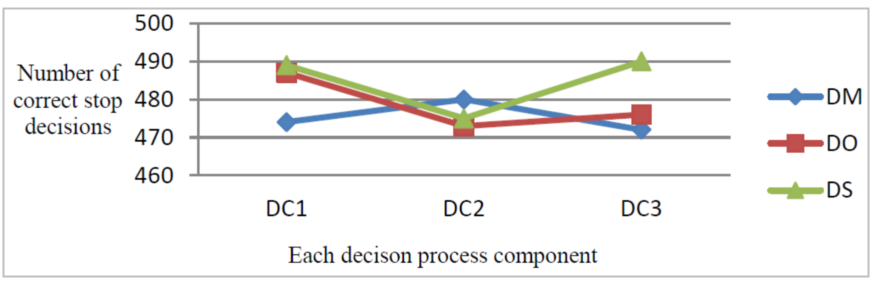


Figure 4 Results of correct stop decisions at the 95% IS error-free rate (see online version for colours)



Figures 5, 6, 7 and 8 are associated with the 97% IS error-free rate. Figure 5 shows the comparison between incorrect move decisions caused by each IS role during each decision-process component, while Figure 6 shows the comparison between the correct move decisions caused by each role.

Figure 5 Results of incorrect move decisions at the 97% IS error-free rate (see online version for colours)

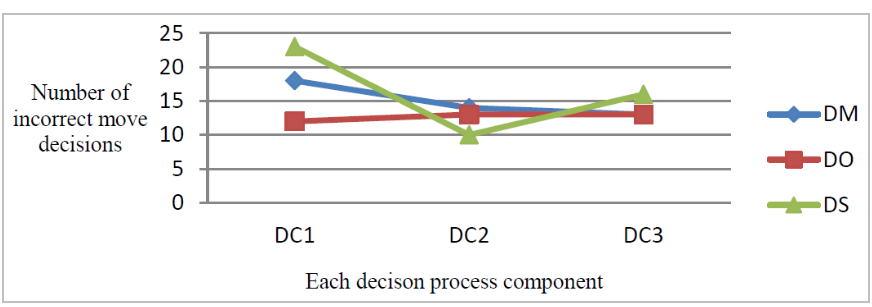


Figure 6 Results of correct move decisions at the 97% IS error-free rate (see online version for colours)

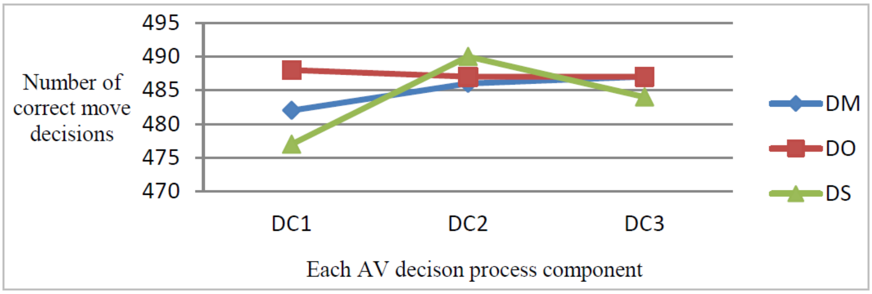


Figure 7 shows the comparison between incorrect stop decisions caused by each IS role during each decision-process component, while Figure 8 shows the comparison between the correct stop decisions generated by each role.

Figure 7 Results of incorrect stop decisions at the 97% IS error-free rate (see online version for colours)

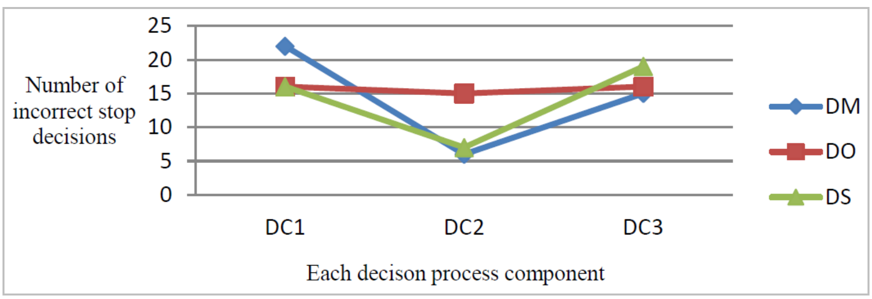
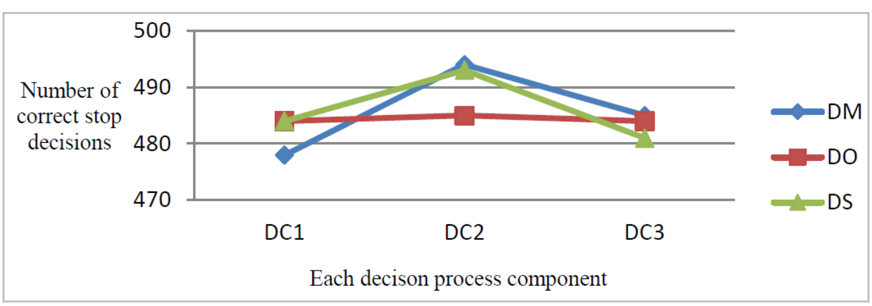


Figure 8 Results of correct stop decisions at the 97% IS error-free rate (see online version for colours)



Figures 9, 10, 11 and 12 are based on the IS 99% error-free rate. Figure 9 shows the comparison between the incorrect move decisions caused by each IS role during each decision-process component, while Figure 10 shows the comparison between the correct move decisions generated by each role.

Figure 9 Results of incorrect move decisions at the 99% IS error-free rate (see online version for colours)

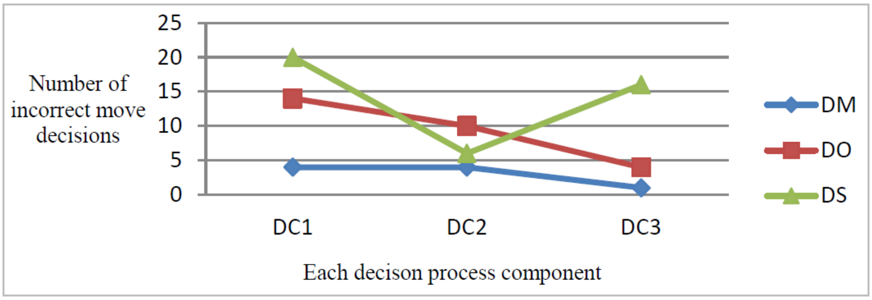


Figure 11 shows the comparison between the incorrect stop decisions caused by each IS role during each decision-process component, while Figure 12 shows the comparison between the correct stop decisions

Figure 10 Results of correct move decisions at the 99% IS error-free rate (see online version for colours)

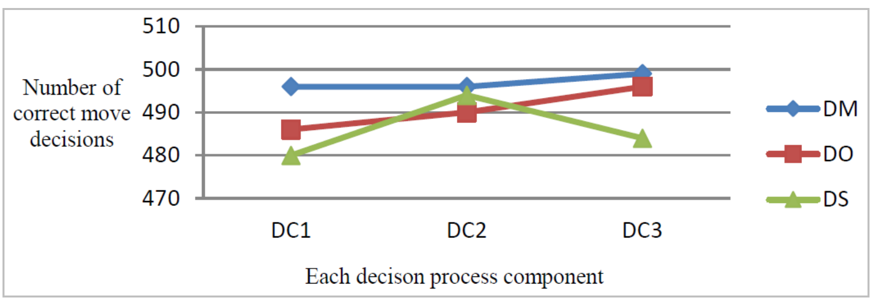
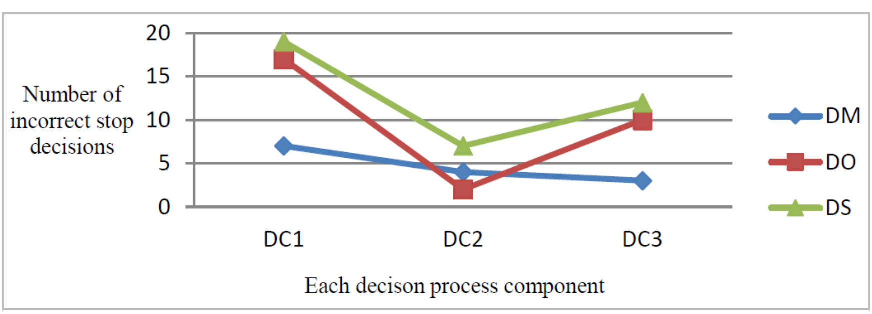
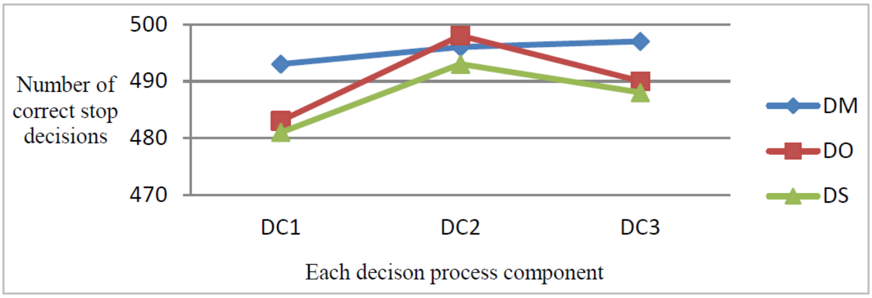


Figure 11 Results of incorrect stop decisions at the 99% IS error-free rate (see online version for colours)



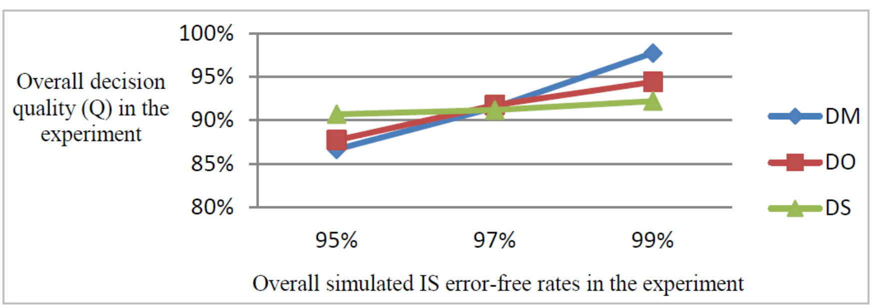
As seen in Figures 1–12, each IS role varies in generating correct or incorrect decisions. In other words, all the figures present very different patterns when we focused on each decision-process component individually. In contrast, the curves in most of the figures partially overlapped or are interwoven, rather than completely separated. This means that, at the individual process component level, no IS role was able to dominate other roles in generating better driving decisions.

Figure 12 Results of correct stop decisions at the 99% IS error-free rate (see online version for colours)



Furthermore, we summarised the above results to analyse the overall driving quality across the all three decision-process components as well as 'to-stop' and 'to-move' driving scenarios. In other words, we used model (1) to process the numbers in Tables 6, 7 and 8 to evaluate the quality for each IS role. As seen in Figure 13, when the simulated IS error-free rate was as low as 95%, IS in the DS role generated the greatest driving-decision quality. At the same IS error-free rate, IS in the DO role generated the second-best decision quality, and the DM role generated the poorest decision quality. However, as the error-free rate began to exceed 95%, the converse became true. When the rate was 95%, it was not very obvious whether the DS, DO, or DM role of IS would generate the greatest or poorest decision quality. When the rate was 97%, it was clear that IS in the DM role would generate the greatest decision quality, IS in the DO role would generate the second-best quality, and IS in the DS role would generate the poorest decision quality.

Figure 13 Overall decision quality generated by each IS role (see online version for colours)



The analysis of the above results shows the multiple effects of IS roles on the driving-decision quality of autonomous vehicles. We highlight and discuss our findings in the following section.

6 Summary of findings and discussion

Overall, although IS may have three decision roles in autonomous vehicles, our experiment findings show that no single role consistently dominated the others. Specifically, either the DS or DM role of IS would outperform the remaining IS role in generating the greatest driving-decision quality, depending on their associated IS error-free rates. This also indicates that any of these two roles would possibly generate the worst driving-decision quality as well. Nevertheless, the IS role of DO generates neither the greatest nor the worst driving-decision quality, regardless of variations in the error-free rate.

Certain interesting implications derived from the above findings are worth further discussion. The Society of Automotive Engineers (SAE, 2016) standards state that autonomous vehicles can be managed and classified according to several levels. Level 5 is the highest level, referring to full automation. Levels 4 to 0 autonomous vehicles refer to partial or no automation. However, when asked about whether IS should completely replace humans in making driving decisions, many people are still clueless regarding the issue, although they are aware of the importance of addressing it. With this study, they now have more clear options to consider and decide whether IS should serve in the DM, DS, or DO role in their autonomous vehicles. For example, some individuals may select autonomous vehicles in which the IS play the role of DM if they are more tolerant of IS-related driving errors than human-made driving errors. If they are less or not tolerant of such errors, autonomous vehicles in which IS play a DS or DM role may be more suitable for them.

Another important implication of this study relates to the issue of the transitioning or delegating decision authority from human drivers to IS. As Bonnefon et al. (2016) stated, future autonomous vehicles must address this issue because they may sometimes have to make decisions about whether or not to sacrifice lives for the greater good. For example, they may possibly need to decide to sacrifice some pedestrians to save more passengers or scare some passengers to save more pedestrians. In this study, we further showed that, when IS plays a DS or DO role, human drivers have unquestionable decision authority and thus no transition is needed. In contrast, when IS plays a DM role, it is necessary to have well-defined mechanisms for decision authority transition and delegation in autonomous vehicles.

7 Concluding remarks

The main contributions of this study are two-fold. First, because the related studies remain limited in prior literature (Hegner et al., 2019; Biondi et al., 2019; Ro and Ha, 2019), this is the first study to ascertain and examine the interaction between people and computers from the perspective of profiling the decision roles of IS in autonomous vehicles. In other words, this study complements related prior studies and thus enriches the literature regarding autonomous vehicles. For example, this study not only identified the IS roles of DM, DS, and DO, but also simulated their impact on decision quality in autonomous vehicles. Additionally, this study presents a concise model for computing or estimating the decision quality of autonomous vehicles, i.e., Q in model (1). Second, this study has very useful implications for practitioners. The identified decision roles of IS in autonomous vehicles can be easily applied to existing industrial frameworks to manage or classify autonomous vehicles. For instance, the IS decision roles are completely compatible with well-established SAE (2016) standards, such as the driving automation levels 0 to 5. However, this study has some limitations. The most obvious one is that this study's findings, regardless of the identified decision roles or their impact on decision quality, are mainly based on theories in prior literature or our internal experiment. In other words, our findings have not been externally validated by the autonomous vehicle industry, including managers and designers across different autonomous vehicle vendors or manufacturers. This limitation highlights research topics for future investigations to pursue. In conclusions, this study is a critical first step and we would like to encourage future scholars and practitioners to continue investigating this important research area.

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