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PRE PRINT

Delmas, M., Camps, V. & Lemercier, L. (2022). Effects of environmental, vehicle and human factors on comfort in partially automated driving: A scenario-based study. *Transportation Research Part F: Traffic Psychology and Behaviour, 86*. https://doi.org/10.1016/j.trf.2022.03.012

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Effects of environmental, vehicle and human factors on comfort in partially automated driving: A scenario-based study

Maxime Delmas [a, *], Valérie Camps [b] and Céline Lemercier [c]

[a, c] Cognition, Languages, Language and Ergonomics (CLLE) laboratory, University of Toulouse - Jean Jaurès, Toulouse, France

[b] Toulouse Computer Science Research Institute (IRIT), Paul Sabatier University, Toulouse, France

*Corresponding author

[a] Email: maxime.delmas@univ-tlse2.fr; Postal address: Université Toulouse - Jean Jaurès, Maison de la Recherche, 5, allées Antonio-Machado, 31058 Toulouse Cedex 9, France

[b] Email address: Valerie.Camps@irit.fr

[c] Email address: celine.lemercier@univ-tlse2.fr

Declaration of interest: none.

Abstract

Although it is key to improving acceptability, there is sparse scientific literature on the experience of humans as passengers in partially automated cars. The present study therefore investigated the influence of road type, weather conditions, traffic congestion level, vehicle speed, and human factors (e.g., trust in automated cars) on passenger comfort in an automated car classified as Level 3 according to the Society of Automotive Engineers (SAE). Participants were exposed to scenarios in which a character is driven by an SAE Level 3 automated car in different combinations of conditions (e.g., highway × heavy rain × very congested traffic × vehicle following prescribed speed). They were asked to rate their perceived comfort as if they were the protagonist. Results showed that comfort was negatively affected by driving in downtown (vs. highway), heavy rain, and congested traffic. Interaction analyses showed that reducing the speed of the vehicle improved comfort in these two last conditions, considered either individually or in combination. Cluster analysis revealed four profiles: *trusting in automation*, *averse to speed reduction*, *risk averse*, and *mistrusting automation*. These profiles were all influenced differently by the driving conditions, and corresponded to varying levels of trust in automated cars. This study suggests that optimizing comfort in automated cars should take account of both driving conditions and human profiles.

Keywords: driving automation, discomfort, drivenger, passenger, scenario

1. Introduction

Driving automation is currently a major issue for both the automotive industry and the scientific community. Its development could reduce the number of accidents, traffic congestion, and even the carbon footprint of this type of transport (Hartwitch et al., 2018). It could also extend the mobility of older people, which is a major challenge in aging societies. Higher levels of automation could also allow drivers to relax and engage in nondriving activities. These higher levels of automation will soon be available to the general public, starting with automated cars classified as Level 3 by the Society of Automotive Engineers (SAE, 2016). This level of automation will allow drivers to delegate control of the vehicle to the automated system, without the need to supervise it, although they will have to be ready to take over control if necessary. The driving activity will thus be shared over time between the vehicle and the human behind the wheel. In this context, the latter will become a *drivenger*, alternating between driver and passenger status.

The drivenger as driver has been extensively documented in the scientific literature. Peak criticality for this status occurs during the transfer of control from the automated system to the human. Owing to factors such as the loss of situational awareness, this takeover phase can prove difficult for drivers (Navarro, 2018). In addition, this inherent criticality can be exacerbated by both human and environmental factors. For instance, Li et al. (2018) showed that takeover quality is poorer for older drivers and in adverse weather conditions. Driving performance has also been shown to be impaired immediately after takeover, illustrated for instance by erratic visual exploration of the environment (Navarro, 2018).

There is therefore no shortage of research on the drivenger as driver, regarding takeover and post-takeover driving performances. By contrast, very few studies have focused on the drivenger as passenger. Nevertheless, ensuring that the latter has a positive experience is crucial to the acceptance and use of this technology (Hartwich et al., 2018). It can thus be regarded as one of the keys to ensuring that the expected benefits of driving automation can be fully realized (Banks & Stanton, 2016).

In order to understand how the drivenger's experience as a passenger could be improved, it is useful to look at the more abundant scientific literature concerning higher levels of automation, where the human is always a passenger. In this context, comfort is the most frequently studied factor (e.g., Bellem et al., 2018). According to these authors, comfort is commonly associated with a feeling of wellbeing and the attribution of a positive valence to the eliciting entity. It can also be associated with the absence of discomfort and uneasiness. Along with safety and efficiency aspects, enhanced comfort is considered by some industry experts, research providers and public authorities to be one of the main motivations for the development of automated driving (ERTRAC, 2019). A close relationship has been highlighted between comfort, trust, and acceptance of automated vehicles (Bellem et al., 2018). While both trust and acceptance are vital to the use of a system, comfort can be regarded as a potential lever of automated vehicle adoption (Bellem et al., 2018).

The most relevant approach to improving comfort during automated driving would appear to be to look at the factors that ensure passenger comfort in manually driven cars. Passenger comfort has been shown to depend mainly on the driver's driving style (Bellem et al., 2016). Transferring these results to automated driving, we can assume that it is important to identify the automated driving styles that provide the best experience for passengers (Hartwich et al., 2018). In this perspective, Beggiato et al. (2020) have for instance investigated participants' automated driving style preferences, giving them a choice between a dynamic or defensive style or a replay of their own manual driving style. Results showed that passengers felt more comfortable with a more defensive driving style, characterized by a lower speed, smoother accelerations, and earlier decelerations.

Guidelines on how automated vehicles should drive in order to ensure passenger comfort are therefore gradually emerging from the scientific literature. However, there are still many gaps that remain to be closed. First, the majority of studies investigating comfort during automated driving have focused on SAE Levels 4 and 5, with very few looking at the lower levels of automation (i.e., SAE Levels 1-3). Second, one of the main limitations of these studies is that they have not considered factors encountered in real-life driving situations, such as adverse weather conditions or traffic congestion. And yet these factors have an effect on comfort during manual driving (e.g., Beggiato et al., 2020; Faria et al., 2018), and could also have an effect on comfort during automated driving. As argued by Rossner and Bullinger (2020), factors that influence perceived safety in manual driving are also factors that influence perceived safety during highly automated driving.

The aim of the present study was thus to examine the effects of road type, weather conditions, traffic congestion level, and vehicle speed on the perception of comfort in a partially automated car. Road type, weather conditions and traffic congestion level were selected because they are known to influence driving task complexity (Fuller, 2000), and are encountered by drivers on a daily basis. Vehicle speed was selected because it is one of the main parameters of automated driving styles, and influences driving task complexity (Fuller, 2000). The present study was conducted online using a scenario-based method (see Section 2.2.1 for more details).

We also examined participants' profiles, as previous studies had shown that they can influence perceived comfort. Alongside manual driving style (e.g., Bellem et al., 2018) and trust in automated cars (Monsaingeon et al., 2020), we considered driver locus of control (Özkan & Lajunen, 2005), as this might influence the perception of comfort in automated vehicles. A driver with a high internal locus of control may not be comfortable delegating control to the vehicle, and this effect could be accentuated under unfavorable driving conditions, where control is even more important.

In summary, the main objectives of our study were to (a) investigate the impact of different driving conditions on the perception of comfort in a partially automated vehicle, and (b) examine how far this perception relies on manual driving styles, trust in automated cars, and driver locus of control.

2. Method

2.1. Participants

Participants were all French speakers, and were recruited via Facebook groups or by email (professional and personal networks). The only condition for taking part was to have a valid driver's license. Participants were not remunerated for taking part. The sample consisted of 201 participants (135 women and 66 men; M_{age} = 33.08 years, *SD* = 15.33, range = 18-82). Their mean driving experience was 13.57 years (*SD* = 14.77), 76.6% drove more than once a week, and 55.9% more than three times a week. Finally, 16.9% had already used automatic cruise control (ACC) or a lane centering system, and 7% had already used ACC coupled with a lane centering system.

2.2. Materials

2.2.1. Scenarios

2.2.1.1. Rationale

Studies focusing on comfort in autonomous cars have been based on experiments either on real roads (Bellem et al., 2016; Oliveira et al., 2019) or in a simulator (Bellem et al., 2018; Hartwich et al., 2018; Scherer et al., 2015; Siebert & Wallis, 2019; Trende et al., 2019). Using these kinds of technologies to explore how different factors may interact to affect the perception of comfort requires substantial investment in both time and money. Anderson's experimental protocol (Anderson, 1982, 1996) therefore offers a viable alternative. This methodology, based on information integration theory, allows several factors and their mutual interactions to be investigated at the same time. It relies on scenarios where participants are asked to evaluate combinations of factors, rather than individual ones. A complete factorial plan is necessary to determine the impact of each individual factor on the overall judgments, and to study all possible interactions (Anderson, 2008). Anderson's methodology has been successfully implemented and validated in various research areas (Hurgobin et al., 2020), including automated driving (Monsaingeon et al., 2020). We therefore used it in the present study to examine comfort in automated vehicles.

2.2.1.2. Scenario composition

The first names and gender of the protagonists in the scenarios were adapted to those of each participant, using common French names, so as to make it easier for participants to put themselves in the protagonists' shoes. The first names were taken from the methodology described in Monsaingeon et al. (2020). *Marie* was used for women over the age of 40 years, and *Julie* for those aged 40 or under. *Jean* was used for men over 40, and *Julien* for those aged 40 or under.

We constructed 24 written scenarios (in French), according to four within-participant factors: Type of road (highway vs. secondary vs. downtown) × Vehicle speed (prescribed speed vs. 20 km/hr below prescribed speed) × Weather conditions (clear weather vs. very rainy) × Traffic congestion level (few vehicles vs. many vehicles).

After reading each scenario (e.g., “Julien is on the **highway**. His vehicle is driving at the **prescribed speed**. The weather is **clear**. There are **few vehicles** on the road”), participants were asked the following question: “If you were Julien, how comfortable would you feel?” They indicated their responses on a 20-point scale ranging from 1 (*Not at all*) to 20 (*Absolutely*).

To avoid a number preference bias, no numbers were displayed on the response scale (Hurgobin et al., 2020). The questionnaires were developed on the Qualtrics online platform. The order of presentation of the different scenarios was randomized.

2.2.1.3. Scenario instructions

During the instruction phase, participants were asked to read each scenario of the questionnaire carefully, and to answer by taking into account all the information contained in the stories. They were informed that they would be able to modify their answers during the first (familiarization) phase, but not during the subsequent (experimental) phase. Finally, participants were told that after reading each scenario, they would have to estimate how comfortable they would be if they were the protagonist. *Being comfortable* was defined as a sense of wellbeing and the absence of uneasiness and discomfort.

The vehicle in which the story protagonist was seated was described as partially automated, that is, capable of automatically maintaining the speed and position of the vehicle on the road. However, the system might ask the driver to resume manual driving if necessary.

2.2.2. Multidimensional Driving Style Inventory (MDSI)

Participants' manual driving style was assessed using the Multidimensional Driving Style Inventory (MDSI; Taubman et al., 2004). This scale consists of 44 items relating to driving situations. These items are divided into eight factors corresponding to different driving styles (Taubman et al., 2004): dissociative driving style (8 items), anxious driving style (7 items), risky driving style (5 items), angry driving style (5 items), high-velocity driving style (6 items), distress-reduction driving style (4 items), patient driving style (4 items), and careful driving style (5 items). Participants were asked to rate how closely these situations matched their feelings, thoughts and behaviors while driving on a 6-point scale ranging from 1 (*Not at all*) to 6 (*Absolutely*).

The 44 items of the original version were translated into French by three expert researchers: two native French speakers and one English–French bilingual. Their translations were compared and a final version of the French questionnaire was agreed.

2.2.3. Traffic Locus of Control Scale (T-LOC)

Participants' type of driver locus of control was assessed using the Traffic Locus of Control Scale (T-LOC) developed by Özkan et al. (2005), and adapted to Western culture by Warner et al. (2010). It is an adaptation of the concept of locus of control (Rotter, 1966) to the field of driving.

The scale consists of 17 items, divided into four factors: other drivers (6 items), self (5 items), vehicle/ environment (3 items), and fate (3 items). Participants are asked to rate the possibility othat these 17 items had caused or would cause an accident in relation to their own driving style and conditions. Responses were expressed on a 5-point scale ranging from 1 (*Not at all possible*) to 5 (*Highly possible*).

The T-LOC was translated in French using the same method as for the MDSI.

2.3. Procedure

Participants clicked on the link they had received via social media or email, and carried out the study online without the experimenter.

The experimental procedure followed the recommendations given by Anderson (2013). The experiment began with a general description of the study and a free and informed consent form. Participants were then asked to provide their gender, age, and driving expertise (i.e., years with a driving license, frequency of car use in the past 6 months, number of miles driven in the past 6 months). Instructions were then given to participants. This step was followed by a familiarization phase featuring 12 scenarios, including the most *extreme* ones, in order to induce a wide spectrum of responses. The subsequent experimental phase comprised the full 24 scenarios. Once this phase was completed, participants were invited to complete the T-LOC and MDSI. They were then asked to indicate their level of confidence in automated cars on a scale ranging from 1 (*Low*) to 5 (*High*), and their past experience with automated driving systems (*None*, *ACC or lane centering*, *ACC and lane centering*).

2.4. Data analysis

In accordance with Anderson's methodology (Anderson, 2008), we submitted the data to an analysis of variance (ANOVA). We examined the main effects of the four factors (i.e., type of road, vehicle speed, weather conditions, and traffic congestion level) and their possible interaction effects on the perception of comfort. In cases where Mauchly's sphericity test indicated that the assumption of sphericity had been violated, and epsilon was > .75, we applied the Greenhouse-Geisser correction. Given the multiplicity of comparisons, the significance threshold was set at .001, and the Bonferroni correction was used for post hoc tests (Jafari & Ansari-Pour, 2019).

In order to highlight participants' profiles, we then performed a cluster analysis based on their comfort ratings in the different experimental conditions (see Section 3.3 for more details on clusters formation). We followed the procedure advocated by Hofmans and Mullet (2013) for data collected with Anderson's methodology, and used a nonhierarchical centroid-based method (Euclidean distances) called K-means clustering. This algorithm uses all the data points and is less susceptible to outliers than other techniques. K-means clusters are constructed so that the mean behavior of each group is distinct from that of all the other groups (MacQueen, 1967). Finally, using ANOVAs and $\chi 2$ tests, we tested the clusters for statistically significant differences in profiles. All statistical analyses were carried out using

IBM SPSS (version 25) software. All reported statistics were cross-checked for consistency with statcheck.io (Epskamp et al., 2016).

3. Results

3.1. Participants' characteristics

Participants' characteristics at the whole sample and cluster levels are summarized in Table 1.

Table 1. Participants' characteristics for the whole sample and each cluster

	Clusters				
Participants' characteristics	Cluster 1 (*n* = 51)	Cluster 2 (*n* = 29)	Cluster 3 (*n* = 75)	Cluster 4 (*n* = 46)	Total (*N* = 201)
Sex (%)					
Female	25 (49.0)	21 (72.4)	53 (70.7)	36 (78.3)	135 (67.2)
Male	26 (51.0)	8 (27.6)	22 (29.3)	10 (21.7)	66 (32.8)
Age in years (*SD*)	35.59 (17.96)	28.83 (9.83)	33.57 (15.48)	32.20 (14.55)	33.08 (15.33)
Years with driver's license (*SD*)	16.04 (16.97)	9.69 (8.82)	13.75 (15.17)	12.98 (14.35)	13.57 (14.77)
Trust in automated cars (*SD*)	3.47 (1.12)	2.66 (1.23)	2,43 (1.00)	1,74 (1.02)	2.57 (1.23)

Prior experience with ADS (%)					
None	38 (74.5)	25 (86.2)	54 (72.0)	36 (78.3)	153 (76.1)
ACC or lane centering	10 (19.6)	2 (6.9)	14 (18.7)	8 (17.4)	34 (16.9)
ACC + lane centering	3 (5.9)	2 (6.9)	7 (9.3)	2 (4.3)	14 (7.0)
Car use frequency (%)					
< Once a week	12 (23.5)	7 (24.1)	21 (28.0)	7 (15.2)	47 (23.4)
1-3 times a week	11 (21.6)	3 (10.3)	18 (24.0)	9 (19.6)	41 (20.4)
3-5 times a week	11 (21.6)	5 (17.2)	10 (13.3)	15 (32.6)	41 (20.4)
> 5 times a week	17 (33.3)	14 (48.3)	26 (34.7)	15 (32.6)	72 (35.8)
T-LOC* (*SD*)					
Other drivers	3.88 (.77)	4,07 (.54)	4,02 (.56)	4,12 (.56)	4.01 (.62)
Self	2.62 (.97)	2,48 (.97)	2,55 (.94)	2,57 (.87)	2.56 (.93)
Vehicle and environment	3.37 (.80)	3,62 (.82)	3,57 (.66)	3,52 (.76)	3.51 (.74)
Fate	2.46 (.84)	2,83 (.77)	2,78 (1.03)	2,57 (1.05)	2.66 (.96)
MDSI** (*SD*)					
Dissociative DS	1.99 (.58)	2.06 (.65)	2.02 (.69)	2.03 (.62)	2.02 (.64)
Anxious DS	2.46 (.87)	2.35 (.63)	2.50 (.73)	2.53 (.90)	2.48 (.79)
Risky DS	1.70 (.89)	1.72 (.68)	1.75 (.85)	1.56 (.67)	1.69 (.80)
Angry DS	2.50 (1.07)	2.57 (1.07)	2.49 (1.02)	2.38 (1.02)	2.48 (1.03)
High velocity DS	2.20 (.78)	2.23 (.69)	2.32 (.78)	2.21 (.89)	2.25 (.79)
Distress reduction DS	2.36 (.69)	2.52 (89)	2.38 (.85)	2.15 (.70)	2.34 (.79)
Patient DS	4.38 (.96)	4.45 (.86)	4.51 (.88)	4.52 (.99)	4.47 (.92)
Careful DS	4.81 (.74)	4.87 (.63)	4.83 (.69)	4.88 (.69)	4.84 (.69)

Note. ADS = automated driving system; ACC = automatic cruise control; T-LOC = Traffic Locus of Control Scale; MDSI = Multidimensional Driving Style Inventory; DS = driving style.
Percentages may not be equal to 100, owing to rounding.
* Ratings were given on a 5-point scale.
** Ratings were given on a 6-point scale.

3.2. Analyses conducted on the whole sample

We ran a 3 (type of road: highway vs. secondary vs. downtown) × 2 (weather conditions: clear weather vs. very rainy) × 2 (traffic congestion level: few vehicles vs. many vehicles) × 2 (vehicle speed: prescribed speed vs. 20 km/hr below prescribed speed) ANOVA on comfort ratings.

Three of the main effects were significant:

(1) Type of road, $F(1.56, 199) = 8.73$, $p < .001$, $\eta^2_p = .04$. Pairwise comparisons were conducted to examine differences between types of road. Comfort was higher in the highway condition than in the downtown one (see Table 2).

(2) Weather conditions, $F(1, 200) = 172.95$, $p < .001$, $\eta^2_p = .46$. Comfort was higher for the clear weather condition than for the very rainy one (see Table 2).

(3) Traffic congestion, $F(1, 200) = 166.03$, $p < .001$, $\eta^2_p = .45$. Comfort was higher when there were few vehicles rather than many (see Table 2).

No significant main effect of vehicle speed was found.

Table 2. Mean (standard deviation) comfort ratings reported by the whole sample according to type of road, weather conditions, and traffic congestion level

Factor	*M* (*SD*)

Type of road	
Highway*	10.41 (4.39)
Secondary	10.22 (4.23)
Downtown*	9.83 (4.55)
Weather conditions	
Clear	11.76 (4.37)
Very rainy	8.55 (4.78)
Traffic congestion level	
Few vehicles	11.19 (4.22)
Many vehicles	9.11 (4.55)

Note. * $p < .001$.

Three two-way interaction effects and one three-way interaction effect were significant.

(1) Between type of road and weather conditions, $F(2, 195) = 13.70$, $p < .001$, $\eta^2_p = .06$. When the weather conditions were clear, comfort ratings were lower for downtown than for highway or secondary. However, when the weather was very rainy, comfort ratings did not differ between types of road (see Table 3).

Table 3. Effect of Type of road x Weather conditions interaction on mean comfort ratings and standard errors

Factor		*M*	*SE*
Type of road	*Weather condition*		
Highway	**Clear weather**	12.2	.32
	Very rainy	8.62	.35
Secondary	**Clear weather**	11.87	.31
	Very rainy	8.56	.34
Downtown	**Clear weather**	11.21	.33
	Very rainy	8.46	.35

(2) Between weather conditions and vehicle speed, $F(1, 197) = 44.43$, $p < .001$, $\eta^2_p = .18$. When the weather conditions were clear, comfort ratings were higher if the vehicle was driving at the prescribed speed. However, when the weather was very rainy, comfort ratings were higher if the vehicle was driving at 20 km/hr below the prescribed speed (see Table 4).

Table 4. Interaction between weather conditions and speed on mean comfort ratings and standard errors

Factors		*M*	*SE*
Weather conditions	*Speed*		
Clear weather	**Speed limit**	12.28	.35
	20 km/hr below speed limit	11.24	.34
Very rainy	**Speed limit**	8.00	.35
	20 km/hr below speed limit	9.09	.36

(3) Between traffic congestion level and vehicle speed, $F(1, 197) = 33.68$, $p < .001$, $\eta^2_p = .14$. When there were few vehicles on the road, comfort ratings were higher if the vehicle drove at the prescribed speed. However, when there were many vehicles on the road, comfort ratings were higher if the vehicle drove at 20 km/hr below the prescribed speed (see Table 5).

Table 5. Effect of Traffic congestion level x Speed interaction on mean comfort ratings and standard errors

Factors	*M*	*SE*

Traffic congestion level	*Speed*		
Few vehicles	**Speed limit**	11.5	.33
	20 km/hr below speed limit	10.9	.32
Many vehicles	**Speed limit**	8.78	.34
	20 km/hr below speed limit	9.45	.34

(4) Between weather conditions, traffic congestion level and vehicle speed, $F(1, 193) = 11.66$, $p < .001$, $\eta^2_p = .06$. When the weather conditions were clear and there were few vehicles on the road, comfort ratings were higher if the vehicle drove at the prescribed speed. However, if the weather was very rainy with many vehicles on the road, comfort ratings were higher if the vehicle drove at 20 km/hr below the prescribed speed (see Table 6).

Table 6. Effect of Weather conditions x Traffic congestion level x Speed interaction on mean comfort ratings and standard errors

Factors	*M*	*SE*

Weather conditions	*Traffic congestion level*	*Speed*		
Clear weather	**Few vehicle**	**Speed limit**	13.97	.35
		20 km/hr below speed limit	11.99	.39
	Many vehicles	**Speed limit**	10.59	.39
		20 km/hr below speed limit	10.49	.37
Very rainy	**Few vehicles**	**Speed limit**	9.03	.37
		20 km/hr below speed limit	9.78	.38
	Many vehicles	**Speed limit**	6.97	.35
		20 km/hr below speed limit	8.41	.38

3.3. Cluster analyses

The cluster analysis yielded two- and four-cluster solutions. After analysis, the differences in responses for the two-cluster solution were smaller than the differences in responses for the four-cluster one. We therefore opted for the latter, in order to have four very distinctive response profiles. Analysis showed a link between trust in automated cars and cluster formation, $F(3, 197) = 21.71$, $p < .001$, $\eta^2_p = .25$. No other profile factors were related to cluster formation. On each cluster, we ran the same analyses we had applied to the whole sample: Type of road × Weather conditions × Traffic congestion level × Vehicle speed ANOVAs. Means and standard deviations for each condition at cluster level are summarized in Table 7.

Table 7. Mean comfort rating means and standard deviations (in parenthesis) for each cluster, regarding type of road, weather conditions, traffic congestion level, and vehicle speed

	Clusters			
	Cluster 1 (n = 51)	Cluster 2 (n = 29)	Cluster 3 (n = 75)	Cluster 4 (n = 46)
Factors	M (SD)	M (SD)	M (SD)	M (SD)
Type of road				
Highway	15.67 (2.10)	10.28 (1.73)	10.56 (1.97)	4.42 (2.16)
Secondary	15.25 (2.39)	10.63 (1.59)	10.05 (1.80)	4.64 (2.34)
Downtown	15.47 (2.05)	10.28 (1.73)	9.38 (2,39)	3.98 (2.24)
Weather conditions				
Clear weather	16.14 (2.20)	11.03 (1.45)	12.79 (2.28)	5.69 (2.84)
Very rainy	14.78 (2.52)	9.84 (2.07)	7.20 (2.44)	3.00 (1.52)
Traffic congestion level				
Few vehicles	16.03 (2.14)	10.95 (1.32)	11.52 (1.80)	5.44 (2.70)
Many vehicle	14.90 (2.36)	9.92 (1.72)	8.47 (2.04)	3.26 (1.70)
Vehicle speed				
Prescribed speed	15.52 (2.47)	12.33 (2.50)	9.33 (1.62)	4.11 (2.05)
20 km/hr below prescribed speed	15.40 (2.31)	8.53 (2.67)	10.66 (1.93)	4.59 (2.30)

3.3.1. Cluster 1: Trusting in automation

The first cluster was called *trusting in automation*, as its members had the highest level of trust in automated cars (M = 3.47, SD = 1.12). Additionally, they expressed a very high overall level of comfort (*M* = 15.45, *SD* = 2.02). Mean comfort ratings were the highest when driving on the highway, with clear weather, few vehicles and at the prescribed speed (max = 18.49), and remained positive even for the lowest ratings, when driving on secondary roads, with very rainy weather, many vehicles and at the prescribed speed (min. = 12.47).

According to the effect sizes, the order of importance of the factors was as follows for this cluster: (1) traffic congestion, $F(1, 50) = 16.28$, $p < .001$, $\eta^2_p = .25$, and (2) weather conditions, $F(1, 50) = 15.35$, $p < .001$, $\eta^2_p = .24$. Mean comfort ratings were higher when (1) there were few vehicles on the road, and (2) Weather conditions were clear. Type of road and vehicle speed had no significant effect for this cluster.

Analysis revealed two interactions between factors for this cluster. Weather conditions interacted with vehicle speed, $F(1, 47) = 23.80$, $p < .001$, $\eta^2_p = .32$. When weather conditions were clear, mean comfort ratings were higher if the vehicle was driving at the prescribed speed. By contrast, when the weather was very rainy, mean comfort ratings were higher if the vehicle drove 20 km/hr below the prescribed speed. Traffic congestion also interacted with vehicle speed, $F(1, 47) = 17.56$, $p < .001$, $\eta^2_p = .26$, following the same logic. When there were few vehicles on the road, mean comfort ratings were higher if the car was driving at the prescribed speed. By contrast, when there were many vehicles on the road, mean comfort ratings were higher if the car was driving 20 km/hr below the prescribed speed.

3.3.2. Cluster 2: Averse to speed reduction

The second cluster was called *averse to reduced speed*. Members of this cluster expressed their highest level of comfort when driving on the highway, with clear weather, with few vehicles, and at the prescribed speed (max. = 16.93). They expressed the lowest level of comfort if, in the same conditions, the car was driving at 20 km/hr below the prescribed speed (min. = 6.10). Their overall mean comfort rating was moderate (*M* = 10.43, *SD* = 1.25), as was their trust in automated cars (*M* = 2.66, *SD* = 1.23).

According to the effect sizes, the only important factor for this cluster was vehicle speed, $F(1, 28) = 20.38$, $p < .001$, $\eta^2_p = .42$. Mean comfort ratings were higher when the vehicle speed was 20 km/hr below the prescribed speed. Type of road, weather conditions and traffic congestion level had no significant effect for this cluster.

Analysis revealed two interactions for this cluster. Weather conditions interacted with vehicle speed, $F(1, 25) = 46.49$, $p < .001$, $\eta^2_p = .62$. When weather conditions were clear, mean comfort ratings were higher if the vehicle drove at the prescribed speed. However, when the weather was very rainy, there was no difference in mean comfort ratings between the two vehicle speed conditions. Traffic congestion also interacted with vehicle speed, $F(1, 25) = 20.73$, $p < .001$, $\eta^2_p = .43$. When the car was driving at the prescribed speed, mean comfort ratings were higher if there were few vehicles. However, when the car was driving 20 km/hr below the prescribed speed, mean comfort ratings were higher if there were many vehicles.

3.3.3. Cluster 3: Risk averse

The third cluster was called *risk averse*, and contained the most participants (*n* = 75). The latter displayed their highest level of comfort when driving on the highway with clear weather, with few vehicles on the road, and at reduced speed (max. = 15.89). By the same token, they displayed the lowest level of comfort when driving downtown with very rainy weather, with many vehicles on the road and at the prescribed speed (Min = 5.11). Their overall mean comfort rating was moderate (*M* = 10.00, *SD* = 1.49), as was their trust in automated cars (*M* = 2.43, *SD* = 1.00).

According to the effect sizes, the order of importance of the factors was as follows for this cluster: (1) weather conditions, $F(1, 74) = 174.13$, $p < .001$, $\eta^2_p = .70$, (2) traffic congestion level, $F(1, 74) = 119.76$, $p < .001$, $\eta^2_p = .62$, and (3) vehicle speed, $F(1, 74) = 35.35$, $p < .001$, $\eta^2_p = .32$. Mean comfort ratings were higher when (1) Weather conditions were clear, (2) there were few vehicles on the road, and (3) vehicle speed was 20 km/hr below the prescribed speed. Type of road had no significant effect for this cluster. Analysis revealed no interaction effects.

3.3.4. Cluster 4: Mistrusting automation

The fourth cluster was called *mistrusting automation*, as its members had the lowest level of trust in automated cars (*M* = 1.74, *SD* = 1.02). In addition, they expressed a very low overall level of comfort (*M* = 4.35, *SD* = 2.04). Moreover, they felt uncomfortable even in their favorite conditions, namely on the highway, with clear weather, few vehicles on the road, and at the prescribed speed (max. = 8.11). They expressed the lowest level of comfort when driving on the highway, with very rainy weather, with many vehicles, and at the prescribed speed (*M* = 2.04).

According to the effect sizes, the order of importance of the factors was as follows for this cluster: (1) weather conditions, $F(1, 45) = 78.3$, $p < .001$, $\eta^2_p = .64$, and (2) traffic congestion level, $F(1, 45) = 57.45$, $p < .001$, $\eta^2_p = .56$. Mean comfort ratings were higher when (1) Weather conditions were clear and (2) there were few vehicles on the road. Type of road and vehicle speed had no significant effect for this cluster. Analysis revealed no interaction effects.

4. Discussion

In the present study, we evaluated the impact of different driving conditions on the perceived comfort of a passenger in a partially automated car. We used scenarios in which we manipulated the type of road, weather conditions, traffic congestion level, and vehicle speed.

Our first goal was to determine whether these driving conditions influenced perceived comfort. At the whole sample level, results showed that perceived comfort in SAE Level 3 automated cars could be influenced by driving conditions that bring an increased risk of critical events (e.g., crowded downtown, reduced visibility and control in heavy rain, proximity to other road users in dense traffic). However, interaction analyses revealed that reducing vehicle speed could moderate the negative individual and joint influences of heavy rain and the presence of many vehicles on the road. These results can be viewed through the prism of the task-capability interface (TCI) model of the driving process (Fuller, 2000). Although this model was developed in the context of manual driving, it could also apply to partial automation, where the drivenger has to switch between manual and automated driving. According to the TCI model, speed adaptations allow drivers to reduce the difficulty of the driving task when facing high task demands or impaired capabilities (e.g., reduced visibility), and hence maintain as low a level of crash risk as possible. However, automated systems with rigid driving styles (e.g., always following the prescribed speed) do not take these variations into account. The resulting dissonance between drivers' capabilities and task demands could thus lead to a feeling of discomfort, owing to an increase in perceived risk. Fuller (2000) argued that this discomfort increases as drivers approach the point at which they will no longer be able to meet the task demands. In the context of partially automated cars, drivers may have to take over control of the vehicle in situations that exceed their capabilities (e.g., takeover at high speed with adverse weather conditions), which may lead to anxious anticipation, and perhaps explain the poor takeover performances highlighted in previous studies (Gold et al., 2016; Li et al., 2018).

Cluster analysis revealed four behavioral profiles, showing that the influence of driving conditions was not homogeneous. Two of the clusters were exact opposites, with participants in one of them expressing comfort no matter what (*trusting in automation*), and participants in the other one expressing discomfort no matter what (*mistrusting automation*). The two remaining clusters were opposed on their appreciation of vehicle speed, with one of them expressing very low comfort if the vehicle drove at a reduced speed in favorable driving conditions (*averse to speed reduction*), and the other feeling more comfortable with the reduced speed in every condition (*risk averse*). Overall, the comfort of 85.57% of the participants was negatively influenced (with large effect sizes) by adverse driving conditions. For 73.26% of these, however, this effect was lessened by reducing the speed of the vehicle.

The second goal of this study was to determine whether individual factors influenced perceived comfort. Cluster analyses revealed an effect of trust in automated cars, with a high level of trust for the *trusting in automation* cluster, medium levels for both the *averse to speed reduction* and *risk averse* clusters, and a low level for the *mistrusting automation* cluster.

Previous findings (i.e., Bellem et al., 2018) had suggested that manual driving styles have an effect on perceived comfort in automated driving, but this was not the case in the present study. For example, we might have been expected individuals in the *Averse to speed reduction* cluster to have higher scores in the high-velocity driving style than the rest of the sample had. The absence of any such results can be explained by participants overestimating their adaptive driving behaviors (e.g., patient driving style), and underestimating their maladaptive driving behaviors (e.g., high-velocity driving style), leading to only minor variations across the sample. Similarly, driver locus of control proved to have no influence in this study. This may be because the T-LOC questionnaire failed to capture part of the experience of being a passenger in a vehicle. Five of the items in this questionnaire are dedicated to the *self* dimension, but this concerns the respondent as an active driver. It would be useful to develop a specific drivenger locus of control questionnaire, to consider the alternating status of the human behind the wheel of a partially automated vehicle.

The present study is a new step towards understanding the variables that influence comfort in automated vehicles. Yet, these results need to be interpreted in consideration of a few methodological limitations. First, this study is based on written scenarios. Further studies should thus replicate these findings in simulator and real road studies. In fact, participants might for instance experience more discomfort when facing critical events in real driving conditions. Another limitation of the present study is the fact that most participants had no experience with automated driving systems (ADS). However, previous studies have shown that familiarity with ADS has a significant effect on trust with these systems (e.g., Oliveira et al., 2019). The same type of effect could therefore be observed with comfort. Finally, the scenarios described in this study were quite general regarding the details of the different situations. This was an intentional choice, as it allowed for a specific focus on the effect of the variables of interest without adding too much noise. Yet, this is also a limitation as comfort might change dynamically in the presence of these variables. For instance, participants may experience discomfort peaks when the ego-vehicle comes close to other vehicles, or due to stop & go in heavy traffic. Further studies replicating these findings on simulator or on-road could use a continuous comfort assessment method, such as pressing more or less hard on a handset control (e.g., Beggiato et al., 2020).

5. Conclusion

In conclusion, our results suggest that driving conditions have an effect on passenger comfort during partially automated driving. They also suggest that adapting the speed of the automated vehicle in unfavorable driving conditions would help to reduce the resulting discomfort for most individuals. Trust in automated cars has been highlighted as a key factor when trying to improve comfort in SAE Level 3 automated cars. Future studies should also investigate the influence of speed adaptation on the drivenger's experience and takeover performance during partially automated driving. They should also consider the experience of the drivenger in greater depth. In addition to comfort, other facets of the drivenger's experience deserve to be explored, such as anxiety and enjoyment. Finally, in line with Monsaingeon et al. (2020), the present study confirms the relevance of using a scenario-based methodology in the context of driving automation, and extends it to the study of comfort in partially automated cars.

Author contributions

The authors confirm contribution to the paper as follows:

Maxime Delmas: conceptualization, methodology, software, formal analysis, investigation, resources, writing - original draft.

Valérie Camps and Céline Lemercier: supervision, funding acquisition, conceptualization, methodology, resources, writing - original draft.

All authors reviewed the results and approved the final version of the manuscript.

Funding

The present work was funded by Occitanie Regional Council (France), and the neOCampus project (Paul Sabatier University, Toulouse, France).

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