Effects of Automated Interfaces on Secondary and Tertiary Driving Tasks

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ABSTRACT

This paper describes a simulation study aimed at identifying optimal levels of automation for different driver tasks to improve the driving experience. The study consists of 8 participants driving 3 different automated routes in a driving simulation. This research is part of a larger effort to understand the effects of automation on driver tasks and aid in the development of design guidelines for predictive interfaces. This paper builds on current knowledge about predictive interfaces in the automotive context for two key questions: 1) How does the addition of automated interfaces affect driver perception of the overall driving experience? 2) What are the differences between automating interfaces for secondary and tertiary driver tasks? The results show participants prefer automated interfaces in their cars and automation in tertiary tasks rather than secondary tasks. These results provide a stepping stone for future research and design of automated interfaces.

Author Keywords

Keywords: Driving simulation; Predictive user experience; Automated interface design; Automotive HMI.

INTRODUCTION

Imagine you are walking down a busy road in an urban area. All of a sudden, you receive a message on your phone which needs answering right away. While you reply to your message your pace naturally slows down. Attention can only be divided, and when you focus on your phone rather than walking, you tend to slow down. This scenario does not involve any major consequences, but how does this translate into driving?

When doing more than one task at the time, tasks have an order of importance and divide the performer’s attention accordingly. In the prior example one task is more critical than the other. Because the person tries to keep the same pace, walking is the primary task and answering the message is the secondary task. In an automotive context, tasks are divided into primary, secondary and tertiary tasks [4]. As the amount of tasks increase, so does a person's cognitive load. [3] This causes the chance of overload, or an inability to process all the relevant information and perform the primary task properly. Overload can lead to task errors, and in a specifically automotive context reduces safety [18, 20].

Engaging in multiple tasks at the same time is becoming more frequent. Ubiquitous computing in everyday tasks brings new challenges in human-machine interaction [21]. With more computing power introduced into the automobile, drivers have much more functionality at their fingertips than before. All of these come with the need to acquire and analyze information, reducing the mental bandwidth available for paying attention to the road [18, 20]. It is these many complex interactions that can lead to user confusion and obnoxious interactions [5, 8]. In order to manage a world with countless interfaces more efficiently, automation could be a suitable solution. By automating parts of the functionality, users are empowered to use these many functionalities with less effort.

To create clarity for these interfaces where the user has to acquire and analyze large amounts of data, recommender systems are used. These systems scan and filter content based on learning algorithms and so increase relevance of content. For instance, Netflix and YouTube use recommender systems in their video stream services [1, 2, 6, 14]. The aim of these systems is to optimize viewing experience by minimizing the effort needed for decision selection [15]. Yet, the effectiveness of these systems is measured by the amount of content consumed. Although these recommendations make the experience simple, their key performance indicators are content focussed rather than user focussed [9, 10, 11].

To execute anticipatory design [17] successfully, it is argued that a holistic approach is needed. This includes the user's consciousness-intentional activities in the foreground as well as designing the smart technology in the background [5]. This notion has been expanded by Ju and Leifer who provide a useful framework that focuses more on the human element in such complex interactions [8]. In the effort of designing anticipatory interfaces for this study, the researchers took these frameworks to heart. In combination with extensive experience in automotive design and automation [15], this led to a variety of anticipatory interface proposals that can be used as a benchmark for automation in automotive interfaces.

This paper looks into automating different tasks that coincide with the driver and investigates the effect on the driver's performance and user experience of the drive. The goal is to explore and recommend the optimal level of automation of driver-related tasks for a more holistic driver experience. In addition, it provides insights into how the type of tasks automated play a role in the experience. By using a simulation environment (shown in Figure 1) and custom-made automotive functionalities, each with a different level of automation, this study provides both qualitative and quantitative results that create a clear picture of the effect of automation on different types of user tasks. These insights can be used for future design principles, for automotive areas and beyond. They serve the future of automation for decision and action selection, ultimately directing them towards a more human-centered approach.

Figure 1. Image of the driving simulation environment.

Method

Participants

To get a varied group of participants, people are selected based on gender, age, and driving experience that includes but is not limited to right-hand side driving. The group consists of 8 participants with ages between 20 to 62 years (*M* = 35.88, *SD* = 14.73) and a mean of 16.19 years of driving experience (*SD* = 14.21). There is an even split of 4 female and 4 male participants. No participants has prior experience with driving or simulation experiments. All participants drive on a daily basis for either commuting or leisure. All participants are recruited from outside of the company and given a £20 Amazon gift card as compensation for their participation.

System

To conduct the experiment a purpose-built virtual driving simulator is used. The simulation includes realistic vehicle dynamics and physics. The simulated vehicle is modeled after a 2017 Volkswagen Golf GTI in both visual and audio representation and driving behaviour. The simulation environment is displayed on three 27 inch 1080p monitors that are positioned in a slight arch to provide a user with a 90 degree field of view. The displays are mounted on an aluminium prototyping rig that includes an adjustable driving seat, gaming steering wheel with haptic feedback and an industrial grade digital instrument cluster. A 12.9 inch iPad pro is mounted within easy reach of the user and functions as the head unit. The head unit, instrument cluster, and simulation are made in Unity 3D and run as separate applications connected over a wireless UDP or OSC connection.

The environment has dynamic traffic agents that can interact with each other, traffic lights and the participant's vehicle. The traffic drives on the right-hand side of the road and speed limits have been removed to simplify the drive. The context of the drive is set on a summer day in rural Northern America which includes ample trees and green hills. The only buildings in the environment are final destinations to give the participants a clear end to each drive.

Interface Functionalities

For this study four common driving tasks are selected. The tasks are chosen to cover four categories: planning, exploring, setting, and picking. Tasks are also divided to cover secondary and tertiary tasks. Secondary tasks are kept to the instrument cluster and tertiary tasks to the head unit [19]. Of the four tasks used in this study, one is a secondary task and three are tertiary tasks [4]. The tertiary tasks are, setting the navigating, calling, and setting the in-car climate control. The secondary task is activating adaptive cruise control (ACC) [12], which changes the car's driving by automating headway distance and speed.

The automotive functionalities are designed according to the levels of automation (LoA) defined by R. Parasuraman et al. [15] which are shown in Table 1. These functionalities are created with three LoA: *low automation, medium automation,* and *high automation*. According to this framework automation has four stages: information acquisition, information analysis, decision selection, and decision implementation. Below every function is described according to this framework with the focus on decision selection and action selection.

Climate Control

The climate can be set using a combination of sliders, toggles and buttons on the head unit. This is how they differ for each level of automation:

low automation: Settings are visible at all times but not set to the correct setting (LoA = 1).

medium automation: Settings are visible at all times and are already set by the system but can be changed by the user (LoA = 7).

high automation: Settings are not visible unless requested by pressing the icon, the settings are automatically set (LoA = 8).

Navigation

A place to navigate can be picked from a scrollable list. Besides scrolling, the interface also has a search field to query the list which can be seen in Figure 2. By selecting an item in the list the navigation starts on the head unit. The way this functionality differs is as follows:

low automation: A list can be opened at will and can be scrolled through using a swipe gesture. At the top of the list there is a search field. When the field is selected a virtual keyboard appears (LoA = 2).

medium automation: The same list as with the *low automation* drive except that three predicted routes are loaded at the top of the list. The predictions have a distinctive color from the rest of the UI (LoA = 3).

high automation: The route is loaded automatically 5 second after the start of the drive, the route can be cancelled and re-loaded (LoA = 7).

Call

The call function works similar to the navigation. Both use a similar list structure but with different icons. The list can be searched and when an item is selected the call will start followed by an audio file that plays a dial tone which ends without anyone picking up.

low automation: The same as with the navigation drive, except with different icons (LoA = 2).

medium automation: The same as with the navigation drive, except with different icons; (LoA = 3).

high automation: The call starts automatically and is announced using a 5 second timer on the head unit (LoA = 6).

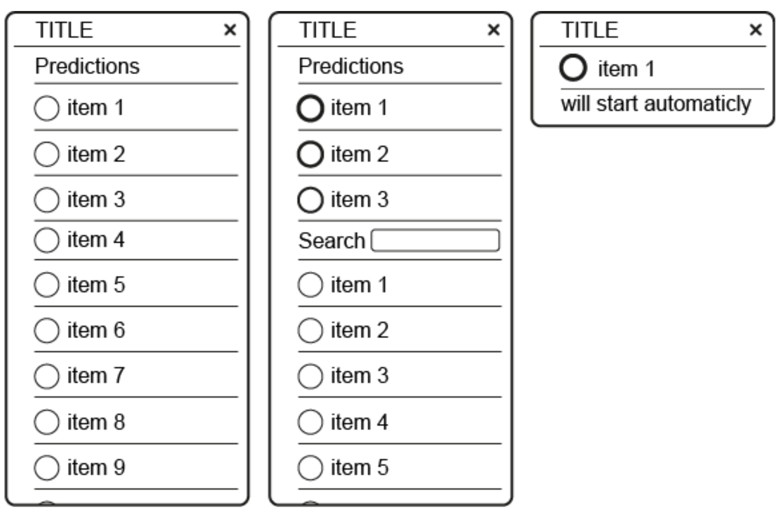

Figure 2. Navigation and call list wireframes, from left to right: *low automation* - *medium automation* - *high automation*.

Adaptive Cruise Control

ACC is a function that influences the car’s driving and has to be activated by the driver. It automates the velocity of the vehicle and adapts to other traffic. This study focuses on how this feature is activated. In the system, ACC can be activated by pressing two buttons simultaneously on the steering wheel. Notifications for ACC were shown in the instrument cluster.

low automation: Manual activation, no additional automation (LoA = 1).

medium automation: The car will suggest the driver to activate ACC via a text message. Besides the text notification, there is an audio and a visual cue. The driver chooses whether to activate ACC or not (LoA = 4).

high automation: The car will activate ACC automatically using a 5 second countdown. Besides the text notification and timer, there is an audio and a visual cue; (LoA = 6).

Drive

Participants start with a practice drive to get comfortable with the simulation. Depending on the participant's confidence the practice drive takes between 4 - 6.5 minutes. Afterwards, the participant will drive three similar routes in a randomized order. Each drive is loaded with a different driving interface as described in Interface Functionalities. Before every drive, each functionality is explained including the possibility for participants to ask questions. All three drives have the same starting point, similar length, road types, and amount of intersections. Each drive consists of 2 km of driving to complete tertiary tasks and an additional amount of road to allow for the use of ACC.

Analysis

The three test drives are recorded by two wide angle cameras and one DSLR camera to provide the researchers with different perspectives to analyze the drive. A dedicated microphone records the interview and conversations before, during, and after the drive. The collected footage is later transcribed and analyzed to use in an affinity diagram.

On top of comparing events that occurred during the test drives an interview is held after the drive. This interview includes questions such as a rating stress level, which interface is preferred, the helpfulness of the car, which drive the participant would consider driving again, and perceived intuitiveness of each drive. The interview is free-form to leave room for the researchers to ask specific questions about events that happen during the drive.

In addition to these qualitative results for every drive, the amount of driver errors, and the time it took participants to finish are counted. Errors are considered unintended driving and breaking of traffic laws. To compare the participant's lap-time an optimal time for every drive is established. The optimal time for each drive is based on the drive length, the number of interactions, the number of stoplights, and the suggested speed. The deviation of the optimal time and the average lap-time can be compared for each of the drives. The quantified data is graphed using box-and-whisker plots, with whiskers representing the lowest and highest datum within 1.5 inter quartile range (IQR) of the lower and upper quartile respectively [7]. The results are used to match and confirm the affinity diagram results.

Results

Driving Performance

Driver Errors

As can be learned from Figure 3, going from *low automation* (*Mdn* = 4.5) to *medium automation* (*Mdn* = 2.5) has a significant effect of reducing errors while driving. Jumping from *medium automation* to *high automation* (*Mdn* = 2) results in a near perfect drive for some participants. These numbers suggest that automating tertiary tasks benefit the primary task. However, for some participants *high automation* functions created confusion or panic, resulting in driver errors.

Drive Time

Figure 3 shows the time to complete the drive compared to the optimal driving time. Noticable is that participants find places to pause or slow down their driving to interact with the interface. This explains why the *low automation* drive (*Mdn* = 2.42) is the slowest. Participants wait for traffic lights, slow down in the right lane, or choose to interact when there is less traffic. With more automation, there is a reduction in this behaviour resulting in a faster drive. Observations from the *medium automation* drive (*Mdn* = 1.63) show a reduction in time compared to the *low automation* drive. The *high automation* drive (*Mdn* = 1.88) results are scattered; some of the users were confused by the *high automation* interface.

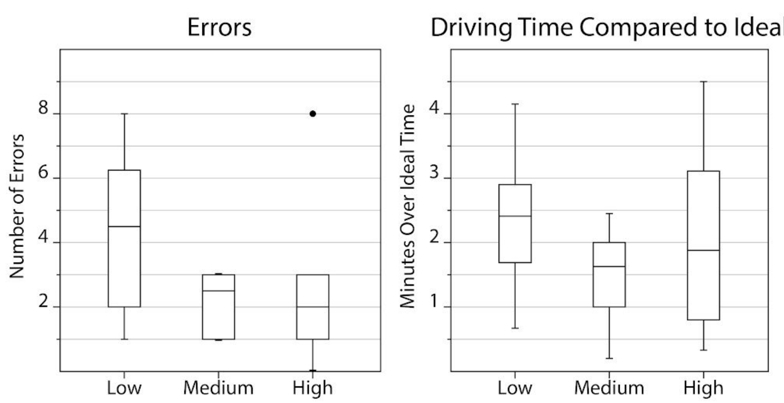

Figure 3. Left: Number of observed errors. Right: Difference of participants' observed driving time to each drive's optimal driving time.

User Experience

Stress

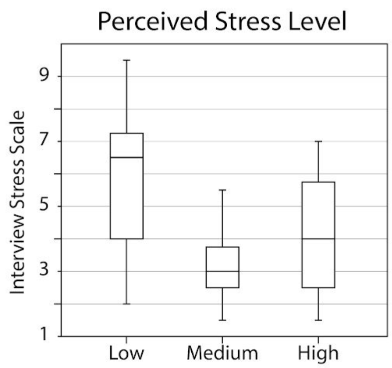

Figure 4. Participants' perceived stress level, from left to right: *low automation* - *medium automation* - *high automation*.

Participants describe their level of stress on a scale of 1 - 10 for each drive, as plotted in Figure 4. The *low automation* drive is considered the most stressful (*Mdn* = 6.5). The least stress is experienced during the *medium automation* drive (*Mdn* = 3). There is a rise in stress from the *medium automation* to the *high automation* drive (*Mdn* = 4). An explanation for these results is that for the *high automation* drive participants expressed a lack of control and in some cases confusion. This upswing can be understood better when combined with the results of how drivers perceive automation in secondary and tertiary tasks.

Automation Preference Per Functionality

Figure 6 shows the preferred LoA per functionality of all drives including the option to select none. The tertiary tasks: calling, navigation, and climate settings have similar results. Here participants prefer *medium automation* or *high automation* and react positively to a reduction of input.

The ACC functionality is a secondary task and directly affects the primary task. As Figure 6 indicates, in the case of ACC a suggestion is strongly preferred over no suggestion. Participants reacted negatively when the system activated ACC without the need of their input; as was done in the *high automation* drive. In one case this led to incomprehension and disbelief, *"Why would a car choose to tell me when to drive in cruise control?"*

Automation Perception

Figure 5 shows results for automation perception. Based on these preferences the *medium automation* drive is the most helpful and most intuitive by receiving 5 votes for each. The *medium automation* and *high automation* drive each received 3 votes to be re-driven. Participants that voted to re-drive the *high automation* drive state that they prefer the *medium* *automation* drive, but find the *high automation* drive the most exciting and novel. Seven participants stated that they would use the *medium automation* interfaces in their cars today.

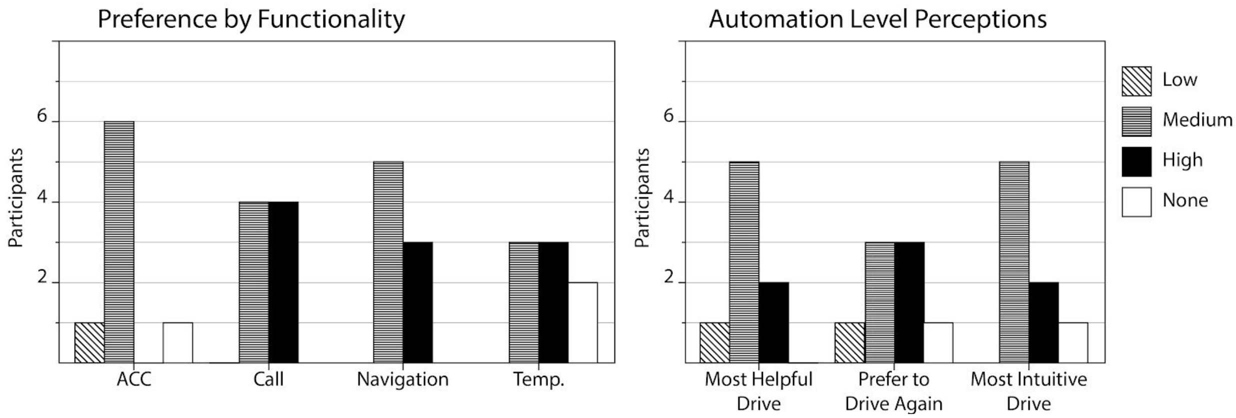

Figure 5. Left: Participants' preferences of LoA per functionality. Right: Perceptions of all three drives for helpfulness, preference to drive again, and intuitiveness.

Conclusion

The results are in line with the expectation that automating driver tasks benefits the driver experience. When looking at the functionality for the tertiary tasks, more automation of functionalities is preferred over *low automation*. Increased automation significantly reduces driver errors and leads to faster driving times given the interface is correctly understood.

The *medium automation* drive is the favourite among participants. The *medium automation* drive is considered the least stressful, the most helpful, and the most intuitive. The *medium automation* variant is preferred for secondary tasks, such as activating ACC. Qualitative data suggests that the *medium automation* drive is favored by providing a more desirable sense of control over the *high automation* drive.

Participants are impressed by some of the *high automation* functionalities. Participants give equal votes to re-drive the *medium automation* and *high automation* drive, crediting novelty to the latter. Some suggest that if more time were to be spent with the *high automation* interface, participants could change their vote from *medium automation* to *high automation* for the most preferred drive. The *high automation* drive scored negatively with participants for the level of authority the system takes when engaging ACC without their consent.

To summarize, looking at different types of automated tasks creates two rules of thumb:

1. Drivers want more automation and react positively to removing control over tertiary tasks while driving.
2. Drivers want less or no automation and react negatively to removing control over secondary tasks while driving.

Discussion

Confusion during the *high automation* drive could be due to a greater learning curve, possibly because the interface differs the most from the current industry norm. It could also be, that learning capabilities are poor when the attention is not solely focussed on a functionality [16]. The best way for a user to learn could be to eliminate other ongoing tasks first [13]. This explains the pausing behavior observed in the drives. Users interact and explore the tertiary interfaces more when the primary task is on hold versus while driving. Alternatively, a functionality can be taught before the user engages in the primary task of driving, or to educate the driver with controlled coaching during the drive. Future research is required to understand how to best educate drivers about functionalities in the vehicle.

"[A]t its core, user experience has been about presenting the user with information and options so she can make a decision" [17]. Therefore, it makes sense that the *medium automation* interface is considered the more intuitive than *low automation*. The information has already been processed and so less effort is required to make a choice. Following this logic, it would be expected that the *high automation* would be the most intuitive, since it virtually requires no input at all. Yet, it is not considered intuitive, nor is it the most preferred. If there is no decision to be made by the user what is left of the user experience? It raises questions on how the quest for minimizing effort through automation correlates with the user's ability to have a choice?

When participants mention a lack of control with the high automation interface, they could be referring to a lack of choice. As the *high automation* interfaces make the decision for the user the lack of interaction can be unexpected and lead to confusion. There is a possibility that automated systems of LoA 7 and above [15] break from traditional user experience because the user's involvement is subpar.

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