Level of Automated Car Feedback on Regulatory Compliance

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Abstract

Car accidents as prevalent cause of deaths and injuries present a need to develop new technologies as support for drivers. Automation and more specifically automated feedback is one of them. This study examined the impact of levels within automated feedback on regulatory speed and headway distance compliance based on the four-stage information processing model proposed by Parasuraman (Ramanathan Parthasarthy et al., 2021). Speed and headway distance were measured while participants (N = 29) drove the same route in four different conditions, each implementing a different automated feedback level (control, information, assessment and decision). A repeated measures ANOVA showed no significant results and therefore no evidence for difference in behavior of speed and headway distance compliance. Due to several limitations future research addressing the relationship between compliance and feedback, while considering possible mediators, is needed to clarify and elaborate on those findings.

Level of Automated Car Feedback on Regulatory Compliance

Regulatory compliance, which can be defined as conforming to laws and regulations, is supposed to ensure traffic safety by regulating traffic scenarios and instructing car drivers to adhere to guidelines (Ramanathan Parthasarthy et al., 2021). Still, car accidents are a prevalent cause of death and injuries, oftentimes traced back to drivers showing little regulatory compliance (Thomas et al., 1990). Reasons for non-compliance are endless but generally causes of car accidents can be divided into three main categories including interpretation errors, observation errors and planning errors (Thomas et al., 1990). Exceeding speed limits and disregarding distance to the car ahead by engaging in behaviors like tailgating represent some of the most prevalent ones (De Pauw et al., 2014).

Available data on traffic accidents could be reason enough for many to have inhibited interest in driving. Nonetheless, the car industry successfully promotes their cars by offering endless gadgets and features one can possibly think of from bioweapon defense filters and integrated karaoke systems to streaming and video game applications (Mayo & Kay, 2022). Still, more and more people pick up on the many downsides connected to driving. Some of them being the environmental impact that cars have, and risks connected to participating in daily traffic (Joireman et al., 2004). Those concerns and needs regarding traffic safety have led the car industry to push for technological advancements covering aspects of car automation which support or even replace the drivers’ information processing steps.

Automation can be defined as partial or full replacement of actions which initially have been carried out by a person (Parasuraman et al., 2000). The higher the level of automation, the more information processing and execution is done by the car instead of the driver. Previous research suggests that automation can increase situational awareness and therefore compliance (Weaver et al., 2020), which in turn could pose a solution to the previously mentioned concerns.

To understand how the level of automation and human errors, possibly leading to traffic accidents, are connected, Parasuraman et al. (2000) proposes a simple four-stage model of human information processing. The model divides information processing applied to automation into four steps, narrowing down the process of each section and defining the stages ‘Sensory processing’, ‘Perception/working memory’, ‘Decision making’ and ‘Response selection’. Sensory processing refers to the step of information acquisition and describes the process where the vehicle collects and filters out important information from the environment which it will then present. Perception/working memory is referred to as Information analysis and describes the vehicles’ ability to use the first acquired data to summarize is and make predictions by using an algorithm. In the third stage Decision making, referred to as Decision selection, the vehicle proposes available and suitable choices which are based on the previously collected and processed data. The fourth stage Response selection refers to Action implementation, where the vehicle carries out one of the previously proposed actions and therefore replaces the human in that aspect completely.

Feedback is considered to be an important part of car automation since it replaces steps of the information processing on stimuli inside and outside the car. Studies have shown that factors which are related to the driver have the highest impact on traffic accidents, two of them being speeding behavior and lack of knowledge to which headway distance can be assigned to (Martins & Garcez, 2021). Research suggests that automated feedback leads to an increase of regulation compliance like adhering to speed limits (Chen & Donmez, 2022) which suggests that feedback can provide a solution to the risks of traffic. A study by Feng and Donmez (2013) presented possible explanations for those results, stating that automated feedback helps to decrease the drivers’ mental workload and therefore increase traffic safety.

Considerable research has been done on the effects of fully autonomous cars and effects of general car automation on behavior (Mahmoud et al., 2022). However, barely any research has been conducted exploring whether the effects of information processing steps within automated feedback differ, and therefore need to be distinguished in their effects on traffic safety. Based on recent findings (Chen & Donmez, 2022) one may argue that higher level of automated feedback leads to higher regulation compliance, considering that the driver is presented with a more limited choice of actions, meaning the mental workload decreases (Walker et al., 2001). Further, higher levels of information processing within the feedback could increase the sense of moral obligation by posing a direct request instead of presenting sole information (Sutinen & Kuperan, 1999).

This research will focus on regulatory compliance as an indicator for traffic safety, considering that traffic regulations and laws are meant to ensure highest traffic safety and thereby obeying them should suggest lowest risk for accidents. This study investigates two behaviors belonging to regulatory compliance: speed and headway distance. Both have been found to be very influential in traffic accidents and therefore important predictors of traffic safety (Martins & Garcez, 2021). Speed is considered to be a main contributing factor to accidents which makes it a good measure for regulatory compliance (Yao et al., 2019). According to Ding et al. (2020) rear-end crashes were found to be the most prevalent accident type, suggesting headway distance to be a good predictor of road safety.

Being able to predict which level of automated feedback increases regulatory compliance most, contributes to a better understanding of driving behavior and therefore might have implications for increasing traffic safety. Consequently, the purpose of this research is to answer the question whether the effect of automated feedback on regulatory compliance differs between the different steps of the information processing model. In order to address the question two hypotheses will be introduced:

<u>*Hypothesis 1:*</u> *The higher the level of automated car feedback, the stronger regulatory compliance to speed will be.*

<u>*Hypothesis 2:*</u> *The higher the level of automated car feedback, the stronger regulatory compliance of distance to the car ahead will be.*

Method

Participants

In total the sample included 29 participants, which were recruited from SONA participant pools and by word of mouth. The inclusion criteria were language proficiency in English or Dutch, age minimum of 18 years or older, and having a valid driver's license. The final sample consisted of 29 participants. Of these participants 48,28% (N = 14) identified as men and 51,72% (N = 15) identified as women. The average age of the participants was 33,5 years with a standard deviation of 17,58. Moreover, the mean age for women was 26,6 and the mean age for men was 41. On average the participants drove between 1000 and 5000 kilometres per year and had their driver’s license for an average of 14,17 years.

Procedure

The research conducted at a facility of the University of Groningen, used an experimental within-subjects design with four conditions in which four different levels of automated feedback were manipulated. In each of the manipulated conditions, the participants got feedback on their speed and on their distance to the car in front them, which constituted our two independent variables. Speed was measured on eleven sections throughout the route: Two scenarios with a speed limit of 80 km/h (Section 1 and 2), two scenarios where the speed limit was 80 km/h and a car was driving ahead (Section 3 and 4), a section where the speed limit was 60 km/h and the road was more narrow than before (Section 5), two scenarios with a speed limit of 50 km/h through the city (Section 6 and 7), a scenario leaving the city with a speed limit of 80 km/h (section 8), a scenario leading to the highway with a speed limit of 100 km/h (section 9), a section on the highway with a speed limit of 100 km/h and a car ahead and last a section on the highway with no car ahead and a speed limit of 100 km/h.

Upon arrival the participants were informed about the goal and the procedure of the experiment and were required to sign a consent form before filling in a questionnaire. The questionnaire asked the participants about their demographics and their driving experience. Participants were then asked to answer questions regarding their driving ability. Then, participants were asked about their affinity with technology and attitudes towards automation in driving and advanced driver assistance systems. The questionnaire, which took around 7 minutes, was available both in English and Dutch. Next, participants were introduced to the driving simulator, while measuring the speed and headway distance in the different traffic scenarios. The two main variables measured were speed (km/h) and time headway (s) as measure for headway distance. The participants did a short test drive of 10 minutes to familiarize themselves with both the setting and simulator, before completing an approximately 10-minute-long route 5 times. Meanwhile participants received automated feedback under different levels of automation each time. In the “Information acquisition” condition participants got feedback on their exact speed and distance to car ahead. In the “Information analysis” condition no information about the values of speed and distance were provided, only a visual assessment (thumbs up or thumbs down) of compliance to regulations was presented. In the “Decision selection” condition, written suggestions were presented, implying to either maintain speed and distance or decrease speed and increase distance. The feedback design for each condition was chosen based on a small questionnaire which gathered preferences about different types of visual representations. The experiment lasted on average 90 minutes in total and was conducted over the course of three weeks and allowed the participant to enter a lottery with a price of 25 euros or granted SONA credits for participants that were recruited from the SONA pool.

Measures

Speed Compliance

Each participants' speed was measured for each condition eleven times throughout the route. Then the speed compliance variable was computed by subtracting the actual speed from the speed limit from all eleven sections for each condition. Resulting with negative values for participants that drove faster than the speed limit and a value of zero or higher for participants that drove as fast as the speed limit indicated or slower. Implementing all values from the eleven sections, a mean speed compliance variable was created per condition.

Distance Headway Compliance

In order to measure the 'distance to car ahead' compliance, the study measured the minimum time headway (MTHW) in seconds before the participants' car would impact the car ahead. This was recorded at section three, four and eleven of the route, since those were the only sections in the simulation, which presented a car ahead. From those three sections an average MTHW was calculated and used for further analysis. A standard value in traffic for headway distance is considered to be 2 seconds (Taieb-Maimon & Shinar, 2001) which was used to create a compliance variable by subtracting the actual time headway from the normative time headway (2 seconds) for each condition. The increase of headway distance compliance is represented by the increase of measured time starting and including zero, whereas negative values represent noncompliance to the normative distance.

Results

In order to test the hypothesis "The higher the level of automated feedback, the higher regulatory compliance on speed will be." an omnibus ANOVA f-test was used. As shown in Table 1, in the control condition the variable 'Speed compliance' had a mean of 4.45 (*SD* =

4.12) with a minimum of -7.0 and a maximum of 13 showing that most participants drove 4.45 km/h slower than the speed limit allowed. In the information condition of ‘Speed compliance’ participants on average drove slightly faster than in the previous condition with a mean of 4.35 (*SD* = 4.58), a minimum of -5.48 and a maximum of 13.53. In the assessment condition participants drove slightly slower than in both previous conditions with a mean of 4.91 (*SD* = 4.50), minimum of -5.29 and a maximum of 17.65 and in the decision condition participants drove slowest on average compared to all other conditions with a mean of 5.56 (*SD* = 4.34), a minimum of -,25 and a maximum of 15.33.

Table 1

Descriptive Statistics for speed compliance

	N	Minimum	Maximum	Mean	Std. Deviation
Control	29	-7.00	13.00	4.45	4.12
Information	29	-5.48	13.53	4.35	4.58
Assessment	29	-5.29	17.65	4.91	4.50
Decision	29	-.25	15.33	5.56	4.34

The variables “Control”, “information” and “Assessment” were normally distributed contrary to the condition ‘Decision’, which did not meet the assumption of normality. Further, no evidence was found that the assumption of sphericity was violated ($X^2(5) = 3.19$, $p = .67$). To test the effect of different information processing steps in automated car feedback on speed compliance, a repeated measures ANOVA was performed. There was no significant difference in speed compliance for the different levels of automated car feedback found ($F(3,84) = 1.66$, $p = .181$).

Figure 1

Descriptive plot of Repeated Measures ANOVA analysis for speed compliance

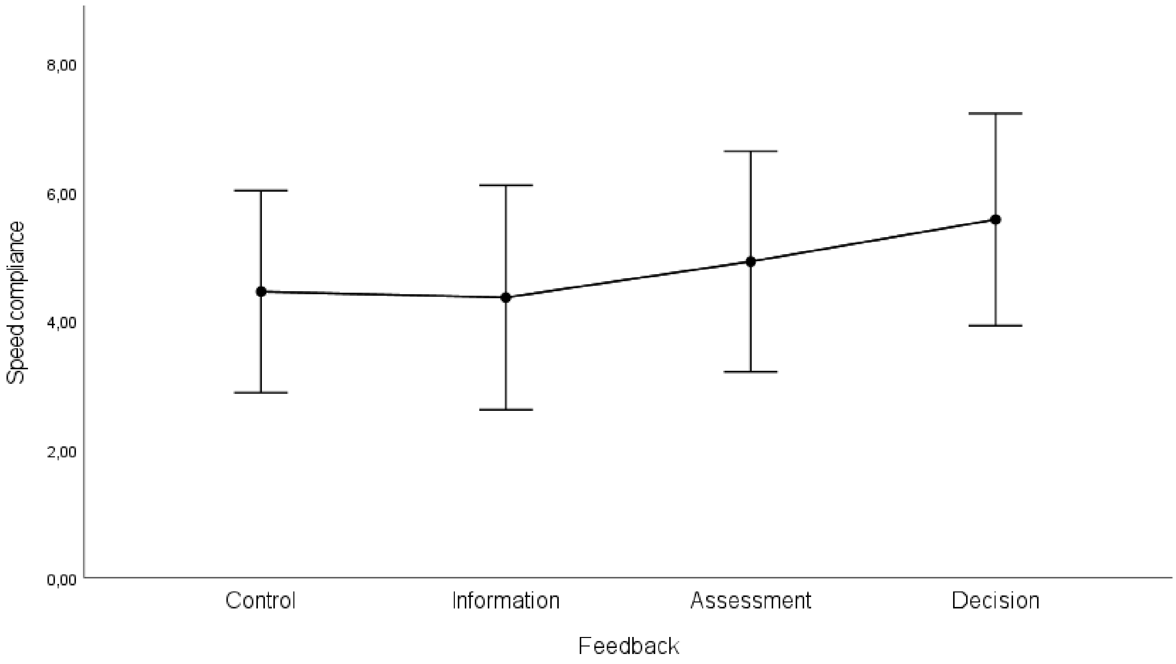

Table 2

Tests of Within-Subjects Effects for speed compliance

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
automation	Sphericity Assumed	26.68	3	8.89	1.66	.18

To test the hypothesis "the higher the level of automated feedback, the higher the regulatory compliance to headway distance will be" the omnibus ANOVA f-test was used. For the variable headway distance compliance only 26 participants were included, since three out of the 29 were not suitable. As table 3 shows, the control condition for headway distance compliance had a mean of 1.2 (*SD* = .72) a minimum of -.62 and a maximum of 1.76. The information condition had a mean lower than in the previous conditions of 1.15 (*SD* = .46) a minimum of -.46 and a maximum of 1.78, the assessment condition had a mean again lower than the two previous conditions of 1.08 (*SD* = .39) with a minimum of .34 and a maximum of 1.75 and the decision condition a mean of 1.11 (*SD* = .34) with a minimum of .00 and a maximum of 1.64 with a slight increase in mean compared to the assessment condition.

Table 3
Descriptive Statistics for headway distance compliance

	N	Minimum	Maximum	Mean	Std. Deviation
Control	26	-.62	1.76	1.20	.72
Information	26	-.46	1.78	1.15	.46
Assessment	26	.34	1.75	1.08	.39
Decision	26	.00	1.64	1.11	.34

Only the “assessment” condition was normally distributed. Additionally, Mauchly’s test of sphericity showed evidence for a violation of the assumption of sphericity ($X^2(5)$ = 11.86, p = .04). In order to account for the violation of sphericity, the Greenhouse-Geisser correction was used for further analyses. Results showed no significant effects for the different levels of automated feedback on headway distance compliance ($F(2.37,59.16)$ = .60, p = .58).

Figure 2

Descriptive plot of Repeated Measures ANOVA for headway distance compliance

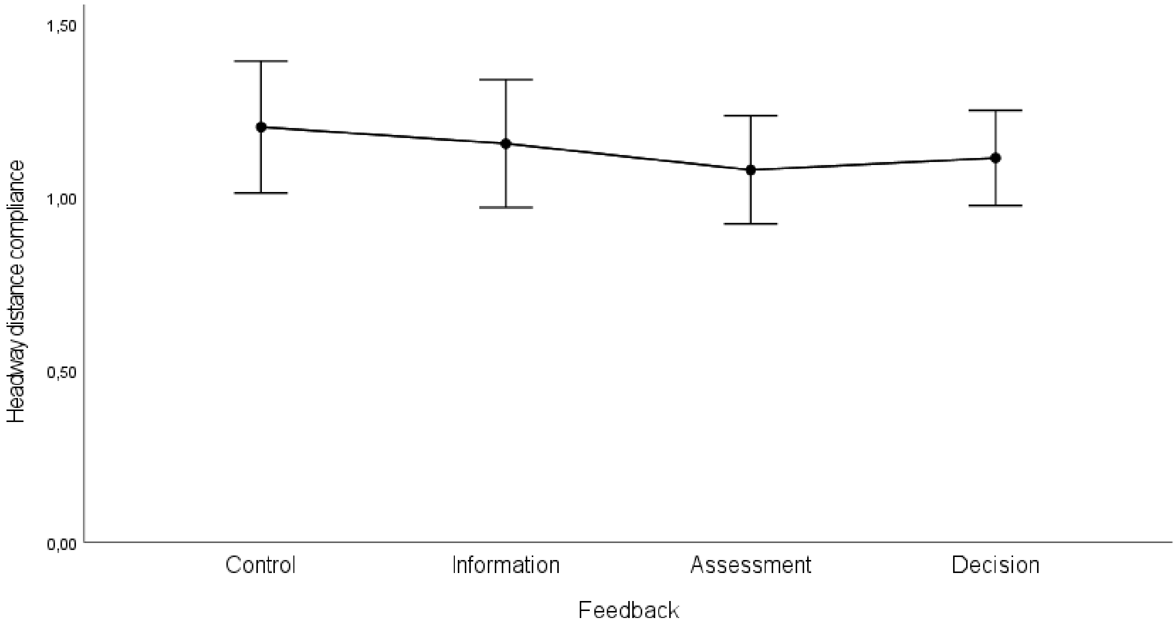

Table 4

Tests of Within-Subjects Effects for headway distance compliance

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
automation	Sphericity Assumed	.22	3	.08	.60	.62
	Greenhouse-Geisser	.22	2.37	.10	.60	.58

Discussion

How to improve traffic safety, ensure smooth traffic flow and thereby decrease death and injury rates is a question which becomes more and more pressing with the constant advancements in technology and increasing demand for cars additionally to the increase in worldwide population. With the multitude of offers for automized features in cars the logic question follows, which level of automation and therefore to which extent replacement of human action is most beneficial and finally safest. This study focused on speed and headway distance both in regard to compliance, being two important contributing factors for car accidents (Thomas et al., 1990). Consequently, this study was designed to answer the question whether higher levels of information processing within automated car feedback lead to higher regulatory compliance regarding speed and headway distance.

When looking at the descriptive statistics of speed compliance, a trend can be observed which suggests stronger speed compliance in relation to higher level of automated car feedback. This is in line with the theory that direct requests pose a stronger sense of moral obligation (Sutinen & Kuperan, 1999), which in turn might lead to increased compliance as suggested by the results of this study. Further, for the condition “Decision” the assumption of normality was violated. Since an ANOVA is quite robust to the violation of normality which would usually increase the risk of type 1 error, the analysis was still conducted. When considering the main analysis, no significant differences in the means of the four levels of automation (control, information, assessment, decision) regarding ‘Speed compliance’ were found, suggesting the contradiction of the first hypothesis. Therefore, the violation of normality did not affect the final conclusion drawn from the results.

For the variable headway distance compliance, a trend can be observed (Table 3) which shows that the range of values becomes narrower with the increase of information processing in the automated feedback. Further, the graph visualizes a weak trend showing that headway distance compliance decreased when the level of information processing within the feedback increased, opposing the second hypothesis. This finding, even when non-significant, is supported by a study which found that drivers engaged in more risky behavior when feedback was provided for those (Jermakian et al., 2017). A possible explanation is the drivers’ feeling of alleged increase of control over the situation.

The conditions “Control”, “Information” and “Decision” violated the assumption of normality but as well as for the variable speed compliance, here the ANOVA analysis was still conducted due to its’ robustness for the type 1 error. Since there was evidence for a violation of sphericity, the Greenhouse-Geisser correction was used, which finally did not have an effect on the conclusion equally as the violation of normality, since the results were non-significant. The repeated measures ANOVA showed no significant results, suggesting no evidence for the effect of automated feedback on compliance behavior between the different stages of the information processing model and therefore rejecting the second hypothesis.

The non-significant findings regarding speed and headway distance compliance are in line with several other studies, showing no significant effect of automated feedback on risky driving behavior like tailgating (headway distance) and speeding (Bao et al., 2020). Nordhoff et al. (2021) found that driving behavior like engaging in secondary tasks (for example texting, calling, using the navigation system, using the radio), does not change when comparing manual driving and driving in a partially automated car. Those findings are in line with the findings of this study, suggesting that automation, here in form of feedback, does not have an effect on behavior in regard to compliance. Hensch et al. (2020) found that the positioning of the feedback screen had significant effects on the glance behavior of the drivers, suggesting that a heads-up display would engage the driver more and may enhance taking the displayed feedback into consideration. The current study used a heads-down display which might have contributed to the non-significant results for both speed compliance and headway distance compliance. Further, a study by Chen and Donmez (2022) suggested based on their findings, that in order for the driver to comply to feedback and adapt their behavior, feedback should include associated risks additionally to presented information about targeted behaviors. The feedback used in this study did not include any information about associated risks which might have decreased the importance for the driver of taking the feedback into account.

A limitation of this study is that it did not control for whether the participants actually monitored the feedback, resulting in possible disengagement with it or non-acknowledgement. By measuring eye movement or placing the feedback display based on previously mentioned findings (Hensch et al., 2020) this concern could be accounted for and counteracted. Another limitation of this study was the duration of 90 minutes where each participant had to drive the same route five times which could have had a negative impact on the attention. Further, the experiment was conducted in a simulator and not in a real-life setting. This might have led the participants to get bored and less attentive and possibly no taking the situation as seriously as in real traffic scenarios. This effect was possibly taken into account and controlled for by randomizing the order of conditions. Nevertheless, this might still have had an impact on the overall significance of the results. Another limitation of the study might have been that the different information processing steps reflected by the feedback were not different enough. By designing them in a way that participants could have distinguished them more, they might have had a bigger impact.

For future research we suggest taking into consideration possible mediators. Feng and Donmez (2013) researched the willingness to seek out and accept feedback in the workplace in relationship to the effect of the feedback on the work. Their results showed that higher willingness to ask for feedback and accept it is related to the ability to integrate and apply it. Those findings might have implications on possible mediators related to driver characteristics. Another aspect to consider which was also presented by Feng and Donmez (2013), stated that compliance is increased when the behavior is knowingly monitored. This finding could be implemented into a future study by ensuring that the participants are being made aware that the presented feedback and the response is being recorded. Further, a larger sample in future studies might be important to implement, considering that weak trends could be observed in the current study and should be investigated further to confirm or reject them. An interesting implication of this study is the opposing effect shown between speed compliance and headway compliance, which shows opposing trends with the increased level of information processing within the feedback. For future research it would be interesting to investigate whether this effect can be replicated and whether different risk behaviors need to be counteracted differently and therefore need different kind of feedback.

To conclude, speed and headway distance are two main contributors to traffic safety and are the most prevalent causes of death and injury (De Pauw et al., 2014). Automation and more specifically automated feedback are a substantial part of reducing the risks connected to traffic safety. This study examined whether the different information processing steps within feedback had an effect on speed and headway distance compliance. No significant results could be found, nevertheless did the results show a trend for speed compliance, indicating that increased information processing feedback is related to increased speed compliance. For headway distance, the trend showed that the higher the level of information processing within the feedback was, the lower headway distance compliance was found to be. Those findings have important implications for future research addressing and suggesting the implementation of possible mediators like driver characteristics and placement of feedback screens. Instead of using head down displays, an option would be the use of head up displays which has shown to lead to longer glance behavior, which in turn might increase the attention and implementation of the provided feedback. Consequently, eye movement and feedback design should be considered in future research. To make the differentiation between different information processing steps easier to detect, layout or general design should be considered (for example implementing different colours or experimenting with sizes). Additionally, a combination of visual and sonic feedback might be interesting to investigate to research whether an increased effect can be found.

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