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Who is performing the driving tasks after interventions? Investigating drivers' understanding of mode transition logic in automated vehicles

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ABSTRACT

Mode awareness is important for the safe use of automated vehicles, yet drivers' understanding of mode transitions has not been sufficiently investigated. In this study, we administered an online survey to 838 respondents to examine their understanding of control responsibilities in partial and conditional driving automation with four types of interventions (brake pedal, steering wheel, gas pedal, and take-over request). Results show that most drivers understand that they are responsible for speed and distance control after brake pedal interventions and steering control after steering wheel interventions. However, drivers have mixed responses regarding the responsibility for speed and distance control after steering wheel interventions and the responsibility for steering control after gas pedal interventions. With a higher automation level (conditional driving automation), drivers expect automation to remain responsible more often compared to a lower automation level (partial driving automation). Regarding Hands-on requirements, more than 99% of respondents answered that drivers would keep their hands on the steering wheel after all intervention types in partial automation, while 60–95% would place their hands on the wheel after various intervention types in conditional automation. A misalignment between actual logic and drivers' expectations regarding control responsibilities is observed by comparing survey responses to the mode transition logic of commercial partially automated vehicles. To resolve confusion about control responsibilities and ensure consistent expectations, we propose implementing a consistent mode design and providing enhanced information to drivers.

1. Introduction

1.1. *Design challenges for mode transition interaction in automated vehicles*

Transitions of control and monitoring create a range of driver interactions with automated vehicles (Merat and Lee, 2012). One of the key challenges is to design a natural and intuitive driver interaction with automated vehicles (Ackermann et al., 2019; Naujoks et al., 2019). This requires a deep understanding of human cognition and the ability to design interactions in automated vehicles that can communicate easily (Carsten and Martens, 2019; Schieben et al., 2019) and match drivers' mental models. A mental model is a representation of a part of the world to which incoming new events are mapped, which influences the interaction (Carroll and Olson, 1988; Halasz and Moran, 1983). Norman (1983) argued that interaction design needs not to be technically accurate—and that it usually is not—but must be functionally accurate to map onto a mental model. If the interaction is inconsistent or difficult to understand, it can disrupt drivers' mental models, leading to confusion and misunderstanding, which can result in inappropriate use (Parasuraman and Riley, 1997; Sarter and Woods, 1995). A consistent and predictable interaction helps to facilitate trust in the automation system (Ososky et al., 2013). However, the current interaction design insufficiently considers mental models which drivers use to represent their interaction with automated vehicles. Banks et al. (2018), Endsley (2017), and Wilson et al. (2020) found that—in on-road studies—drivers

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were not sufficiently aware of which functions were active after mode transitions, even when user interfaces displayed the current driving mode. It is well-known that there is often a misfit in how engineers technically design automation and the user awareness of these functionalities (Norman, 1983). Failure to design the interaction of mode transitions in consideration of the mental model may lead to reduced trust in the automated vehicle, decreased adaptation of automation, and a higher risk of accidents (Becker and Axhausen, 2017; Viktorová and Sucha, 2018). Consequently, this needs to be addressed by design choices early in the development stages.

1.2. Current issue in driving automation

As technology advances gradually, automated driving is classified into different driving automation modes. The widely used mode classification is the SAE definition (SAEInternational, 2021), with six technology-based levels ranging from Level 0 (No Driving Automation) to Level 5 (Full Driving Automation). Each level represents varying responsibilities between the drivers and the automated vehicles. Level 1 (Driver assistance) and Level 2 (Partial automation) driving automation are widespread in the global vehicle market (Shirokinskiy, 2021). Level 1 driving automation includes either longitudinal control or lateral control. The main form of Level 1 driving automation is known as Adaptive Cruise Control (ACC), which maintains a driver-set speed and distance from the vehicle ahead. Partial driving automation includes not only ACC but also Lane-keeping Assist (LKA). Therefore, partial driving automation assists the drivers with steering, acceleration, and braking tasks. Level 3 (Conditional automation) driving automation can perform the driving task in specific conditions, but drivers need to remain prepared to take control when prompted by the vehicles. Nowadays, vehicles can operate at several levels of automation, thus offering different driving modes to the drivers, which may change during a drive cycle because of driving automation limitations or driver interventions. In these transitions, mode confusion can occur when drivers fail to understand the current automation mode in operation (Sarter and Woods, 1995). This issue is also well-recognized in the aeronautics field, where airline pilots are assisted by complex automation systems (Dehais et al., 2015). The automation system in a modern aircraft is a complex structure with a variety of states. A specific operational state of the automation system may not be immediately critical for the aircraft pilot to be aware of. However, it is crucial for the pilot to identify and understand the states in which the system is operating (King, 2011). Not knowing the current automation state may yield conflicts between human operators and automated systems and are defined as automation surprise (Sarter et al., 1997). As a result, questions arise about the system's behaviour: What is it doing now? Why did it do that? What is it going to do next? (Wiener, 1989). Mode confusion may also lead to adverse behavioural and cognitive effects, such as risky decision-making or attentional tunnelling (Dehais et al., 2012). It can be expected that these effects are more likely to occur in amateur drivers compared to professional pilots. Consequently, the understanding of the capabilities and limitations of multiple levels of automation in vehicles has become more difficult. Mode transitions between manual, assisted and automated driving modes will increasingly occur, making it hard for drivers to keep track of the currently active driving mode and possibly affecting drivers' experience and acceptance of automated driving. However, the rapid technically driven development has not allowed a human-centred design that considers drivers' understanding and expectations when interacting with automated vehicles (Homans et al., 2020; Seppelt et al., 2018; Yang et al., 2017).

Mode awareness comprises knowledge about the currently active automation, its performance and drivers' tasks and responsibilities (Sarter and Woods, 1995). An essential component in mode awareness is the user interface and how it guides transitions between automation modes (Carsten and Martens, 2019; Nordhoff et al., 2023). Table 1 presents an inventory made by the first two authors and summarises how different car manufacturers have different approaches to activating and deactivating driving automation features, i.e., ACC and LKA, in their vehicles. It indicates whether the Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA) functions of each manufacturer in each row are activated or deactivated based on the interaction method in each column. It demonstrates that manufacturers use various interaction methods for activating and deactivating the functions, which challenges drivers to develop a matching mode transition logic when interacting with automated vehicles. Furthermore, there are different nuances in each of the ways of interaction, making it even more complex for drivers to follow a thread and nearly impossible to transfer knowledge from one vehicle to another. For example, when both Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA) are activated, the function that is disengaged if a driver uses the brake pedal differs per car brand and model. Therefore, rather than expecting the drivers to adapt to the automated vehicles, manufacturers should understand and design the interaction with automated vehicles. Specifically, they should focus on mode transitions between different modes of automation, aligning them with the driver's expectations. In this study, we investigate drivers' expectations and understanding of the transition logic while proposing interaction design recommendations.

1.3. Research objectives

There is a lack of knowledge regarding how drivers understand mode transitions in their interactions with driving automation. To shed light

Table 1
ACC and LKA ways of interacting in commercial partially automated vehicles.

Way of interacting	Activation				Deactivation/Override												Source
	Button		Lever		Button		Lever		Brake pedal		Steering wheel		Accelerate				
Function	ACC	LKA	ACC	LKA	ACC	LKA	ACC	LKA	ACC	LKA	ACC	LKA	ACC	LKA			
Brand																	
Audi		x	x			x	x		x	x			x[a]	x[a]			Audi A8 (2021) Owner's manual
Honda	x	x			x	x			x								Honda HR-V (2022) Owner's manual
Hyundai	x	x			x	x			x			x	x[a]				Hyundai G70 (2022) Owner's manual
Kia	x	x			x	x			x			x	x[a]				KIA K9 (2022) Owner's manual
Mazda	x	x			x	x			x								Mazda CX-5 (2023) Owner's manual
Mercedes-Benz	x				x				x	x		x	x	x			Mercedes-Benz S-Class (2022) Owner's manual
Tesla			x	x			x	x	x	x		x					Tesla Model3 (2023) Owner's manual
Toyota	x	x			x	x			x	x		x		x[a]			Toyota Mirai (2022) Owner's manual
Volvo	x	x			x	x			x	x			x[a]	x[a]			Volvo XC90 (2022) Owner's manual

Note: Table 1 is an inventory made by the first two authors.
[a] Deactivate the function when drivers press the accelerator pedal for a long period.

on this topic, we developed an online survey to acquire knowledge regarding driver understanding of which actions follow different mode transition cases in partial and conditional driving automation. The understanding of mode transitions by drivers is analysed according to automation driving mode (partial and conditional driving automation) and intervention type (brake pedal steering wheel, gas pedal control, and take-over request) as explanatory variables. We expect that this study contributes to filling the gap in research by examining drivers' understanding and expectations of mode transitions during interaction with automated vehicles.

2. Method

With a lack of existing research in this area, the online survey enables comprehensive exploration by inquiring about various mode transition cases and gathering data on drivers' understanding of mode transitions in automated vehicles.

2.1. Recruitment and respondents

The online survey was created with the survey platform Qualtrics (https://www.qualtrics.com) and distributed between December 2022 and February 2023 through Prolific (https://www.prolific.com) and social media (LinkedIn and mail). In the Prolific platform, we used a purposive sampling strategy targeting participants from the United Kingdom and the United States through the prolific platform. These two countries were chosen based on the hypothesis that differences in driving styles between the United States and the United Kingdom might influence the mode-switching behaviour of automated vehicle drivers. By focusing on these regions, we aimed to capture potential response variations arising from these differences. Similarly, when recruiting respondents via prolific, we ensured an equal gender ratio (female/male). In order to investigate the potential association and/or interdependence between the respondents' answers by country (United Kingdom and United States), gender and age, a Contingency analysis was conducted. The results showed that there was no impact on respondents' choice. For other countries, the number of respondents was insufficient to justify firm conclusions. Consequently, to achieve a more comprehensive understanding of the mental models associated with mode transition in automated vehicles, we included responses from all participating countries, from both Prolific and social networks respondents, in the final analysis.

Therefore, in total, 926 respondents answered the survey. Drivers with a driving license for more than one year were eligible for the survey, including those without prior experience with automated vehicles and current users of partially automated vehicles. To ensure the collection of high-quality data, we implemented measures through Qualtrics to prevent duplicate responses and identify non-human respondents. Before the analysis, an initial quality filtering process was carried out to remove respondents who did not complete the entire survey and whose survey completion time was less than 180 s. The resulting sample size was 838 (90.50%). Within the resulting sample, the median time to complete the survey was 431 s.

- Age: the number of respondents per age range was 262(19–29), 281 (30–39), 141(40–49), 78(50–59), 56(60–69), and 20 over 69.
- Gender: 408 were female, 420 were male, 6 preferred not to say, and 4 preferred to self-describe.
- Residence of Country: 400 were from the United States, 301 were from the United Kingdom, 58 were from the Netherlands, 21 were from Sweden, 21 were from Germany, and 37 were from Korea, Switzerland, Ireland, France, Belgium, or China.
- Knowledge of automated driving: 83 reported 'I don't have any knowledge about driving automation', 445 reported 'I have a little knowledge about driving automation', 251 reported 'I have moderate knowledge about driving automation', 38 reported 'I have a lot of knowledge about driving automation', and 21 reported 'I know the topic of driving automation extremely well'.
- Driving automation experience: 435 had experience with adaptive cruise control (ACC), 284 with lane-keeping assist (LKA), and 229 had experience with both ACC and LKA.
- Own car: 734 indicated that they have a car, and 104 indicated they don't have a car.
- Car sharing: 221 indicated that they had used car sharing, and 617 indicated they did not have a car sharing experience.

2.2. Survey content

Prior to participating in the study, respondents were informed about the purpose of the survey, that the length was about 10 min and were asked to provide their written consent. Upon providing consent, respondents were directed to a section that requested demographic and driving-related information. To ensure that respondents had a sufficient understanding of automated vehicles prior to completing the survey, the respondents were introduced to the topic with a description of a scenario that results in the disengagement of the driving automation (partial and conditional) as follows:

During your drive, there are several actions or events that may disengage the partial/conditional driving automation. This means that you, as a driver, take action or surrounding events that lead to the partial/conditional driving automation being turned off. In the following section, we will give you a couple of scenarios. Based on these, we ask you to determine the state of the car's driving.

Next, respondents answered the main section regarding their expectations of mode transitions after interventions in partial and conditional driving automation. The intervention types for the study included the brake pedal, steering wheel, and accelerator. The function button-off was excluded from the intervention types because it was deemed unnecessary since the respondent is expected to easily recognise and deactivate this specific function on a feature basis. Additionally, given the potential for confusion during mode transitions in conditional driving automation, a take-over request by the car was added to the intervention types. To investigate the respondent's expectations of mode transition logic regardless of the specific manufacturer's transition logic or suggested logic, no instructions, such as returning to manual driving after a takeover request, were provided. An overview of the survey and the intervention types used in the scenarios is presented in Table 2. In the partial driving automation section, the respondent was presented with scenarios involving "pressing the brake pedal," "turning the steering wheel", and "pressing the gas pedal." In the conditional driving automation section, scenarios also included "a take-over request from the car." Disengagement initiated by automated vehicles was not provided to the respondents.

For each of the seven scenarios presented in the survey, the respondent was asked to indicate who would primarily perform the speed, distance, and steering control after the interventions. Fig. 1 shows

Table 2
Intervention types and automated driving of seven scenarios.

	Intervention type			
	You press the brake pedal. (*Brake pedal*)	You turn the steering wheel to override the car steering. (*Steering wheel*)	You press the gas pedal to speed up above a set speed. (*Gas pedal*)	The car asks you to take over control of the car. (*Take-over request*)
Partial driving automation	Scenario 1	Scenario 2	Scenario 3	–
Conditional driving automation	Scenario 4	Scenario 5	Scenario 6	Scenario 7

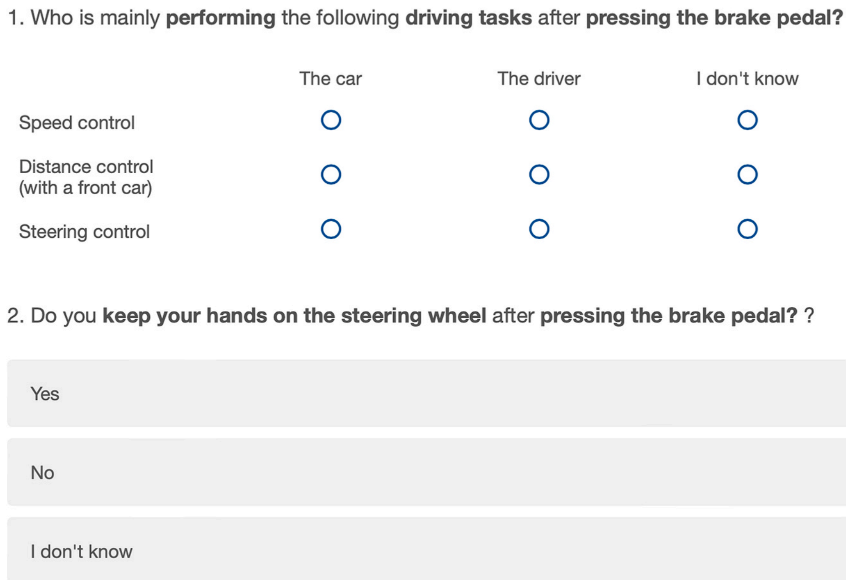

Fig. 1. Questionnaire of scenario 1 & 4.

the questionnaire of Scenario 1 in Table 2. Additionally, the respondent was asked whether he/she would keep their hands on the steering wheel following the intervention. In the scenario involving a take-over request from the car, the respondent was also asked to provide multiple responses detailing the actions he/she would take to regain control in such situations.

2.3. Method of analysis

All survey questions had categorical response options. We conducted two main types of statistical analyses. First, descriptive statistics were calculated for each questionnaire item. Second, the data was analysed using a nominal logistic regression model in the JMP Pro 17.0 software for statistical analysis to understand the factors influencing respondents' choices regarding control responsibility in different intervention scenarios. The analysis was conducted except for the respondents who answered, "I don't know" (less than 3% of responses averaged over questions).

3. Results

The results for control responsibility in partial and conditional driving automation are discussed in Sections 3.1 and 3.2, respectively.

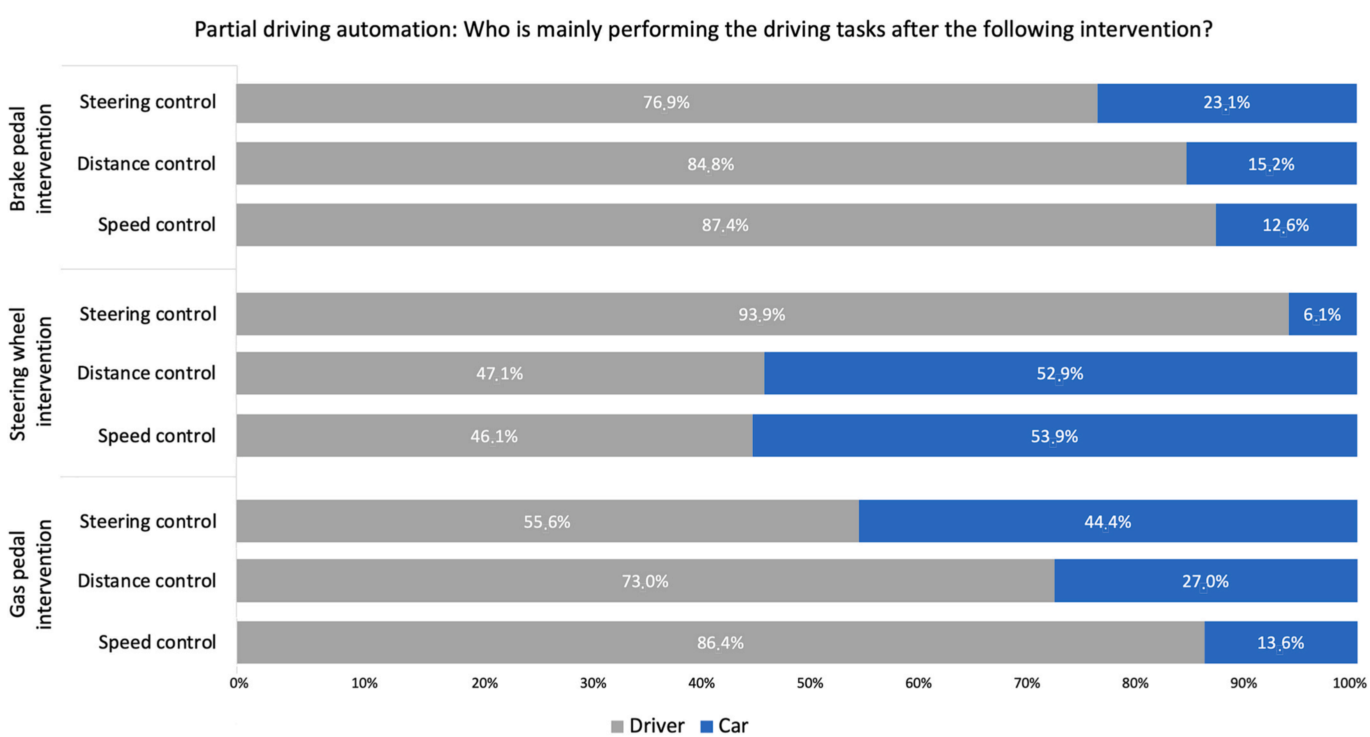

Fig. 2. Control responsibility after intervention in partial driving automation.

3.1. Control intervention of partial driving automation

Fig. 2 shows the respondents' choice of control responsibility (driver vs. car) by *Intervention type* and *Control* in partial driving automation. After brake pedal intervention, more than 70% of the respondents answered that the driver controls all control items. 76.9% of respondents answered that the driver performs steering control, 84.8% of respondents answered that the driver performs distance control, and 87.4% of respondents answered that the driver performs speed control. After steering wheel intervention, 93.9% of respondents answered that the driver performs steering control. However, 47.1% of respondents answered that the driver would perform distance control after the steering wheel intervention, and 46.1% of respondents answered that the driver would perform speed control after the steering wheel intervention. After gas pedal intervention, 73.0% and 86.4% of the respondents answered that the driver controls distance control and speed control, respectively. However, 55.6% of respondents answered that the car would perform the steering control after the gas pedal intervention.

Regarding Hands-on requirements, more than 99% of respondents answered that drivers would keep their hand on the steering wheel after all *Intervention types*, as shown in Fig. 3.

Nominal logistics analysis was conducted with *Intervention type* and *Control* as independent variables and respondents' choice of control responsibility (driver vs. car) as a response variable. The Whole Model Test revealed statistically significant evidence suggesting that the independent variables (*Intervention type* and *Control*) played a significant role in determining whether respondents chose the driver or the car as being responsible for controls ($\chi^2(8, N = 7232) = 1095.03$, $p < .0001$, $R^2(U) = .129$, $AICc = 7411.2$, $BIC = 7473.15$). The effect likelihood ratio tests indicated that *Intervention type*, *control*, and the interaction between *Intervention type* and *Control* were statistically significant. The results of the effect likelihood ratio test, McFadden Pseudo-R-squared, and Cramér's V are presented in Table 3. The McFadden Pseudo-R-squared statistic (McFadden and Zarembka, 1974) was used to assess the model's fit, and Cramér's V was employed as a measure of effect size. Table 4 presents parameter estimates from multinomial regression analysis of the response of control responsibility (driver vs. car) on *Intervention type* and *Control*. There is an interaction between the type of intervention and control in respondents' choices. Respondents tend to indicate that with steering wheel intervention, the vehicle maintains speed and distance control. However, with brake pedal intervention, respondents tend to indicate that these controls are transferred to the driver. The coefficients of brake pedal intervention had relatively high positive values, implying that, all else being equal, respondents anticipate the driver to take control following a brake pedal intervention.

Furthermore, the original contingency table (Reynolds, 1977) was split up into three intervention types, as presented in Table 5. Each sub-table represented one level of intervention, as shown in Table 5 first column. A comparison of the fit of the sub-table to the whole model table is shown as a percentage of the model fit, indicating the contribution of each intervention level to the entire model. The analysis results demonstrate that the steering wheel intervention model accounts for 55% of the entire logistic regression model. Furthermore, Cramér's V indicated a strong effect size for the steering wheel intervention mode.

Table 3
Effect likelihood ratio tests in partial driving automation.

Parameters	L-R χ^2	*df*	*p*-value	Pseudo-R-squared	*Cramér's V*
Intervention	110.29	2	<.0001	.013	.12
Control	50.18	2	<.0001	.006	.08
Intervention[a]Control	802.35	4	<.0001	.095	.33

[a] *Note: Cramér's V* $\leq$ *0.2* means the results are weak, .2 < *Cramér's V* $\leq$ *0.6* means the results are moderate, and .6 < *Cramér's V* means the results are strong.

Table 4
Parameter estimates from multinomial regression analysis of partial driving automation.

Variable	*Coeff.*	*Std Error*	χ^2	*p*-value
Intercept	1.15	.03	1331.8	<.0001
Intervention (Brake pedal)	.47	.05	106.83	<.0001
Intervention (Gas pedal)	−.13	.04	9.71	.0018
Control (Distance)	−.29	.04	46.79	<.0001
Control (Speed)	.06	.04	1.53	.2169
Intervention (Brake pedal)[a] Control (Distance)	.39	.06	38.95	<.0001
Intervention (Brake pedal)[a] Control (Speed)	.26	.07	16.40	<.0001
Intervention (Gas pedal)[a] Control (Distance)	.26	.06	20.68	<.0001
Intervention (Gas pedal)[a] Control (Speed)	.77	.06	149.88	<.0001

[a] Note: The target level is that the driver will take control after the intervention.

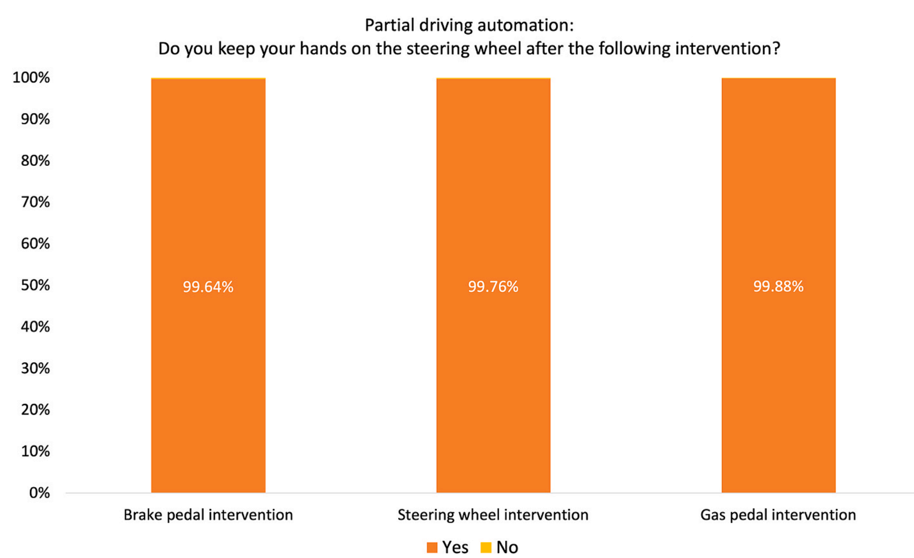

Fig. 3. Hands-on requirement in partial driving automation.

Table 5
Contingency analysis of the respondents' choice of partial driving automation.

Intervention	n	*df*	*-Loglikelihood*	R square (*U*)	χ^2 (likelihood ratio)	*p*-value	*Percentage of the model fit*	*Cramér's V*
Brake	2431	2	16.80	.015	33.595	<.0001	31%	.12
Gas pedal	2403	2	96.53	.068	193.053	<.0001	17%	.28
Steering wheel	2398	2	305.67	.193	611.348	<.0001	55%	.50

*Note: percentage of the model fit is loglikelihood/full mode loglikelihood.

3.2. Control intervention of conditional driving automation

Fig. 4 shows the respondents' choice of control responsibility (driver vs. car) by *Intervention type* and *Control* in conditional driving automation. After brake pedal intervention, 74.1% and 82.8% of the respondents answered that the driver would perform the distance and speed control, respectively. However, only 51.9% of respondents answered that the driver would perform steering control, whereas 48.1% answered that the car would perform the steering control. After the steering wheel intervention, 85.4% of the respondents answered that the driver would perform the steering wheel control, but 43.4% answered that the driver would perform speed and distance control. Regarding gas pedal intervention, 40.8% of respondents answered that the driver would perform steering control after the intervention, while 67.3% and 82.3% answered that the driver would perform distance and speed control. Furthermore, after intervention due to a take-over request, for all controls, less than 10% of respondents answered that the car would perform them.

As shown in Fig. 5, 34.2%, 23.1%, and 39.7% of respondents answered that they would not keep their hands on the steering wheel after brake pedal, steering wheel, and gas pedal interventions. Moreover, 4.9% of respondents reported not keeping their hands on the steering wheel after taking over control by the take-over request.

Nominal logistics analysis was conducted with *Intervention type* and *Control* as independent variables and respondents' choice of control responsibility (driver vs. car) as a response variable. The Whole Model Test revealed that there was statistically significant evidence to suggest that the model is useful in differentiating between respondents' choices ($\chi^2(11,\ N = 9657) = 1959.64$, $p < .0001$*, $R^2(U) = .170$, $AICc = 9608.09$, $BIC = 9694.17$). The effect likelihood ratio tests indicated that *Intervention type*, *Control*, and the interaction between *Intervention type* and *Control* were statistically significant. The results of the effect likelihood ratio test, McFadden Pseudo R-squared, and effect size are presented in Table 6. Table 7 presents parameter estimates from multinomial regression analysis of the response of control responsibility (driver vs. car) on *Intervention type* and *Control* in conditional driving automation. A notable proportion of respondents answered that the driver would perform control after the TOR intervention, resulting in negative coefficients for the other interventions. The interaction between *Intervention type* and *Control* demonstrates how a certain intervention has a different impact on the understanding of the driving responsibility of certain control. Specifically, the respondents answered that the driver performs the speed control after the gas pedal intervention, while relatively many respondents answered that the car performs the speed control after the steering wheel intervention.

Furthermore, the original contingency table was split up into four intervention types, as presented in Table 8. Each sub-table represented one level of intervention, as shown in Table 8 first column. The descriptive analysis showed that respondents answered that the driver would perform controls after take-over requests (TORs). Consequently,

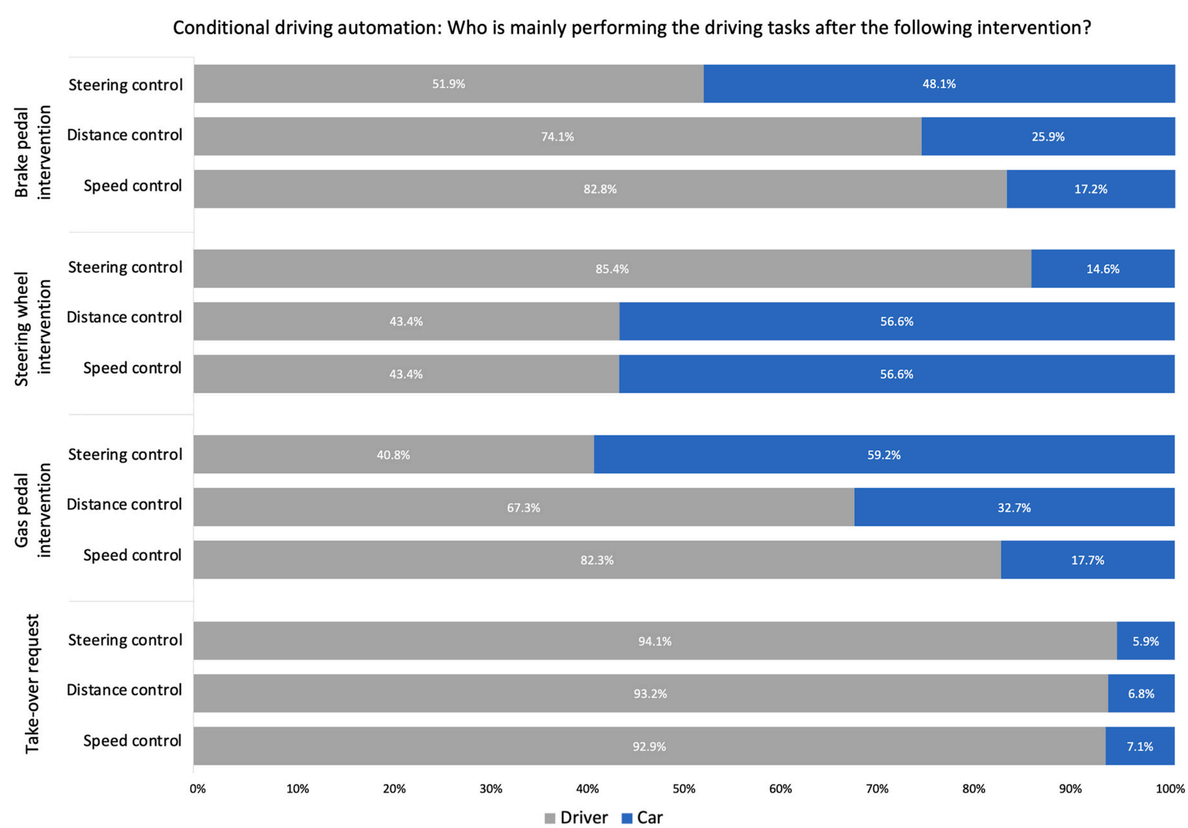

Fig. 4. Understanding of control after intervention in conditional driving automation.

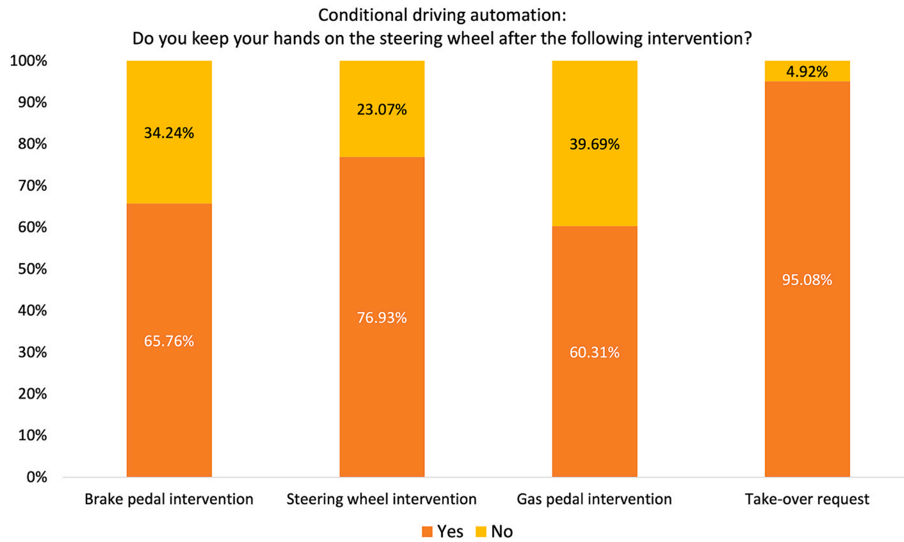

Fig. 5. Hands-on requirement in conditional driving automation.

Table 6
Effect likelihood ratio tests of conditional driving automation.

Parameters	L-R χ^2	*df*	*p*-value	Pseudo-R-squared	*Cramér's V*
Intervention	879.70	3	<.0001[a]	.076	.30
Control	26.45	2	<.0001[a]	.002	.05
Intervention[a]Control	869.26	6	<.0001[a]	.075	.30

[a] Note: Cramér's V ≤ .2 means the results are weak, .2 < Cramér's V ≤ .6 means the results are moderate, and .6 < Cramér's V means the results are strong.

Table 7
Parameter estimates from multinomial regression analysis of conditional driving automation.

Variable	*Coeff.*	*Std Error*	χ^2	*p-value*
Intercept	1.15	.04	1600.0	<.0001[a]
Intervention (Brake pedal)	−.25	.04	31.39	<.0001[a]
Intervention (Gas Pedal)	−.52	.04	142.28	<.0001[a]
Intervention (Steering wheel)	−.74	.04	279.12	<.0001[a]
Control (Distance)	−.12	.04	8.79	.0030[a]
Control (Speed)	.21	.04	25.38	<.0001[a]
Intervention (Brake pedal)[a] Control (Distance)	.27	.06	19.03	<.0001[a]
Intervention (Brake pedal)[a] Control (Speed)	.47	.06	50.85	<.0001[a]
Intervention (Gas pedal)[a] Control (Distance)	.21	.06	12.48	.0004[a]
Intervention (Gas pedal)[a] Control (Speed)	.70	.06	118.80	<.0001[a]
Intervention (Steering wheel)[a] Control (Distance)	−.56	.06	87.38	<.0001[a]
Intervention (Steering wheel)[a] Control (Speed)	−.88	.06	213.54	<.0001[a]

[a] Note: The target level is that the driver will take control after the intervention.

the choice model based on TORs presents a distinct perspective compared to other intervention models. As a result, the impact of the choice model by TORs on the overall model is found to be insignificant.

The study also explored the methods for transitioning the control when receiving a take-over request. The results showed that 34% of respondents chose 'pressing a button', 55% of respondents chose 'pressing the brake pedal', 73% of respondents chose 'putting hands on the steering wheel', 46% of respondents chose 'turning the steering wheel', and 4% of respondents chose 'pressing the gas pedal'.

3.3. *Response comparison between partial driving automation and conditional driving automation*

We also checked the individual correspondence between results for two automation levels (partial driving automation and conditional driving automation). Fig. 6 presents the value of the ratio difference between respondents who answered 'The car' and 'The driver' for the responsibility of each task after the intervention in partial and conditional automated driving. A value closer to zero indicates a large difference in understanding the responsibility after the intervention among the respondents. Specifically, the ratio difference in response in responsibility for the speed and distance control after the steering wheel intervention and steering control after the gas pedal intervention is close to zero for both partial and conditional driving automation. Regarding the answer difference between partial and conditional driving automation, the linear fit model in Fig. 6 is *Conditional driving automation* $= -.15 + .95 \times$ *Partial driving automation* ($F(1,7) = 41.33$, *p*-value $<.001$, $R^2 = .86$). The regression coefficient of the *Partial driving automation* variable is almost 1, indicating that the trend of control responsibility choice on intervention is similar between partial and conditional driving automation. However, the intercept, −.15, indicates that a higher percentage of respondents in conditional driving automation indicated that the car would perform each task after the intervention compared to partial driving automation. The difference in drivers' understanding of control responsibilities between partial and conditional driving automation will be discussed further in Section 4.2.

4. Discussion

This study investigated drivers' understanding of their responsibilities after different intervention types in partial and conditional automated driving. Although drivers seem to associate specific control interventions with driving functionalities, drivers did not have a dominant mental representation of mode transition logic in several scenarios.

4.1. *Drivers' mental representation of mode transition logic*

Our study sheds light on drivers' mental representation of control responsibilities in partial and conditional driving automation. According to the results, drivers have a relatively dominant mental representation

Table 8
Contingency analysis of the respondents' choice of conditional driving automation.

Intervention	*n*	*df*	*-Loglikelihood*	R square (*U*)	χ^2 (likelihood ratio)	*p-value*	*Percentage of the model fit*	*Cramér's V*
Brake	2371	2	93.38	.06	186.76	<.0001	10%	.28
Gas pedal	2401	2	154.60	.10	309.21	<.0001	16%	.36
Steering wheel	2380	2	210.95	.13	421.90	<.0001	22%	.42
Take-over request	2502	2	.52	.00	1.06	.588	0%	.02

*Note: percentage of the model fit is loglikelihood/full mode loglikelihood.

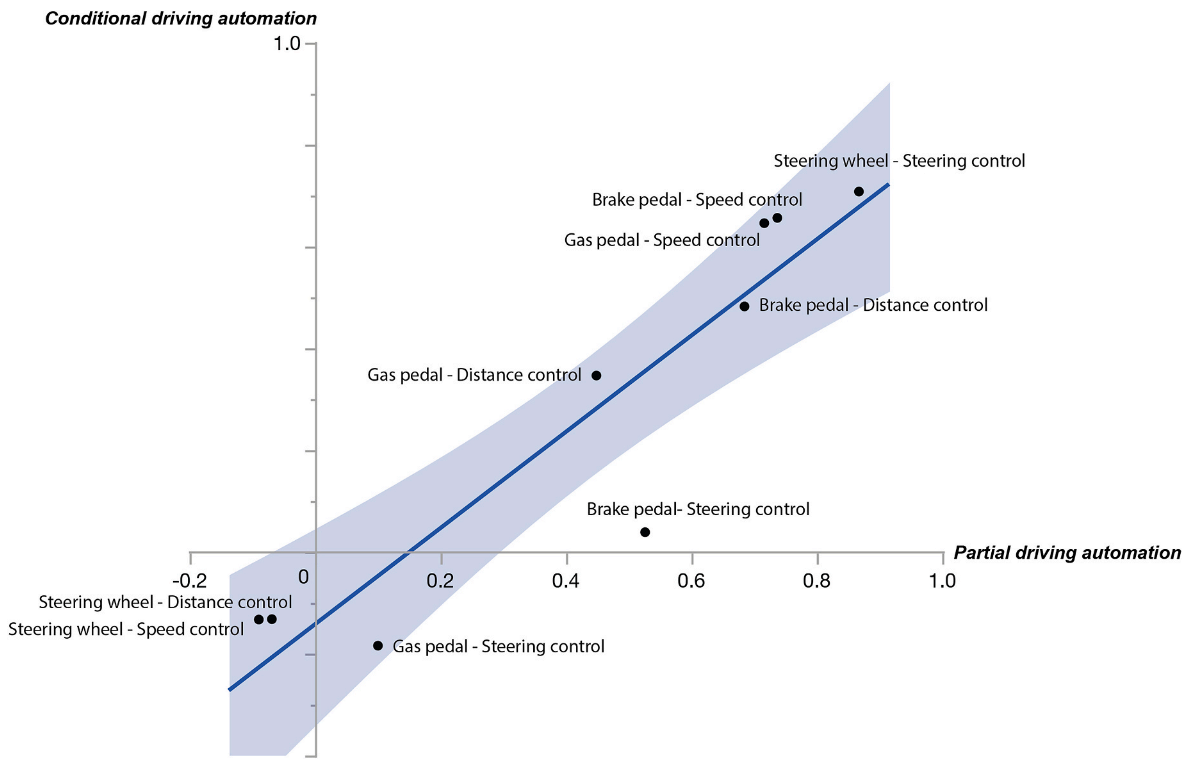

Fig. 6. Value of ratio difference of respondents who answered 'the driver' minus the respondents who answered 'the car' in partial and conditional driving automation
* Note: value explanation sequence 1–2: 1-intervention type, 2-control task.

of their resulting responsibility for speed and distance control after brake pedal interventions and steering control after steering wheel interventions. In addition, gas pedal interventions have been associated with speed control. However, drivers' responses regarding the responsibility for speed and distance control after steering wheel interventions, as well as the responsibility for steering control after gas pedal interventions, are mixed with responses between 44.4 and 55.6%. This tendency is also shown in the contingency analysis results, which indicate that the steering wheel intervention model has relatively higher explanatory power compared to other interventions. This suggests that the variable response tendency is more pronounced in the steering wheel intervention. This can be attributed to the fact that respondents' answers regarding distance control and speed control are almost evenly distributed at a 5:5 ratio when the steering wheel intervention is involved. Additionally, the effect size indicated by Cramér's V demonstrates that there is a substantial association between the steering wheel intervention and the participants' responses. Respondents could also choose 'I don't know' if they were unsure of the answer, but this answer was rarely selected (less than 3% of responses averaged over questions). Hence, it seems that they responded with confidence in their choice. This suggests that the driver population did not have a dominant mental representation of mode transition logic in these scenarios.

4.2. Difference in responsibility understanding between partial and conditional driving automation

Drivers' expectations of control responsibilities show similar tendencies in partial and conditional driving automation. However, with a higher driving automation level, drivers expect more often that the car will still perform the driving task after the interventions, and the intercept in Fig. 6 supports this interpretation. For example, respondents expect that the driver will be responsible for the distance control after the gas pedal intervention and steering wheel control after the brake pedal intervention in partial driving automation. However, drivers' responses regarding the same scenarios are mixed in conditional driving automation. This expectation seems to have arisen from the perception that conditional driving automation is a more advanced automated driving mode compared to partial driving automation, leading to the assumption that it will continue to control the vehicle even after the intervention. In addition, a low percentage of respondents expected to put their hands on the steering wheel after the intervention in conditional driving automation compared to those who expected to do so in partial driving automation. In partial driving automation, more than 99% of respondents answered that they would keep their hands on the steering wheel regardless of the type of intervention. However, in conditional driving automation, respondents had different expectations of whether they should put their hands back on the steering wheel after a brake pedal (66%), steering wheel (77%) or gas pedal (60%) intervention. Only, in the case of a takeover request, drivers understand (95%) that they have to take over all controls and keep their hands on the steering wheel since it is not an intervention of the driver but a request from the car. As more driving automation is integrated into one automated vehicle, the complexity increases, leading to a greater chance of differences between how drivers understand driving automation and how automated vehicles operate. Therefore, it becomes important to provide clear information on control responsibilities and steering wheel requirements, indicating whether drivers should keep their hands on the steering wheel or not.

4.3. Mismatches in control responsibilities

With the integration of multiple levels of driving automation in an automated vehicle, it is important for drivers to comprehend the interaction, specifically the transition logic, to ensure safety and trust. Comparing the current transition logic in commercial partially automated vehicles (see Table 1) with the survey results, a discrepancy between the respondents' expected logic and the actual logic was identified. Fig. 7 illustrates a comparison between responses in partial driving automation and the mode transition logic of commercial partially automated vehicles. The graph on the left shows the respondents' choice of control responsibility by intervention type and control in partial driving automation (edited from Fig. 2). The graph on the right displays the number of brands that deactivate the function after the intervention (edited from Table 1). For example, five 'x' marks next to 'LKA-Steering control on brake pedal intervention' means that five brands have transition logic to deactivate the steering control function after a brake pedal intervention.

Regarding brake pedal interventions, there is a high association between the response and the mode transition logic of commercial partially automated vehicles. For example, respondents (84.8%–87.4%) expected Advanced Cruise Control (ACC) to be deactivated after brake pedal interventions. This matches the mode transition logic of all commercial partially automated vehicles. However, in the case of steering wheel interventions, there is a misalignment. After steering wheel interventions, 93.9% of the respondents expected the driver to take over the steering control, while only 5 of 9 commercial partially automated vehicles in Table 1 have the transition logic to turn off the steering control after steering wheel interventions. Around half of the respondents expected that the driver would assume speed and distance control after steering wheel interventions, while in reality, all automated vehicles continued to handle speed and distance control. Responses regarding gas pedal interventions also show some discrepancies with the actual transition logic, where following gas pedal interventions, respondents were likely to expect the driver to take over speed and distance control, while in reality, about half of the brands do not deactivate speed and distance control.

These findings reveal a misalignment between the actual logic in current vehicles and the drivers' expectations regarding control responsibilities. This misalignment can be partially explained by respondents having experienced vehicles with different transition logic. However, around 50% respond that distance and speed control is deactivated after steering intervention, which does not match any of the 9 current vehicles. The misalignment of LKA may also relate to the control authority of the current LKA. Tesla LKA controls steering with full authority and fully deactivates when overruled. Other LKA systems have limited control authority and assist rather than take over the steering task. This encourages driver involvement and active monitoring. This may partially explain responses to our question, "Who is mainly performing the driving task?" where even with LKA being active, the driver is the main actor in steering. Another factor explaining these responses is the hands-on requirement in current vehicles. This is different in ACC, where virtually all current systems have full control authority and require no use of pedals. The driver's incomplete

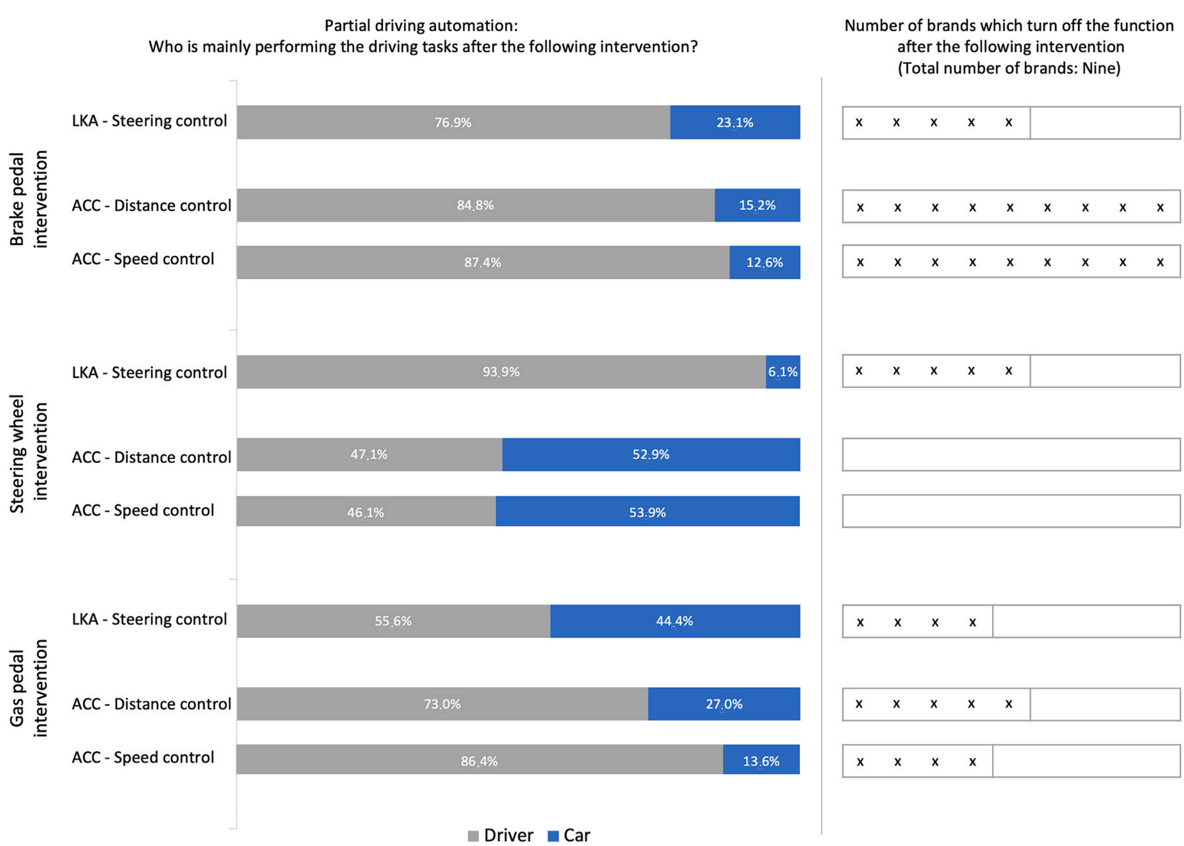

Fig. 7. Comparison mode logic between respondents' answers in partial driving automation in the study and commercial partially automated vehicles.

understanding of the driving mode can be motivated by the difficulty of following these internal state changes in automated vehicles, which has been highlighted in previous works (Flemisch et al., 2012; Lu et al., 2016). Therefore, expectations informed by different sources, ranging from previous experiences to simply incomplete mental models, can manifest as the mismatches we found in the survey.

4.4. Implications of mode transition design and driver training for safety

Recently, road incidents in which vehicles with advanced driving automation (NHTSA, 2021) have been involved led to a call for standardisation of the development of driving automation, specifically for the design of interaction patterns and feedback notifications (Reagan et al., 2021; Wansley, 2022). Our results also show a discrepancy between drivers' expectations and the intended use of designers and developers. The introduction of conditional driving automation will most likely create more confusion with more serious consequences. To enhance safety, we propose a logic in which automated features are disengaged (transition to manual) after a take-over request, similar to the regulation of lane-keeping assist off logic (UNECE, 2021), to prevent safety critical mode confusion. Several studies (Beggiato et al., 2015; Seppelt and Lee, 2019) have shown that drivers generally have difficulties in grasping the limitations of the different driving automation systems, leading to a mismatch in the mental model and unsafe usage strategies due to a lack of understanding. Further, the loss of mode awareness due to the similarity of the different automation modes has been identified as a critical factor for the successful introduction of vehicles offering several automation modes (Carsten and Martens, 2019). Therefore, it is important to design a consistent mode transition logic for drivers to understand their responsibility over the driving task at any given time and ensure a confident transition of control, no matter the preceding intervention and engaged automation mode.

In addition, it is important to improve the information provided to drivers, e.g., through educational means, to improve the mental model of control responsibilities and reduce confusion and inconsistency in drivers' expectations. Efforts to address this have been published, with the hypothesis that driver training has the potential to introduce drivers to central aspects of the human-automation interaction effectively. For example, Carney et al. (2022) have shown that additional training, as opposed to only exposure, is beneficial for a better understanding of ACC limitations. Notably, government agencies and traffic authorities explicitly recommend providing training (Campbell et al., 2018), and other research strongly suggests the positive effect of training on the drivers' mental model (Casner and Hutchins, 2019; Payre et al., 2017). However, while there are example studies on driver training incorporating a range of methods, e.g., from driving simulators to virtual reality approaches and interactive tutorials (Ebnali et al., 2019; Forster et al., 2019; Krampell et al., 2020), the driver training approach is also met with critique. Critics argue that while comprehensive training through simulations and similar means might be suitable for novice drivers in the context of driving schools, they do not address most drivers already on the roads and engaging with increasingly automated systems in their vehicles. In addition, previous research has shown that most drivers, upon collecting a new vehicle, receive none or very limited information about implemented driving automation in their vehicle (Boelhouwer et al., 2020), and very few make an effort to engage with traditional education material, e.g. reading the manuals, or have difficulties transferring the knowledge into real-life application (Oviedo-Trespalacios et al., 2021; Viktorová and Sucha, 2018). Further investigations have discussed the difficulties associated with trial-and-error learning, specifically with regard to developing an accurate understanding of driving automation (Carney et al., 2022; Harms et al., 2020; Novakazi et al., 2020). Thus, efforts have to be made to investigate alternative ways of educating drivers. For example, Feinauer et al. (2022) argue that it is important to explore different learning strategies supporting low-threshold access to support the drivers while using the vehicle in understanding its capabilities and limitations.

4.5. Limitations and further studies

The current study provides insight into the field of driving automation and mode transitions. While it has some limitations, it presents exciting opportunities for further investigation. One limitation is that the study relied on a survey as its primary methodology, which may not accurately reflect drivers' behaviour in real-world scenarios. To address this, future studies could use on-road experiments with real-time mode transition scenarios to provide more reliable and precise results. By tracking drivers' behaviour in real time and assessing their interaction with automated vehicles, results can better reveal how to promote safe driving behaviour. Future research can also use qualitative methods, such as interviews, to explore the reasons behind the mode transition logic that drivers understand. This online survey reveals expectations and possible behaviour in the current state of automation implementation. More specifically, since commercial SAE Level 3 vehicles have not been widely introduced, the study may not reflect the upcoming regulations related to SAE Level 3, such as UNECE regulation. Nevertheless, exploring drivers' expectations regarding transition logic in each scenario holds significance, especially when drivers may not fully understand the transition logic despite being provided with interface guidance or an owner's manual. Furthermore, the study did not account for learning from the interaction effect between drivers and automated vehicles. Users acquire mental models by interacting with systems (Norman, 2013). Since there are few respondents with experience in SAE Level 2 and Level 3 driving, it is unlikely that the participants in the study had set mental models of system operation through the interaction. As such, further research could investigate how drivers adapt to driving automation over time and assess how their mental model shapes as they become more familiar with the technology. This longitudinal approach could track drivers' performance over time, allowing designers to gain insights into how to promote safe driving behaviour and enhance mode awareness. Another critical aspect of automated vehicles is feedback and interface design, which can play an essential role in promoting safe driving behaviour (Kim et al., 2021). Therefore, future studies could focus on developing and testing different types of feedback and interfaces that provide clear and concise information about the current mode and limitations of the automation, thereby reducing mode ambiguity (Kim et al., Under revision). In addition, the interfaces should be designed to be easy to use and understand, enabling drivers to monitor the automated vehicle's performance and develop an accurate mental model of how it works.

5. Conclusion

This study contributes to the investigation of drivers' understanding of mode transition logic in automated vehicles. The study found that drivers do not have a dominant mental representation of mode transition logic in several scenarios. Respondents understand that they will take over the speed and distance control after brake pedal interventions and steering control after steering wheel interventions. However, there is no prevalent mode transition logic for speed and distance control after steering wheel interventions or steering control after gas pedal interventions. Drivers' expectation of control responsibilities exhibits similar tendencies in both partial and conditional driving automation. However, in higher levels of driving automation, such as conditional driving automation, there is a greater likelihood of confusion regarding control responsibilities. As illustrated in Fig. 6, drivers tend to expect the vehicle to retain control over driving tasks even after interventions in conditional driving automation, leading to a misunderstanding of driving responsibility. Notably, disparities exist between drivers' understanding and the mode change logic in current partially automated vehicles, as shown in Fig. 7. While there is alignment in brake pedal interventions between respondents' expectations and commercial partially automated vehicles' mode transition logic, a significant misalignment occurs in steering wheel interventions. In these cases, respondents expect that drivers take control over speed, distance, and steering controls while the vehicles retain the controls. Designing mode transition logic in automated vehicles considering the mental model of drivers is important in ensuring the safe and effective operation of driving automation. Interaction for driving automation should be designed to maintain mode awareness while minimising drivers' workload without providing ambiguity. Hence, designers and manufacturers need to develop the mode transition logic that should be consistent and predictable. This allows drivers to develop a mental model of how the driving automation operates, anticipate mode transitions, and understand their responsibilities regarding the driving task at any given time.

CRediT authorship contribution statement

Soyeon Kim: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Fjollë Novakazi:** Writing – review & editing, Methodology, Conceptualization. **Elmer van Grondelle:** Writing – review & editing, Methodology. **René van Egmond:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Riender Happee:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. The number of respondents in each demographic for ACC and LKA experiences

		Adaptive Cruise Control experience				Lane Keeping Assist experience			
		Yes	No	I don't know if I use it	Total	Yes	No	I don't know if I use it	Total
Age	18–29	137	101	24	262	91	156	15	262
	30–39	147	117	17	281	108	162	11	281
	40–49	76	59	6	141	42	95	4	141
	50–59	44	31	3	78	22	55	1	78
	60–69	22	31	3	56	18	38	0	56
	Over 69	9	8	3	20	4	17	0	20
		Yes	No	I don't know if I use it	Total	Yes	No	I don't know if I use it	Total
Residence country	USA	209	160	31	400	134	247	19	400
	UK	135	146	20	301	81	212	7	301
	Netherlands	37	19	2	58	23	33	2	58
	Sweden	19	5	1	25	12	12	1	25
	Germany	13	6	2	21	11	9	1	21
	Others	22	11	0	33	23	10	1	33
		Yes	No	I don't know if I use it	Total	Yes	No	I don't know if I use it	Total
Gender	Female	202	176	30	408	126	260	22	408
	Male	231	165	24	420	157	254	9	420
	Prefer not to say	1	3	2	6	1	5	0	6
	preferred to self-describe	1	3	0	4	0	4	0	4

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