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Conditionally Automated Vehicles as a Safe and Productive Workspace

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Abstract

Future automated vehicles will allow drivers to reclaim some of their driving time and perform personal or work-related activities while the car is in automated driving mode. However, traditional automotive user interfaces (UIs) are not designed to support such activities. For a vehicle to be considered a safe and productive workspace, we will have to explore how drivers can interact with emerging UIs in a car to engage in complex non-driving related tasks (NDRTs) and safely resume driving when needed. In the second chapter of this thesis, we present a user-elicitation study where we investigate how drivers would want to use gestures and voice commands to interact with augmented reality windshield displays in highly automated vehicles. We argue that it is important to evaluate interaction modalities from the users' point of view before designing unconventional UIs for future automated vehicles. In chapter three, we examine what strategies people use while switching from NDRT to driving. We identified two common takeover strategies (suspension and interleaving) and show that it is important to examine takeover strategies in addition to takeover performance to fully understand takeover in automated vehicles. In the fourth chapter, we present findings from two driving simulator studies. In these studies, we analyze how different factors influence what strategies drivers use during takeovers and the relationship between these strategies and takeover performance. We found that people are more likely to interleave between driving and NDRT when taking over if they are asked to prioritize NDRT or allowed a longer time to take over. We also found that the effect of priority is moderated by the takeover time budget. We did not find any relationship between the takeover strategy and takeover quality in terms of lateral and longitudinal vehicle control while driving in a simple traffic scenario. Drivers took longer to take over driving but glanced at the driving scene faster while following the interleaving strategy compared to the suspension strategy.

Chapter 1. Introduction

Commuting takes up a significant amount of time from people's daily life. One of the most important promises of automated vehicles is that it will allow people to reclaim some of the time they now spend driving. SAE International defined six levels of driving automation, from level 0 (no automation) to level 5 (fully automated driving) (1). Most of the newly released cars on the market have level 2 automation. That means these vehicles have features like lane-keeping assistance and adaptive cruise control to assist drivers. But the driver is still responsible for controlling the car all the time. There are some level 4 driverless taxi services like Cruise and Waymo, but they can operate in small, designated areas and are not available as consumer vehicles. Even in the limited well-mapped roads where these vehicles operate, we frequently see news of them struggling to navigate or follow traffic rules. So, it is safe to say that fully automated vehicles, in which the driver won't have any driving-related responsibilities, are still far ahead in the future. However, vehicle manufacturers are just starting to release level 3 conditionally automated cars in the market (2). These vehicles will be able to operate under certain limited conditions without any input from the driver. When faced with situations where the vehicle cannot drive itself, the system will ask the driver to take over control of the vehicle within a short period of time (approximately 10 seconds (3; 4)). This will allow drivers to engage in other activities which are not possible or safe to perform in a car today. People already multitask frequently while driving, and studies show that people would want to perform various tasks in future automated cars too. Activities that require visual and manual resources (5; 6) or activities that people usually neglect in their daily life (7) are often mentioned as the activities they would like to perform if the driving responsibilities can be shared with vehicle automation.

Several studies have explored the feasibility of using vehicles as a place for work (8; 9; 10; 11; 10; 12). However, conventional automotive user interfaces (UIs) are not designed to support any complex activities while driving. This was done to prioritize safety since performing complex tasks while driving can interfere with safe driving. So, we need to rethink the design of user interfaces in future automated cars so that people can take advantage of the free time advanced vehicle automation promises. However, designing automotive user interfaces so that people can engage in various non-driving-related tasks (NDRTs) in a car without compromising safety is a multi-faceted problem and will require careful consideration of various factors. Researchers are already exploring different technologies for presenting NDRT information in the car. We also need to consider how drivers would want to interact with these new and unconventional user interfaces (12). Driving-related information and warning messages will also need to be presented appropriately to improve driving safety (13). Drivers will need support for switching between driving and other activities in the car. This is another complex but crucial factor that we did not have to think about before the introduction of conditionally automated vehicles. In addition to safety and productivity, we also need to consider other factors like people's trust in the vehicle automation technology (14), human-automation interaction (15), and legal issues (16) before automated vehicles can be considered viable workspace.

The aim of this thesis is to explore how we can support drivers so that they can engage in various activities in conditionally automated vehicles without compromising safety. We do this by focusing on two main aspects related to this problem: productivity and safety. For the drivers to be productive in automated vehicles, the automotive UIs will need to support various complex NDRTs that the drivers may want to perform. So, the UIs of future automated vehicles will likely be vastly different from any kind of UIs we have in today’s vehicles. This will require designing interactions for unconventional automotive UIs, which is the focus of the next chapter in this thesis. Even though several studies explored interactions in conditionally automated vehicles for different interfaces, the approach these studies follow is to design interactions and then test to see how the drivers adopt them. This approach does not always incorporate the feedback of drivers in the design process. In Chapter 2, we start by discussing some of the emerging technologies for user interfaces in future automated vehicles. We then emphasize the need to examine how drivers want to use these emerging interfaces and incorporate that while designing the interaction methods for those interfaces. We used augmented reality (AR) windshield display (WSD) as an interface option in automated vehicles and examined how drivers expect to use gestures and voice commands to perform complex tasks using the interface. This approach can be used for designing interactions in other modalities for similar emerging automotive UIs.

After that, we shifted our focus from productivity to safety in automated vehicles. Specifically, our goal is to ensure a safe transition of control in conditionally automated vehicles when switching between NDRT and driving. In Chapters 3 and 4, we focus on the takeover process (taking back driving from vehicle automation) in conditionally automated vehicles. We show that even though the takeover process has been investigated in prior studies, those studies treated the takeover process as a single-step event and were mostly focused on takeover performance, not takeover strategies. Janssen et al. proposed that, as suggested in interruption literature in other domains, drivers will go through a series of stages for transitioning between driving and NDRT when interrupted by takeover requests in conditionally automated vehicles (17). Based on this framework, we conducted three driving simulator studies to understand the takeover process in greater detail. We start by analyzing the stages involved in the takeover process instead of treating this process as a single-step event in Chapter 3. We found empirical evidence to support the model proposed by Janssen et al. and identified two strategies drivers use for takeovers. Next, we evaluate how the takeover strategies we identified in Chapter 3 relate to driving performance and safety during the takeover process. In Chapter 4, we examine how various factors affect takeover strategies and how different strategies influence takeover performance and engagement in NDRTs. We selected two different NDRTs, which the participants by texting on a smartphone. We focused on various attributes of those tasks, like different cognitive demands and priorities, and evaluated takeover performance both in terms of quality of vehicle control and reaction time. Thus, in the second, third, and fourth chapters, we examine the following research questions:

RQ1. How can we design interactions for unconventional UIs in automated vehicles using a participatory design approach to support complex NDRTs?

RQ2. Do drivers go through a series of stages and adopt different strategies when transitioning from NDRT to driving in conditionally automated vehicles?

RQ3. Which factors affect takeover strategies, and how do takeover strategies influence safety and productivity in conditionally automated vehicles?

Finally, in Chapter 5, we discuss our overall findings from the experiments and how they build on the existing knowledge with an aim to make future automated cars a safe and productive workspace.

Chapter 2. User Interface for Working in Automated Cars

In this chapter, we explore how we can support drivers so that they can be productive in automated vehicles. We discuss how we can design user-defined interactions for future automotive UIs. This chapter is based on the following publication:

Gesture and Voice Commands to Interact With AR Windshield Display in Automated Vehicle: A Remote Elicitation Study. **Nabil Al Nahin Ch, Diana Tosca, Tyanna Crump, Alberta Ansah, Andrew Kun, Orit Shaer.** 2022. Proceedings of the 14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications.

Traditionally, driving-related or other information in a car is presented to the driver either using the dashboard instrument cluster or the center console display. In recent years, we have started to see heads-up displays (HUDs) being introduced in the car to project information like vehicle speed or navigation instructions on some parts of the windshield. Augmented reality (AR) windshield display (WSD) technology expands this to the whole windshield. It transforms the windshield into a transparent display by superimposing text or images on the driving scene (18; 19). It is a promising way to present NDRT information, especially in conditionally or fully automated vehicles, since the driver will not have to focus on driving all the time. WSD provides the benefit of having an extended display and also allows drivers to consume information without having to fully take their eyes off the road. However, similar to any new technology, WSD also introduces new challenges. We have to explore what is the best way to interact with this interface since the traditional haptic and touch interface will be less convenient because of the distance between the driver and the windshield. Several studies have explored the potential as well as the challenges of using AR WSD in a car (20; 21; 22). Researchers have also examined how different interaction methods like gaze (23), speech (24), and gestures (25; 26) can be used to interact with WSD. But we also need to think about this from the drivers' perspective and find out how they expect to use such interaction methods to interact with WSD. We conducted an unmoderated online user elicitation study to examine how people expect to use gestures and voice commands to use WSD to perform various complex multi-step NDRTs. Even though our focus was on WSD in this study, other emerging unconventional technologies for automotive user interfaces also need to be examined similarly before designing the interaction method for them.

Related Work

Augmented Reality Windshield Display

Several automakers have introduced vehicles in the market with HUD feature (27). However, there are no commercially available vehicles currently in the market that extend this feature to the whole windshield. In automated or conditionally automated vehicles, AR WSD technology has the potential to enrich the in-car experience and improve safety (20; 21; 22). It can be used to effectively explain uncertain situations in automated cars (28) and to help elder drivers (29). Providing vehicle information and navigation instruction on WSD can increase drivers' trust in vehicle automation, which in turn enhances the acceptance of automated vehicles (30; 31). Looking at the windshield instead of the center console can improve situational and spatial awareness (32; 33), even in challenging conditions where the visibility is low because of rough weather (34; 35). In conditionally automated vehicles, WSD can positively influence the process of taking over driving from vehicle automation (36) and improve the takeover time in emergency situations (30). In addition to providing support for driving, WSD can help drivers with NDRT in the car. Research shows that using WSD helps drivers maintain their attention on the road (37), enhance situational awareness (38), and improve performance in NDRTs (39).

Drivers also reported experiencing lower cognitive workload while performing NDRTs (40) and found it easier to take over driving when needed (41; 40).

In addition to the usability of WSD, several studies also explored gesture and speech-based interaction methods for the WSD. Researchers mainly focused on finding out how these conventional interaction methods can be applied to interact with this unconventional user interface. Gestures on the windshield (25) and finger gestures on the steering wheel surface (42) have shown encouraging results for performing various NDRTs like media and climate control using the WSD. Some studies restricted gestures to finger-pointing so that the drivers won't have to move their hand off the steering wheel while interacting with the WSD (26; 43). The focus of speech interaction for WSD has also been on simple NDRTs. Wang et al. proposed a button and a mic mounted on the steering wheel to control a virtual assistant displayed on the WSD (44). Prior research also shows that gesture and speech-based interaction was comparable to other interaction modalities in terms of user acceptance and usability, even though haptic interactions were better accepted compared to both (45; 46).

User-Elicitation Studies: Gestures and Voice Commands

User-elicitation study is a participatory design method where the interaction is designed based on feedback from end-users. In such studies, intended users are shown referents (effect of actions), and they are asked to show corresponding signs (an interaction that will result in that specific referent) (47; 48; 49). Research shows that interactions developed using this method are preferred by the users compared to interactions designed solely by designers (50). Even though most such studies are conducted in the lab, they can also be conducted online to produce user-defined interactions (51).

The user-elicitation method has been previously applied to generate various types of gestures for different interfaces. Such studies investigated micro-gestures using only one hand (52), unistroke gestures (53), multitouch gestures on both large and small surfaces (54; 47; 55; 56; 57), motion gestures for mobile devices (58), gestures for tangible interfaces (49), and gestures for AR (59; 60) and VR (61) environments. To explore gesture interaction in automotive interface, elicitation method has been used to study swipe gestures on in-vehicle touch screen (62), air gestures for vehicle infotainment system (63; 64; 65; 66), gestures on steering wheel surface (67) and wearable device (68). In recent years, elicitation studies have also been used to investigate interactions in automated vehicles (69; 70). User elicitation method has also been applied to elicit speech-based interactions to interact with voice assistants (71), multimodal human-computer interaction interfaces (72; 73; 74), smart home devices (75), web browsers on TV (48), unmanned ariel vehicles (76), etc.

These studies demonstrate how user-elicitation studies can be used to investigate how end users want to use an interface. Even though previous studies explored gesture and speech-based interactions in automated vehicles, to our knowledge, this is the first study that investigate such interactions for performing multistep tasks using WSD.

Method

We conducted a within-subjects remote elicitation study to investigate how drivers expect to interact with AR WSD to perform NDRTs using gestures and voice commands. Participants were presented with referents using pairs of images. The images depicted how the WSD will change for that referent, and the participants were asked to demonstrate (using video recordings) which gestures and voice commands they want to use for that referent. A web app was developed to clearly present the referents and to allow the participants to easily record videos of them demonstrating the interactions. Figure 1 shows the interface for referent presentation and video response recording.

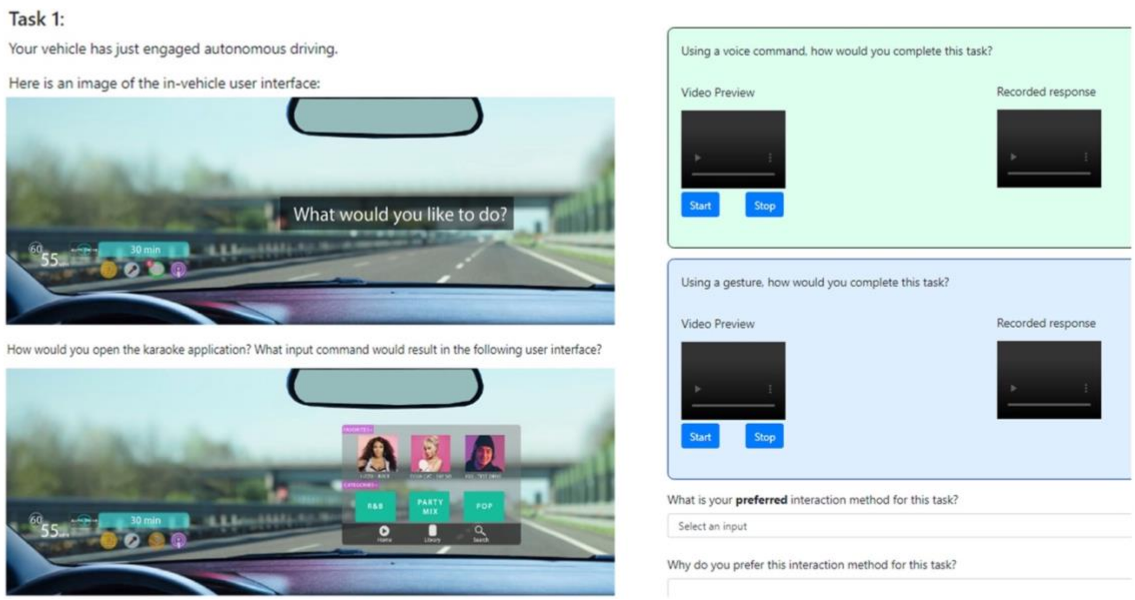

Figure 1 Interface to present referents (left) and to record participant video responses for the interactions (right).

Referents and Experimental Task

People engage in both personal and work-related activities while driving. So, in this study, we presented referents related to various personal and work-related scenarios. We presented 24 referents from four scenarios (two personal and two work-related). Each scenario consisted of five to eight referents which are presented in Table 1. Each participant was presented with referents from one personal and one work-related scenario. So, depending on which scenario they got, each participant demonstrated interactions for 11 or 13 referents. For each referent, the task that was being performed was described in text and also showed using two images. For example, in Figure 1, we see the images that were presented for the referent *open karaoke application from* the *karaoke* scenario. For this referent, the text used to describe the task was "How would you open the karaoke application? What input command would result in the following user interface?" The images show the effect of completing the task (opening the karaoke application). We asked the participants to answer the following four questions for each referent:

1. Using a voice command, how would you complete this task?
2. Using a gesture, how would you complete this task?
3. What is your preferred interaction method for this task?
4. Why do you prefer this interaction method for this task?

For the first two questions, participants recorded video responses to demonstrate the gestures and voice commands they would use to complete the task. For the last two questions, participant selected their preferred modality of interaction for the referent and described the reasoning behind their preference.

Table 1 Most commonly used gestures and voice commands for each referent and the number of participants who suggested them.

No	Referent	Gesture	Voice command
Audiobook (16 participants)			
1	Open audiobook application	Tap(3), Swipe left then tap(2)	Open audiobook(7)
2	Play audiobook <audiobook name>	Tap(6), Hold one finger upright(2)	Play <audiobook name>(4), Resume <audiobook name>(2)
3	Bookmark audiobook section	Tap(3), Two fingers crossed(1)	Add bookmark(1)
4	Rewind 30 seconds	Swirl counter clockwise(3), Tap(3), Wave left(2)	Rewind 30 seconds(4), Rewind(3), Go back 30 seconds(2)
5	Exit audiobook application	Make X with both hands(2), Close palm(2), Wave right(2)	Exit application(2), Return to main menu(2)
Karaoke (15 participants)			
6	Open karaoke application	Tap(4), Mimic holding mic(2), Mimic holding mic and move left and right(2)	Open karaoke(5), Karaoke(2)
7	Select category <category name>	Tap(6), Hold index and little finger upright(1)	Open <category name>(3), <category name>(2)
8	Play song <song name>	Tap(5), Hold seven fingers upright(2)	Play <song name>(8)
9	Play vocals in background	Tap(5), Hold two fingers upright(1)	Play vocals(3), Enable vocals(2)
10	Exit karaoke application	Wave left(4), Wave right(3)	Exit karaoke application(1)
Podcast (15 participants)			
11	Open podcast application	Tap(3), Using two fingers make a circle and tap in the center(1)	Open podcast(5), Open podcast application(3), Open the podcast app(2)
12	Play podcast <podcast name>	Hold three fingers upright(3), Swipe up then tap(3), Tap(2)	Play <podcast name>(6)
13	Bookmark podcast section	Tap(2), Make a plus sign with two fingers(1)	Add a bookmark here(1)
14	Skip to section <section name>	Tap(4), Point left then make a circle with palm(1)	Skip to summary(2)

15	Text <colleague name>a link of podcast	Tap(5), Make a T with two fingers(1)	Send podcast to <colleague name>(1)
16	Exit podcast application	Wave left(3), Make X with both hands(2)	Exit application(2), Close podcast open main menu(1)
Presentation (16 participants)			
17	Open presentation application	Tap(6), Show palm then thumbs up(1)	Open presentation(8), Open presentation application(2), Open my presentation(2)
18	Open presentation <presentation name>	Tap(4), Swipe left then tap(2)	Open <presentation name>(8), Open <presentation name> presentation(2)
19	Start the timer	Tap(4), Make the ok gesture(2)	Start timer(3), Start the timer(2)
20	Go to next slide	Wave left(5), Move hand pointing right(1)	Next slide(8), Next(2)
21	Pause the timer	Tap(4), Show palm(3), Move palm forward(2)	Stop timer(4), Pause the timer(3), Pause(3), Pause timer(2)
22	Display all slides	Tap(4), Close all fingers from open position(2), Open fingers from closed position(2)	Display all the slides(2)
23	Get feedback on presentation	Tap(5), Make two fists(1)	Feedback(2), Give me feedback on my presentation(2)
24	Exit presentation application	Wave right(3), Wave downward(2)	Close the presentation application(1)

Interacting with AR windshield

It can be difficult to conceptualize how the AR WSD will work in a car since most people are not familiar with such emerging technologies. So, we developed images to show how performing different tasks on a WSD interface in a conditionally automated car may look. The WSD we designed for the images is based on the commercially available HUDs available in the market. In our design for the WSD, driving-related information like speed limit, vehicle speed, vehicle automation status, and the time left before the driver will have to resume driving is presented on the lower part of the windshield in front of the driver. The NDRT information is presented on the windshield in front of the passenger side. All driving and NDRT information were projected on top of the driving scene, making it easier for the driver to monitor the road while engaging in NDRTs.

Procedure

At the beginning of the study, the participants were given a brief overview of what they will be doing, and they were informed that they will need to record video responses to complete the study. Then the participants signed the consent form and watched a short video on how WSD may look like in future automated vehicles. We then showed them a video explaining how to use the web app interface to record video responses, and the participant was able to practice recording videos to get familiar with the interface. After that, the participants were given a brief description of the scenario that was randomly selected, and then the referents of that scenario were presented. For example, if the audiobook scenario was selected, the corresponding referents presented to the participants were opening the audiobook application, playing an audiobook, bookmarking a section of the audiobook, rewinding 30 seconds, and exiting the application. After responding to all the referents of the first scenario, referents from the second scenario were presented. Participants could only proceed to the next referents after recording responses for the current referent. At the end of the study, participants answered some demographic questions.

Participants

Using the online platform Prolific, we recruited 43 participants for this study. All the participants reported that they had a valid driving license. We analyzed data from 31 participants who completed the entire study and recorded responses for all the assigned referents. The average age of the participants was 29 (SD=11), and 18 participants identified as men and 13 as women. All 43 participants received $7 for their time.

Data Analysis and Results

User-defined Gestures and Voice Commands

A total of 373 gestures and 373 voice commands (11 referents x 15 participants + 13 referents x 16 participants) were elicited for 24 referents from 31 participants. Among the proposed interactions, 278 gestures and 284 voice commands were distinct. Distinctness was considered per-referent basis. That means if the same interaction was proposed for two different referents, they were considered distinct interactions. The most popular interactions for each referent are presented in Table 1 and the gestures from Table 1 are demonstrated in Figure 2.

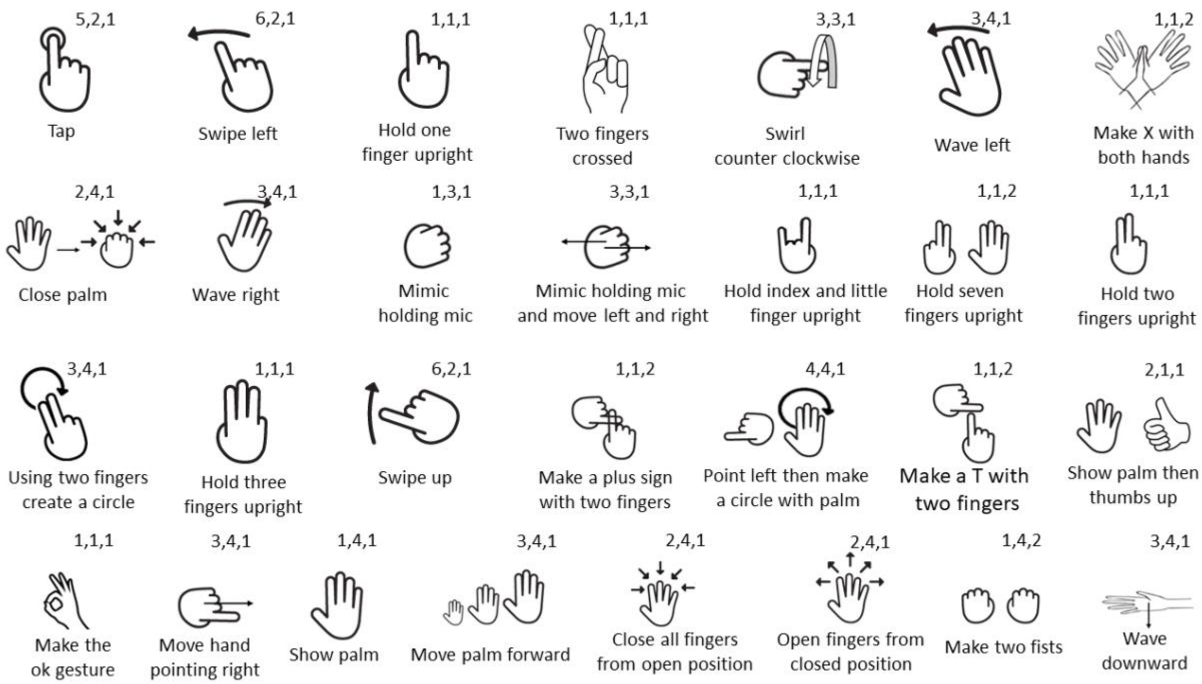

Figure 2 Popular gestures proposed by the participants. Gestures are presented as they appear in Table 1. The number represents the category of the gesture along the 3 dimensions presented in Table 3.

Agreement Rate

We calculated the agreement rate A_r using the formula proposed by Vatavu and Wobbrock (77) to estimate the degree of consensus among participants.

$$A_r = \frac{|P_r|}{|P_r|-1}\sum_{P_i \subseteq P_r}\left(\frac{|P_i|}{|P_r|}\right)^2 - \frac{1}{|P_r|-1}$$

In this equation, A_r is the agreement rate for referent r, P_r is the set of proposed interactions for the referent r, and P_i is the subset of identical interactions. The agreement rate ranges from 0 to 1. The agreement rate is 0 when all participants propose unique interactions and 1 when everyone proposed the same interaction. We calculated the agreement rate for both gestures and voice commands for each referent. Let's consider the referent *Rewind 30 seconds* as an example. Among the interactions proposed by 16 participants for this referent, there were 11 and 10 unique gestures and voice commands, respectively. Groups of three, three, and two participants proposed three unique gestures, and the other eight participants proposed unique gestures. For voice commands, groups of four, three, and two participants proposed three unique ones, and each of the other seven unique voice commands was proposed by one participant. The agreement rates for the gestures and voice commands for the referent *Rewind 30 seconds* was calculated using the following equations.

$$A_{rewind30sec(gesture)} = \frac{16}{15}\left(8\left(\frac{1}{16}\right)^2 + \left(\frac{3}{16}\right)^2 + \left(\frac{3}{16}\right)^2 + \left(\frac{2}{16}\right)^2\right) - \frac{1}{15} = 0.06$$

$$A_{rewind30sec(voice-command)} = \frac{16}{15}\left(7\left(\frac{1}{16}\right)^2 + \left(\frac{4}{16}\right)^2 + \left(\frac{3}{16}\right)^2 + \left(\frac{2}{16}\right)^2\right) - \frac{1}{15} = 0.08$$

The mean agreement rate for gestures was 0.07 (SD=0.04), and for voice commands was 0.08 (SD=0.09). Using a two-sample t-test, we did not find any significant difference between the agreement rates between gestures and voice commands.

Table 2 Agreement rate and preference of interactions for each referent.

Scenario	No.	Referent	Agreement rate		Preferred interaction	
			Gesture	Voice command	Gesture	Voice command
Audiobook (16 participants)	1	Open audiobook application	0.03	0.18	19%	81%
	2	Play audiobook <audiobook name>	0.13	0.06	31%	61%

	3	Bookmark audiobook section	0.03	0.00	12%	88%
	4	Rewind 30 seconds	0.06	0.08	44%	56%
	5	Exit audiobook application	0.03	0.02	31%	69%
Karaoke (15 participants)	6	Open karaoke application	0.08	0.10	7%	93%
	7	Select category <category name>	0.14	0.04	7%	93%
	8	Play song <song name>	0.10	0.27	0%	100%
	9	Play vocals in background	0.10	0.04	27%	73%
	10	Exit karaoke application	0.09	0.00	33%	67%
Podcast (15 participants)	11	Open podcast application	0.03	0.13	0%	100%
	12	Play podcast <podcast name>	0.07	0.14	13%	87%
	13	Bookmark podcast section	0.01	0.00	27%	73%
	14	Skip to section <section name>	0.06	0.01	20%	80%
	15	Text <colleague name>a link of podcast	0.10	0.00	7%	93%
	16	Exit podcast application	0.04	0.01	47%	53%
Presentation (16 participants)	17	Open presentation application	0.13	0.25	25%	75%
	18	Open presentation <presentation name>	0.06	0.24	31%	69%
	19	Start the timer	0.05	0.03	19%	81%
	20	Go to next slide	0.08	0.24	69%	31%
	21	Pause the timer	0.08	0.11	50%	50%
	22	Display all slides	0.07	0.01	50%	50%
	23	Get feedback on presentation	0.08	0.02	12%	88%
	24	Exit presentation application	0.03	0.00	37%	63%

Gesture Classification

We categorized the gestures along three dimensions to evaluate what kind of gestures people frequently proposed. The taxonomy of gestures we used (presented in Table 3) was developed from the taxonomy of surface gestures (47) and gestures for AR environment (60) proposed in prior studies. We extracted three dimensions (form, nature, and handedness) that are relevant to AR WSD from these two taxonomies. The form dimension describes the change in pose and location of the hand while performing the gesture. There are six categories along this dimension. We distinguished tap and swipe gestures because of their similarity to surface gestures. The nature dimension consists of four categories: symbolic, touch, metaphorical, and abstract. Gestures depicting any symbols were considered symbolic gestures. All the tap and swipe gestures were categorized as touch gestures. Gestures expressed through a metaphor fall into the metaphorical gestures category. For example, *mimicking holding a mic* is considered a metaphorical gesture that was commonly used for the referent *open karaoke app*. Rest of the gestures were arbitrary and fall into the abstract category. Some complex gestures can fall into multiple categories in the same dimension. Lastly, based on which hand was used, gestures were classified into three categories along the handedness dimension.

In Figure 3, we present the proportion of gestures in each category. In the form dimension, most of the right-handed gestures fall into the tap (37%) and static pose and path (32%) categories. Most left-handed gestures fall into static pose and path (43%) and static pose (32%) categories. In the nature dimension, touch (50%) and abstract (39%) gestures were the most common. For handedness, gestures were dominantly right-handed (72%).

Table 3 Taxonomy of gesture interactions.

Dimension	Category	Description
Form	Static pose	Hand pose is held in one location.
	Dynamic pose	Hand pose changes in one location.
	Static pose and path	Hand pose is held and hand relocates.
	Dynamic pose and path	Hand pose changes and hand relocates.
	Tap	Static pointing pose moving toward display.
	Swipe	Static pointing pose moving across display.
Nature	Symbolic	Gesture visually depicts a symbol.
	Touch	Gesture pretends to act on touch surface.
	Metaphorical	Gesture is metaphorical.
	Abstract	Gesture mapping is arbitrary.
Handedness	Right	Gesture performed using right hand.
	Left	Gesture performed using left hand.
	Both	Gesture performed using both hands.

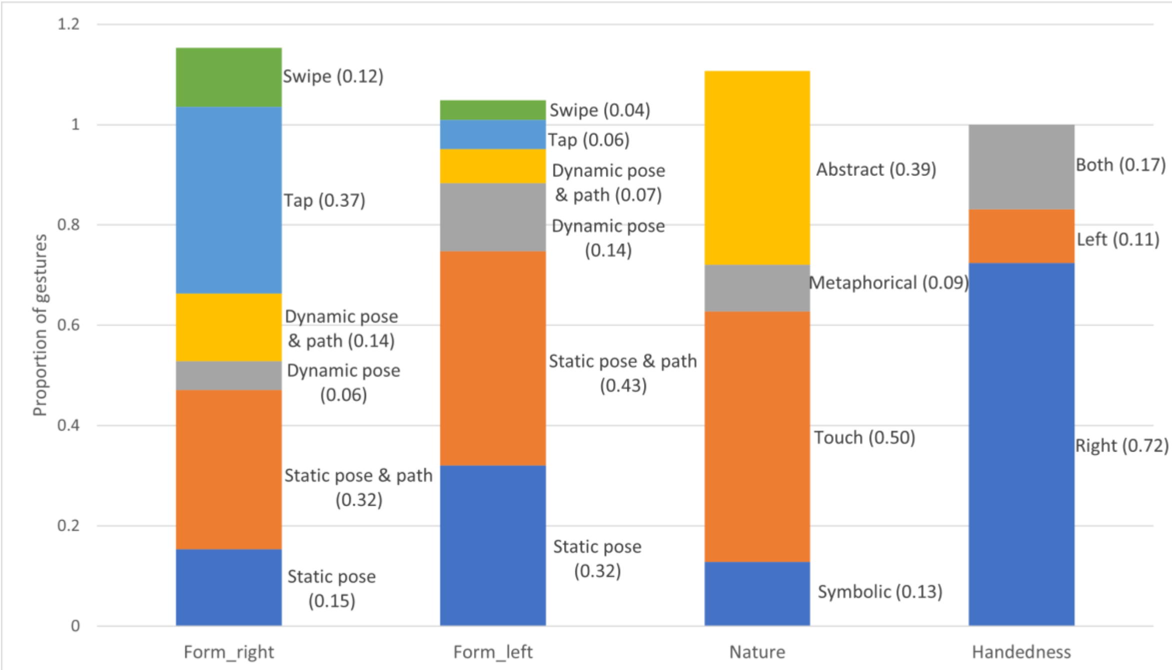

Figure 3 Proportion of gestures in each category along the dimensions described in Table 3. The form dimension has been applied to the right and left hand separately. Some gestures fall into multiple categories along the same dimension.

Voice Command Classification

Based on the taxonomy proposed by Hoffmann et al. (75), we categorized the voice commands elicited in the study along four dimensions (presented in Table 4). Based on the structure and the number of words used, the voice commands are categorized into four categories along the form dimension. We considered any names used in the voice command (name of a song, podcast, presentation, or audiobook) to be a single word. Action and state are the two categories along the nature dimension. Action voice commands describe the action to be executed (e.g. open karaoke application), and state voice commands describe the desired condition (e.g. karaoke). Some voice commands needed the system to be aware of the context to execute, and other voice commands did not require any context. For example, the voice command *exit* used to exit the karaoke application require the system to know which application the command is referring to. Whereas the voice commands *exit the karaoke app* does not require any context. Lastly, voice commands were categorized into simple and complex categories depending on whether the command consists of single or multiple commands.

The proportion of the elicited voice commands along the four dimensions described in Table 4 is presented in Figure 4. Along form dimension, most voice commands fall into the sentence (52%) and two words (33%) category. We also found that most voice commands needed specific context (64%) to be executed, and they were dominantly simple (86%) commands.

Table 4 Taxonomy of voice commands.

Dimension	Category	Description
Form	Single word	Voice command consists out of a single word
	Two words	Voice command consists out of two words
	More words	Voice command consists out of more words without sentence structure
	Sentence	Voice command uses sentence structure
Nature	Action	Voice command states the action to perform
	State	Voice command describes the desired condition
Context	In-context	Voice command requires specific context
	No-context	Voice command does not require specific context
Complexity	Simple	Voice command consists of a single voice command
	Compound	Voice command can be decomposed into simple voice commands

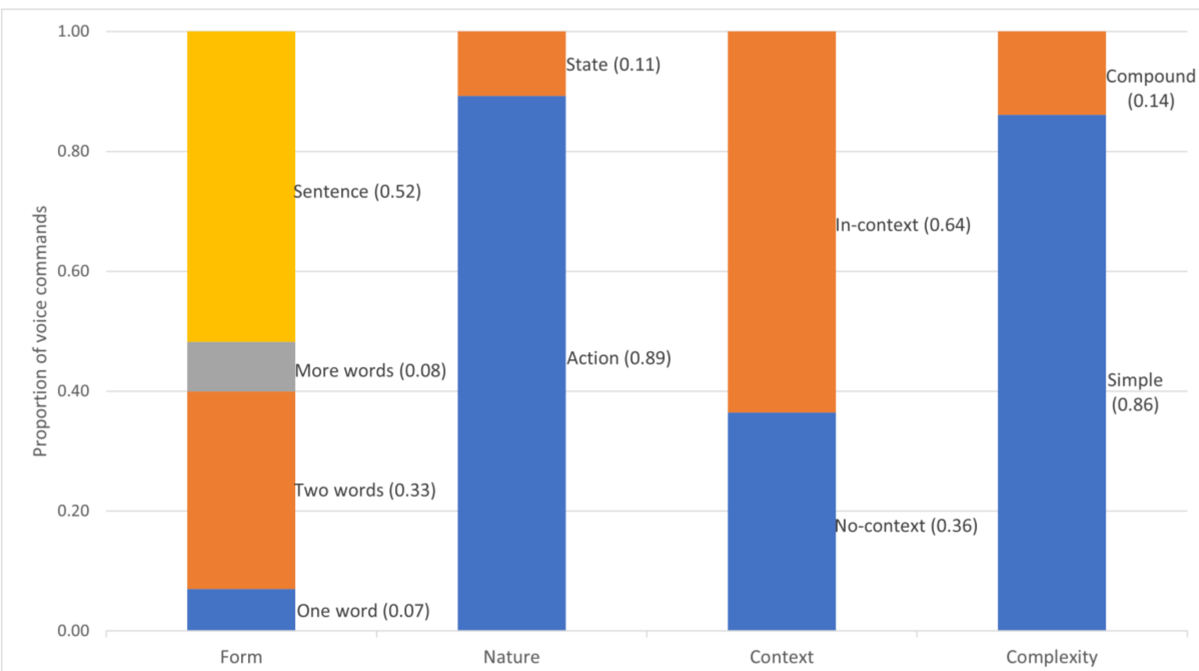

Figure 4 Proportion of voice commands in each category along the dimensions described in Table 4.

Interaction Preference

For most of the referents (21 out of 24), participants preferred voice commands over gestures to perform the intended task. Participants' preference of interaction for each referent is presented in Table 2. Overall, among the 373 instances of interacting with AR WSD, participants preferred voice commands in 276 (74%) instances. We also analyzed which words participants commonly used to describe why they preferred a certain interaction modality for a specific referent. We found that *ease of use* was by far the most common theme they mentioned while explaining the rationale for their preference. Among the 276 instances where the participant stated they preferred voice commands, they often used words like *easy, simple, easier,* and *simpler* (124) to describe interaction using voice commands and words like *hard* and *difficult* (22) to describe their interaction using gestures. For example, while stating why they preferred voice commands for the referent *open karaoke application*, one participant wrote, "Easier to say, harder to show karaoke.". Other common themes we observed were that participants perceived voice commands to be more *precise* and *accurate* (29), easier to *understand* (12), and *quicker, faster,* or *fast* to perform (22). One participant stated, "Easier, quicker, more precise than using a gesture for such a task.". Some participants also appreciated the fact that they don't have to use their *hand* or *hands* (16) while using voice commands to interact with WSD; "I think it would be safer, considering I have to put my hands on the wheel, even if I assume the car would alert me in time.". These themes were also common among the 97 instances where the gestures were preferred by the participants. Some participants stated that gestures were *easy, simple, easier,* or *simpler* (41) for them to perform that particular task; "Since it's a long name I find it easier to point and click on the podcast I want to play.". Other words participants commonly used were *fast* or *faster* (23) and *convenient* (5); "I think it's faster and more convenient, considering the fact I don't have to put my hands on the wheel.".

Discussion

In this study, we examined 373 gestures and 373 voice commands elicited from 31 participants for 24 personal and work-related tasks. We did not observe any significant difference in terms of agreement rate between the two modalities of interaction. The overall consensus among the participants for both modalities of interaction was low compared to similar studies conducted previously (75; 60; 78). This could be caused by the complex nature of the referents we used in the study that required participants to convey some specific information, like the name of an audiobook or podcast. So the participants had to come up with various gestures and voice commands that they may not have used previously to interact with any other systems. Another factor that may have contributed to this diverse set of elicited interactions was that the participants never used AR WSD in real life. So their interactions were less likely to be influenced by legacy bias (79).

We found that a significant proportion of gestures used static pose and path for both the left and right hand. However, the proportion of tap gestures was comparatively higher for the right hand, whereas the proportion of static gestures was higher for the left hand. This suggests that in two-handed gestures, people often used the right hand for movement while keeping the left hand static. This is consistent with prior research that shows that for asymmetrical two-handed actions, the dominant hand often operates in the spatial reference to the action of the other hand (80).

While using voice commands to interact with AR WSD, mostly preferred simple commands that described the action to be performed. A significant proportion of the commands required the system to be aware of some task-specific contexts to be able to execute the command correctly. We also observed participants using similar interactions to perform similar tasks in different scenarios or applications. This suggests that contextual awareness will be crucial while designing interactions for such interfaces.

Our results clearly show people's preference to use voice commands over gestures to interact with WSD. Several prior studies also found a similar preference for interacting with smart-home devices (75) and automotive interfaces (78). Irrespective of participants preference for interaction modality, the most common theme influencing the preference was the ease of use. For some participants, the ease of use meant performing the task quickly and for others it meant the ability to convey some specific information easily. So, even though we see a clear preference for voice commands in our study, it will still depend on individual differences and specific task in question. Moreover, we did not examine various scenarios where gestures could be preferred over voice commands. For example, if the driver is talking to the passenger or in a virtual meeting, using voice commands may be inconvenient.

One limitation of the study is that it was conducted online. The interactions and interaction preferences may be different within a car because of the driving context. We also did not consider scenarios where drivers are talking, so voice commands become inconvenient. We also did not examine how cultural differences might affect interactions car, even though we recruited participants from different continents. Despite these limitations, the findings from our study will benefit future research aiming to generate a user-elicited set of interactions for engaging in complex NDRT using AR WSD.

Chapter 3. Takeover Strategies in Automated Cars

After focusing on productivity in the previous chapter, here we focus on the other major factor related to working in automated vehicles, safety. We specifically look into the process of switching between driving and other activities in highly automated vehicles. This chapter is based on the following publication:

How will drivers take back control in automated vehicles? A driving simulator test of an interleaving framework. **Divyabharathi Nagaraju, Alberta Ansah, Nabil Al Nahin Ch, Caitlin Mills, Christian P Janssen, Orit Shaer, Andrew L Kun.** 2021. 13th International Conference on Automotive User Interfaces and Interactive Vehicular Applications.

Conditionally automated vehicles will be able to operate without the driver's input under certain limited conditions. However, vehicle automation technology is still not advanced enough to tackle many driving situations. So, it is crucial that in conditionally automated vehicles, drivers can quickly and safely take back driving from vehicle automation when asked to. Drivers will need support during this transition phase to ensure a safe and efficient transition of control. The takeover process in conditionally automated vehicles has been investigated in several recent studies (82; 83; 84; 85; 86; 87; 88). This is a complex process that can be influenced by various factors. Research on this area so far mostly focused on takeover quality and treated the takeover process as a single-step event where drivers stop the NDRT and start driving when a takeover request is presented. Janssen et al. proposed that the takeover process consists of a series of steps, similar to interruption in other domains (17). Based on interruption literature, this proposed model suggests that people will often interleave between driving and the NDRT before finally taking over driving responsibility. This framework allows researchers to investigate the takeover process at a granular level and examine different strategies people use during the takeover in addition to takeover quality. While this proposed model is based on task switching and interleaving literature in other domains, this model has not yet been empirically validated. So, we conducted a driving simulator study to investigate if there is empirical support for the stages proposed in this model. We pose the following research questions:

- RQ1. Do drivers interleave while switching from NDRT to driving in a conditionally automated vehicle?
- RQ2. Does the probability of interleaving is affected by the available time to take over?
- RQ3. How do people engage in NDRT while interleaving?

Related Work

Research on takeover in conditionally automated vehicles has been primarily focused on takeover performance in terms of the time it takes to resume driving and the quality of the takeover, and also how various factors affect takeover performance (83; 89; 90; 91). The amount of time needed for the driver to take over safely depends on how long it takes them to develop the necessary situational awareness by gathering information from the surrounding environment.

Gold et al. investigated whether the takeover time is influenced by the amount of time available for the driver to take over (takeover time budget) (90). They found that for a shorter takeover time budget, drivers usually make quicker decisions and react faster, even though that generally results in worse overall quality. Another factor that affects takeover quality is the resources needed for the NDRT. Performing NDRTs that require similar resources (visual and manual) as driving seems to interfere with driving performance more (92). Walch et al. evaluated takeover performance for various driving assistance systems and found that people prefer multimodal (auditory and visual) handover assistance (91). Mok et al. examined takeover timings for distracted drivers in automated vehicles in emergency situations where the vehicle automation is switched off (93). The results showed that drivers were able to safely navigate through the emergency scenario if the obstacle was at least five to eight seconds away from the time of vehicle automation turning off.

These studies provide important information on how various factors affect the timing and quality of takeover in conditionally automated vehicles. But they cannot provide details of the takeover process at a granular level in terms of what strategies people use because the takeover process in these studies is treated as a single-step event instead of a process involving multiple stages. Yet prior work in other domains shows that when interrupted, people often interleave between two tasks before switching. The model for switching between driving and NDRT proposed by Janssen et al. accounts for this phase of interleaving in conditionally automated cars. In this study, we aim to extend existing knowledge on the takeover process by examining different stages drivers go through when disengaging from NDRT and taking over driving.

Method

We designed an experiment where the participants periodically switched between automated and manual driving using a PC-based driving simulator. During the automated driving phase, participants engaged in an NDRT on a laptop. We manipulated the amount of time participants got to take over driving once the takeover request was presented. The experiment setup is shown in Figure 5.

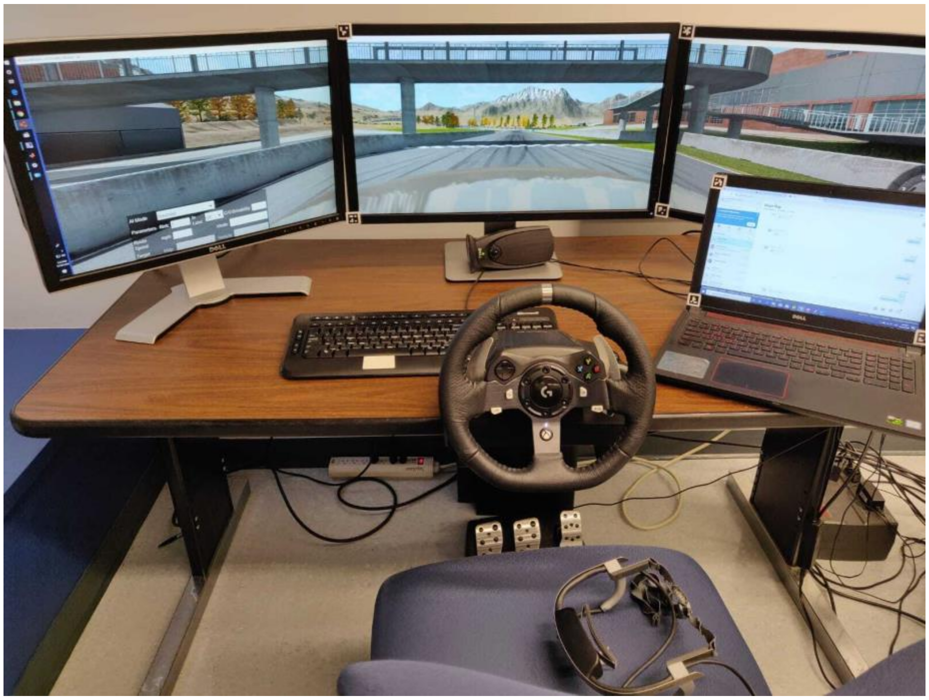

Figure 5 Experiment setup showing the driving simulator, the laptop used for performing the NDRT, and the eye tracker.

Tasks

Driving Task

Participants operated a simulated vehicle on the BeamNG.drive application using a PC-based driving simulator (shown in Figure 5). This application is widely used in similar studies to simulate manual and automated driving (94; 95). Participants drove on a single-lane rural road in the daytime, and there was no traffic on the road. Participants periodically switched between manual and automated driving. In the manual driving phase, participants were responsible for maintaining lateral and longitudinal control of the vehicle. During the automated driving phase, the vehicle was able to operate without any input from the driver, allowing the driver to fully engage in the NDRT.

Twenty-question Task

We used a simplified version of the twenty questions task (TQT) (96) as the NDRT. This task has been widely used as an NDRT in similar studies because of its similarity with many other everyday tasks people perform (97; 87; 98; 99; 100; 101). For this simplified version, participants were asked to guess an item from 18 possible options by asking as few yes or no questions as possible. Each item was located either in the kitchen, bathroom, or living room and had two additional characteristics to help participants identify them. Some sample items used in the task are shown in Figure 6. Before starting the experiment, participants were trained on the TQT. They engaged in the TQT by typing questions on Skype using a laptop located on the right side of the participant.

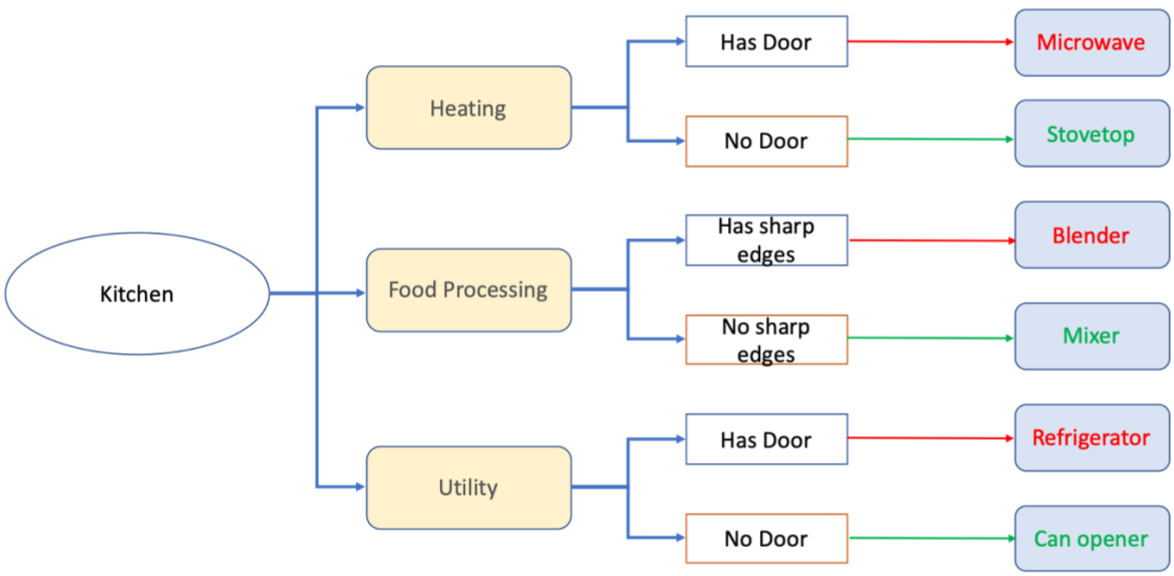

Figure 6 Sample items from the simplified twenty questions task.

Switching Between Tasks

In this experiment, each participant completed two drives and switched from automated to manual driving three times in each drive. We manipulated the takeover time budget (15 and 30 seconds) for two drives. When switching from automated to manual driving, a pre-alert was issued consisting of a beep followed by a voice message, “There is a narrow road and merging ahead.”. After the pre-alert, participants had either 15 or 30 seconds to take over, depending on the condition. If the participant did not resume driving after the pre-alert, an emergency alert saying, "Emergency, take over the control" was issued when there were eight seconds left to take over (7 and 22 seconds after pre-alert in 15 and 30 seconds conditions, respectively). After the takeover time budget (15 or 30 seconds) passed, the vehicle automation was turned off automatically. Participants pressed a key on the keyboard to take over driving. Participants started the TQT when the automated driving phase started, and they could continue the TQT regardless of the pre-alert, emergency alert, or condition of driving automation.

Experimental Design

In this within-subjects study, we manipulated the takeover time budget. In short and long takeover time budget conditions, the takeover request was presented 15 and 30 seconds before the deactivation of vehicle automation. In both conditions, an emergency alert was presented eight seconds before the deactivation of automated driving if the participant did not take control of the vehicle by then. The time budget conditions we selected were based on what the initial conditionally automated vehicles will realistically be able to achieve in terms of allowed takeover window and how we can expect to see improvement in this regard as the vehicle automation technology continues to improve (4; 3). The order of the conditions was counterbalanced between participants.

Each participant completed two drives, one under each condition. In each drive, participants switched from automated to manual driving three times. Each manual and automated driving phase lasted 65 and 100 seconds, respectively.

Participants

We recruited 21 participants for this experiment. All participants were students in the University of New Hampshire and their participation was an optional assignment in a course (students could either participate in the experiment or complete a different assignment). Due to technical difficulties, we could not record complete data from two participants. Thus, the results we present here are from analyzing data from 19 participants. The participants were aged between 18 and 21 years (M=19.26, SD=1.02). Eight participants were men and 11 women. Thirteen participants (68.42%) reported that they held a valid driver's license at the time of the experiment.

Procedure

At first, the participants read the instructions for what they were going to do in the experiment. Then they read and signed a consent form and completed a demographic survey. After that, the participants were trained on the driving simulator to get familiar with its operation and the process of switching between manual and automated driving. Participants also practiced the TQT before starting the first drive. Then we calibrated the eye tracker, and the participants completed one drive each in the long and short takeover time budget condition.

Apparatus and Software

We used a PC-based driving simulator consisting of three 22-inch (diagonally) displays and a Logitech G920 Driving Force steering wheel with brake and acceleration pedals. A 15-inch (diagonally) laptop was used by the participants to engage in the TQT. The BeamNG.Drive application was used to simulate manual and automated driving. We also used an Ergoneers Dikablis head-worn eye tracker to record participants' gaze behavior. Driving-related events (e.g., alerts, vehicle automation on or off), eye tracker data, and participants and experimenter keystrokes were recorded synchronously using the D-lab software at a 60 Hz rate.

Data Collection and Measures

We recorded timestamps for the start and end of the experiment, pre-alert takeover request, emergency alert takeover request, start and end of each manual and automatic driving phase, and each keystroke. From the eye tracker data, we identified when the participant was looking at the driving-related area (displays, steering wheel, or instrument panel) or the NDRT (laptop). We also recorded all the key presses by the participant and the experimenter for performing the TQT.

Takeover Time

Takeover time was calculated as the elapsed time between the presentation of the pre-alert and when the participant pressed the button to take over control of the vehicle.

Transition Stages

In this article, we focused on the stages related to switching from NDRT to driving (stages 0-6) based on the interleaving model (17).

Stage 0 - Performing NDRT: This stage starts at the beginning of the automated driving phase. The participant starts engaging in the TQT at the start of this stage.

Stage 1 – External alert: When the initial takeover request was presented.

Stage 2 – Disengage from NDRT: The first instance is when the participant looks away from the laptop used for the TQT.

Stage 3 – Orient to driving: First glance at the driving scene after the takeover request.

Stage 4 – NDRT suspension: The last time participant engaged with the TQT. This is determined by the last time they either looked at the TQT screen or pressed any key to perform the TQT.

Stage 5 – Physical transfer of control: When the vehicle automation was turned off, either by the driver or because the takeover time budget expired.

Stage 6 – Contribute to driving: This stage lasts from the beginning of the takeover to the start of the next automated driving phase.

Data Analysis and Results

We used linear and logistic mixed-effect regression approaches depending on the dependent variable to analyze the data. This approach allowed us to account for the baseline differences among individuals while assessing the effect of the factors of interest. The significance of the models was estimated using the chi-square test. For each model, the takeover time budget was the fixed effect, and the participant ID was included as a random effect. We also present descriptive statistics and effect sizes.

We evaluated participants' TQT performance (shown in Table 5) to validate their engagement in the NDRT. Participants attempted more items, correctly guessed more items, and incorrectly guessed fewer items in the long takeover time budget condition. This suggests that the participants were reasonably engaged in the NDRT.

Table 5 Participants' performance in TQT

Scenario	Mean attempted items	Mean correct guesses	Mean incorrect guesses
15 seconds	6.11	4.95	0.74
30 seconds	6.53	5.64	0.58

Empirical Evidence for Interleaving Model (RQ1)

Out of the 110 takeovers in this study, drivers followed the sequence of stages proposed in the interleaving model in 71 takeovers (64.5%). This shows that people often interleaved between driving and the NDRT while taking over control from automated driving. But they did not always interleave during takeovers. We found two strategies people use for takeover. In the *interleaving* strategy, drivers went through stages 3 and 4 in sequential order, as proposed in the interleaving model. In other words, drivers glanced at the driving scene after the takeover request, but they disengaged from the NDRT after the initial glance at the driving scene. In the *suspension* strategy, the order of stages 3 and 4 is reversed. People simply stopped the TQT after the takeover request, glanced toward the driving scene, and took over vehicle control.

Effect of Takeover Time Budget (RQ2)

We analyzed whether the probability of drivers adopting a certain takeover strategy is influenced by the amount of time they are allowed for the takeover using a logistic mixed-effects model. We found a significant effect of the takeover time budget on the probability of observing the interleaving strategy; $\chi^2(1)=11.90$, $p<0.001$, $\beta=-1.86$, $SE=0.54$. Drivers were more likely to interleave in longer (80%) takeover time budget conditions compared to shorter (49%) ones.

Utilizing Interleaving Time (RQ3)

We found that people took significantly longer to take over when 30 seconds ($M = 19.20$; $SD = 9.30$) were allowed for them to resume driving compared to 15 seconds ($M = 9.82$; $SD = 3.95$); $\chi^2(1)=73.20$, $p<0.001$, $\beta=9.40$, $SE=1.10$, $d=1.32$. This is consistent with prior studies that suggest that people take over quickly in urgent situations (83).

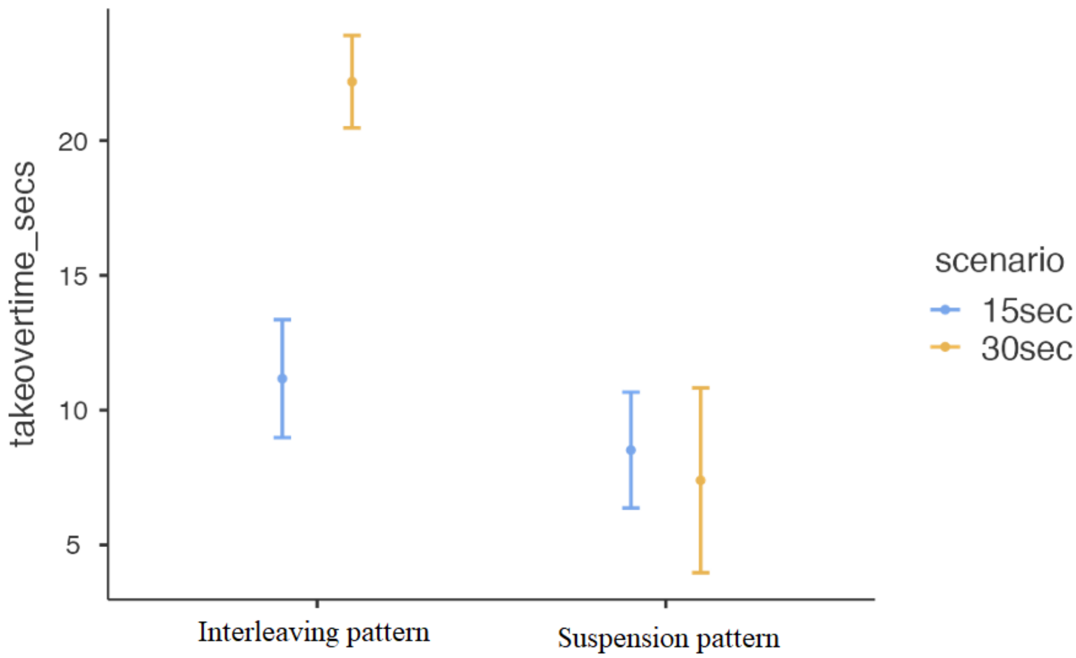

Figure 7 Takeover time for different takeover strategies

Table 6 Participants' actions in TQT during the takeover

Scenario	Stopped	Attempted but not finished	Finished and stopped	New item started
15 seconds	19	29	7	0
30 seconds	12	19	13	11

Another interesting finding was that the takeover strategy influenced the actual time taken for takeovers. Using a mixed-effect model, we found a significant interaction between the takeover time budget and takeover strategy; $\chi^2(1)=20.1$, $p<0.001$, $\beta=10.50$, $SE=2.34$. Takeover time was similar in both 15- and 30-second time budgets for the suspension strategy but not in the case of the interleaving strategy (presented in Figure 7). This suggests that the effect of the takeover time budget on takeover time is moderated by the strategy driver used for taking over.

We also analyzed what people did in the TQT during the interleaving time. We considered the following four options:

1. Stopped: The participant stopped the TQT and switched to driving.
2. Attempted but not finished: The participant continued asking questions but did not guess the item.
3. Finished and stopped: The participant made a correct or incorrect guess and then switched to driving.
4. New item started: The participant guessed an item and started asking questions to guess the next item.

Participants' actions during the takeover time are summarized in Table 6. We found drivers only started guessing new items in longer takeover time budget conditions but not in shorter conditions. Some of the drivers also continued asking questions after guessing an item. This suggests that not all drivers will likely stop the NDRT at a natural breakpoint.

Discussion

In this study, we found empirical support for the interruption model proposed by Janssen et al., and the results show that people often interleave between driving and the NDRT when taking back control from vehicle automation. Drivers follow either the interleaving or suspension strategy for taking over. The takeover time budget is one of the various possible factors that influence the probability of adopting a particular strategy. The takeover time is also affected by the takeover strategy.

These findings will be important considerations while designing the automotive user interfaces of conditionally automated cars that also support safe and productive NDRT engagement. We cannot assume that the driver will simply switch to driving whenever asked to. Since multitasking usually affects task performance negatively, and while interleaving, drivers must allocate limited resources to both driving and NDRT, we will have to investigate how interleaving affect takeover performance. We also need to investigate which driving, and NDRT factors influence the probability of interleaving while taking over. This will provide insights into which types of NDRT will be easier to perform in automated cars and in which situations drivers may need additional support.

We know from prior research that drivers do not always stop a task at the task boundary if they think that will interfere with safe driving during takeover (102). We see similar results in this study (see Table 6). Drivers stopped TQT before guessing an item more often in 15 seconds takeover time budget condition compared to 30 seconds takeover time budget condition. Presumably, drivers thought trying to reach a natural break point in the task could negatively affect their driving performance during takeovers. In contrast, we see more instances of people reaching task boundaries (guessing the item) and even starting a new task in the 30-second conditions.

Our experiment was conducted using a low-fidelity driving simulator in an indoor laboratory environment. Drivers' behavior may be different in a real car on the road, where the risks associated with dangerous driving behavior is obvious. However, we observed the drivers to be engaged in the driving task. Out of the 110 takeovers in the experiment, participants resumed driving before the end of the allowed takeover time budget in 91 instances (82.7%). Thus, our findings from this experiment can provide indicators of what we might expect from drivers in future automated cars.

Participants of our study were young college students. So, the findings may not be generalizable. Even with some limitations, our study provides important insights to build on the existing knowledge in the takeover process in conditionally automated vehicles. Future research will have to investigate takeover strategies in different driving scenarios and for various NDRTs.

Chapter 4. Analyzing Takeover Strategies

In this chapter, we discuss how the takeover strategies identified in the previous chapter relate to driving and NDRT performance during the takeover process. This chapter is based on a manuscript that is in preparation:

Texting in conditionally automated cars: effects on takeover strategy and performance. **Nabil Al Nahin Ch, Jared Fortier, Christian P Janssen, Orit Shaer, Caitlin Mills, Andrew L Kun.** (In progress).

People often multitask in their daily life, and while multitasking, they sometimes have to interleave between those tasks. Even for complicated tasks like driving, when a moment of inattention can create dangerous situations, people often engage in different non-driving related tasks (NDRTs) (6; 103; 104). Multitasking while driving can interfere with safe driving practices. However, studies show that people would want to perform various NDRTs in future conditionally automated vehicles (5; 6; 7). To ensure that people can engage in NDRTs in conditionally automated vehicles, drivers will need support to switch between driving and NDRTs safely. Failure to stop NDRT in a timely manner and properly take over driving responsibilities can negatively affect takeover performance. The transition of control in the context of highly automated vehicles has been examined extensively in previous studies (82; 83; 86; 84; 85; 88; 87). Takeover is a complex process that can be affected by various factors like the takeover time budget, traffic situation, the type of NDRT, etc. Determining how different NDRTs can affect takeover is not trivial either, as there are different approaches to categorizing NDRTs (e.g., cognitive load (105; 106), resources needed (6; 106)).

While researching takeovers in highly automated cars, this process is usually treated as a single-step event, and the focus has been mostly on takeover performance in terms of timing and driving quality. Janssen et al. proposed a framework for takeovers that treat this process as a sequence of distinct stages, similar to research in other domains on interruption. This model allows researchers to examine the takeover process in much finer detail. Based on this framework, we found that when drivers are interrupted (asked to take over driving) in their NDRT, they follow either an interleaving or suspension strategy for takeovers (81). In the interleaving strategy, drivers go back and forth between driving and the NDRT before eventually stopping the NDRT and resuming driving. Which takeover strategy people will follow may depend on various factors like different attributes of the NDRT, traffic conditions, individual differences among drivers, etc. Even though in the previous study, we identified two takeover strategies, we still don't know how these strategies affect takeover and NDRT performance and which aspects of the NDRT influence driver's decision to adopt a certain takeover strategy. In this study, we focus on texting tasks on smartphones as reading and typing emails and texts is one of the most common NDRT people currently perform while driving and want to perform in future automated cars (5; 6). It is crucial to understand how different texting tasks on handheld devices affect takeover strategy and performance since prior research shows a negative effect of such tasks on almost all measures of safe driving (107).

Here, we present findings from two driving simulator studies where participants performed different texting tasks on a smartphone and took over driving when instructed. In the first experiment, we focused on three different texting conversations requiring different cognitive demands; assimilation, retrieval, and generation (discussed more in the section Non-driving related task). In the second experiment, we investigated a multi-step texting task (20-question task) and different priorities for driving and NDRT. We also manipulated the takeover time budget (10 and 30 seconds) in both experiments. We investigated how different cognitive demands of texting conversations, priorities, and takeover time budgets influence takeover strategies. In addition, we evaluated the effect of takeover strategies on takeover performance in terms of timing and quality.

Related Work

Multitasking and Task Interleaving

People often multitask and transition between multiple activities while working, sometimes as frequently as once every three minutes (108; 109). Multitasking can be broadly categorized into concurrent and sequential multitasking. When multiple tasks are performed at the same time and resources are shared simultaneously, it is called concurrent multitasking. In sequential multitasking, multiple tasks are performed by switching back and forth between the tasks (110). For example, driving and talking to the passenger can be considered concurrent multitasking, whereas driving and texting will be sequential multitasking. People interleave between tasks to improve overall performance and maximize the marginal rate of return (111). Interleaving is often initiated by external interruptions, but it can also be self-initiated (112). In this study, we focus on sequential multitasking (interleaving between driving and NDRT) that is initiated by external interruptions (takeover requests).

Numerous prior studies have investigated how various factors like difficulty and priority of tasks affect people's interleaving strategies and how to predict when someone might switch between tasks. Duggan et al. proposed that the perceived marginal rate of return may indicate when people will interleave between tasks (113). The marginal rate of return can be estimated based on the difficulty or importance of the task. Wickens et al. proposed the strategic task overload management (STOM) model to predict task switching based on similar factors; difficulty, priority, interest, and salience (114). Similar effects of cognitive load or difficulty

(115; 116; 117) and potential reward or priority (117; 118; 119) on people's decision to select which task to perform and when to switch tasks.

Texting in Car

Among various NDRTs people perform while driving, some tasks like reading or replying to emails or texts often require them to use handheld devices like smartphones. Texting while driving is common among people around the world (120; 121), especially among young drivers (122; 123). Researchers estimated that thousands of fatalities resulted from texting while driving (124). This is not surprising, considering texting on smartphones negatively affects almost all measures of safe driving. A meta-analysis of 28 research studies found negative effects of texting on driver's reaction time, vehicle control (both longitudinal and lateral), gaze behavior, situational awareness, and accident risks (107). The use of smartphones has also been linked to a lack of situational awareness (125) and an increase in cognitive load (126). This can similarly result in a lack of steering wheel control (127) and slower reaction to events (128; 126), and eventually, a higher probability of causing an accident (129; 130).

Similar adverse effects of texting and smartphone use have been observed on drivers' performance while taking back control in highly automated vehicles. Handheld device manipulation or NDRTs that require visual attention can increase the takeover time (89; 131; 132). In contrast, a study conducted by Zeeb et al. found not effect of similar tasks on takeover time, but a negative effect on the quality of driving after taking over in terms of maintaining a stable lane position (133).

These negative effects of NDRTs are often attributed to the need for physical manipulation of devices. In a meta-analysis of 129 studies, researchers found a strong influence of handheld devices on takeover time, whereas the influence of hands-free NDRTs was relatively small (83). However, several other studies found that even hands-free NDRTs have similar negative effects on driving performance (125; 129). This suggests that the cognitive demand of NDRTs may affect driving performance in a similar way as the manual manipulation of a device does. In their study, Lee et al. found that the cognitive demand for realistic NDRTs interfered with lateral and longitudinal control during takeovers, while the physical and visual attributes of NDRTs did not (105). Similarly, Kaye et al. found that NDRTs on handheld devices and hands-free working memory tasks have similar effects (134). Cognitive demand varies depending on the NDRTs, and retrieving information from memory can interfere with driving in complex traffic scenarios (130).

How much time drivers are allowed to take back control of the vehicle can also influence takeover performance. With shorter allowed time, drivers take over quicker, but they find it difficult to scan their surroundings and establish proper situational awareness (90). With longer allowed time for takeovers, drivers take longer to resume driving (83; 135), but their takeover performance improves (136).

Unlike driving and NDRT performance, very few studies focused on multitasking strategies in conditionally automated vehicles, especially during takeovers. Studies show that people's strategies for transitioning from NDRT to driving are influenced by the NDRT difficulty, the complexity of the driving situation, and the priority or potential reward for NDRT or driving (137; 102; 138; 139; 140). Drivers decide on what stage of NDRT they will suspend the task and resume driving based on performance objectives (138; 102; 140).

Research Questions

These studies demonstrate that multitasking and task switching have been explored extensively in various driving scenarios but not for takeovers. Studies focusing on takeovers have mostly treated the process as a single-step event. So, the primary focus of these studies has been takeover performance. But the takeover strategy in terms of interleaving between driving and NDRT during takeovers has not been studied. A previous study shows that people often treat the takeover request as an interruption and interleave between tasks during takeovers (81). Since multitasking and task interleaving can affect task performance, we need to investigate task interleaving in the context of takeovers in conditionally automated vehicles. Various factors can influence multitasking and takeover strategies. To understand the takeover process in greater detail, we conducted two driving simulator studies.

In the first experiment, we focus on different cognitive demands of texting and examine how that influences drivers' takeover strategies. We also investigate the effect of takeover strategies on takeover performance and drivers' engagement in texting conversations. Thus, we pose the following research questions:

RQ1.1 How do different cognitive demands of texting conversations and takeover time budgets influence takeover strategy?

RQ1.2 How do different takeover strategies affect drivers' engagement in texting conversations and their takeover performance?

In the second experiment, we examine how different priorities of driving and NDRT affect takeover strategies and how that, in turn, influences takeover performance and drivers' engagement in a multi-step texting task. Thus, we examine the following research questions:

RQ2.1 How do the priority and takeover time budget affect takeover strategies?

RQ2.2 How do different takeover strategies affect drivers' engagement in a multi-step texting task and their takeover performance?

Method

Experiment 1

In this within-subjects experiment, we examined whether the takeover strategies (probability of interleaving) are related to different cognitive demands of texting conversations and allowed time for a takeover. We also analyzed how takeover strategies affect takeover performance and engagement in texting conversations. In this experiment, participants periodically switched between manual and automated driving and engaged in an NDRT similar to having a texting conversation using a smartphone. We manipulated the cognitive demands of texting conversations (assimilation, retrieval, generation) and the takeover time budget (10 and 30 seconds). Each participant completed six drives (text type (3) x time budget (2)) in six conditions. The order of the conditions was counterbalanced across participants.

Participants

Twenty-four people (15 men) with an average age of 23.71 years (SD=4.34) participated in the experiment. We could not record driving-related data for 20 drives and eye-tracking data for two drives because of technical difficulties. We discarded data for 14 takeovers because of inaccuracies in eye-tracking data. So, for the takeover strategy, we analyzed data from 24 participants and 412 takeovers, and data from 22 participants and 356 takeovers for takeover performance (only eye-tracking data was used for determining takeover strategy). All the participants held a driver's license and received a $20 gift card for their time.

Experiment 2

In the second within-subject experiment, we examined how the priority of driving or NDRT influences takeover strategy in terms of task interleaving and whether this effect is moderated by the takeover time budget. We also examined the effects of takeover strategy on takeover and NDRT performance. Similar to the first experiment, participants periodically switched between manual and automated driving. During automated driving, participants performed a multi-step texting task. They were instructed to prioritize either the NDRT or driving, and the takeover time budget was either 10 or 30 seconds. Participants completed four drives in four conditions (priority (2) x time budget (2)). The order of the conditions was counterbalanced across participants.

Participants

Twenty-four people (7 women) with an average age of 15.67 years (SD=4.98) participated in this experiment. We could not collect driving-related data for three participants and eye-tracking data for four drives because of technical difficulties. We discarded data for 17 takeovers where the participant did not follow instructions (e.g., changed lanes) or eye-tracking data were inaccurate. So, to evaluate the takeover strategy, we analyzed data from 24 participants and 259 takeovers. To evaluate takeover performance, we analyzed data from 21 participants and 227 takeovers. Participants held a driver's license and received a $20 gift card for their time.

Apparatus and Software

We used a pc-based driving simulator, an eye tracker, and a smartphone for both experiments. We collected data at a 60 Hz rate from the driving simulator and the eye-tracker using Ergoneers D-lab software. Figure 8 shows the experiment setup.

Figure 8 Experiment setup showing a participant wearing the eye tracker and using a smartphone to perform NDRT in the automated driving phase.

Driving Simulator

We used the miniSim driving simulator for the experiments. The simulator is equipped with a driver's seat, steering wheel, pedals, motion system, and instrument panel. The driving scene is displayed on three 48-inch screens. We collected driving-related data (e.g., speed, lane position) at a 60 Hz rate. We also logged the timestamps of other events like takeover requests, driving automation switches, etc.

Eye Tracker

We used Ergoneers Dikablis head-worn eye tracker to record participants' gaze location at a 60 Hz rate. To analyze their gaze behavior, we defined two area-of-interest (AOI), which were detected using 2-D markers. The driving-related AOI consisted of three displays, the instrument panel and the steering wheel. The NDRT AOI was the smartphone display. This AOI moved along with the smartphone and was tracked with the 2-D marker attached to the phone.

Smartphone

Participants used a 6.1-inch smartphone for performing the NDRTs. Smartphone settings were changed to ensure the display was always on and never went to sleep. The phone display was recorded to analyze activities related to NDRTs.

Task

Driving Task

In each drive, participants drove for approximately eight minutes on a straight, two-lane highway in daylight. The width of each lane was 3.66 meters (12 feet). Participants were asked to follow a lead vehicle maintaining a safe distance that was driving at 104.6 km/h (65 mph). There were no other vehicles on the road. Participants periodically switched to manual and automated driving every 60 seconds.

Non-driving-related Task

Researchers used various types of NDRT to examine how that impacts takeover performance in conditionally automated vehicles (141; 142). In the first experiment, we focused on texting conversations because this is NDRT people often perform in a car, and it can negatively affect driving performance. We designed the texting task based on the article by Iqbal et al., where they categorized conversations depending on their cognitive demands (assimilation, retrieval, generation). In the assimilation task, participants were asked to read a short paragraph (mean word count 119) and answer two questions related to the article (e.g., This January, temperatures across Europe reached an all-time high.). This task required participants to acquire new information. In the retrieval task, participants were asked to retrieve some information from memory (e.g., What was the last name of your first boss?). The generation task required participants to generate information like directions from one known location to another (e.g., Please give directions from your home to your favorite local restaurant.). These questions were presented one at a time, and they were designed to stimulate different cognitive demands.

We selected a multistep texting task called twenty questions task (TQT) as NDRT in the second experiment (96). This task has been widely used as NDRT in driving simulator studies (97; 87; 100; 101; 98; 99). In this task, participants were asked to guess an item by asking as few yes or no questions as possible. Similar to many tasks people perform in their everyday life, this task requires problem-solving by planning, generating information, and using working memory. Participants typed questions on Skype to perform the task. Participants were given a list of 10 items ("fruits and vegetables" or "animals") before they started the first drive. They did not have access to the list during the drive. Most generic form of items was used for the task (e.g., dog instead of a particular breed of dog).

Switching Between Tasks

Participants switched from automated to manual driving three times in each drive. Each manual driving phase was 60 seconds. Automated driving phases were 60 seconds plus the time they took to take over after the takeover request. Drivers were instructed to engage in the NDRT during the automated driving phase. After a 60-second phase of manual driving, automated driving was activated, and a beep followed by a voice message (“Automated driving started”) informed the driver. After 60 seconds of automated driving, a takeover request was presented. In the long time budget condition, the takeover request was a beep followed by a voice message (“Take over the vehicle within the next 30 seconds”). If the driver did not resume driving in the first 20 seconds after the initial takeover request, a final alert was presented (“Take over control of the vehicle”). In the short time budget condition, only the final alert was presented as the takeover request. Automated driving was switched off if the driver did not take back control within the allowed time (10 or 30 seconds, depending on the condition). At the start of the manual driving phase, a beep and a voice message ("Manual driving started") were played.

Procedure

Participants started by reading and signing the consent form and completing a short demographic survey. After that, they were given a document with written instructions for the experiment, and the experimenter answered if the participants had any questions about the experimental procedure. Participants were then trained on the NDRT and the driving simulator, first separately and then combined. They completed approximately eight minutes of driving simulator training, where they drove in manual and automated driving mode, switched between automated and manual driving, and practiced NDRT in the automated driving phase. Participants then completed either six or four drives (for experiments 1 or 2) under different conditions. Before starting each drive, the experimenter calibrated and validated the eye tracker. After completing each drive, participants were asked if they were feeling any discomfort or if they wanted to take a break. Participants kept the smartphone used for the NDRT on a stool to their right or left, depending on their preference. While performing the NDRT, participants were instructed to hold the smartphone in front of the steering wheel. The experimenter maintained a checklist to ensure all the necessary steps were followed for each participant and that the participants were following the instructions.

Measures

Takeover Strategy

We identified two takeover strategies (suspension and interleaving) using the data from the eye tracker. In the suspension strategy, participants stopped the NDRT after the takeover request and resumed driving. In the interleaving strategy, participants looked at the driving-related AOI after the takeover request and then returned their gaze to the NDRT AOI before switching to manual driving.

Takeover Performance

Takeover performance is usually evaluated in terms of the quality of the takeover and timing (142; 143). In these experiments, takeover timing was assessed using automation deactivation time (ADT) and gaze reaction time (GRT). These measures have been previously used in similar studies to evaluate reaction time for takeovers (144; 132; 90). ADT was measured as the time between the presentation of the takeover request and the deactivation of driving automation. GRT was measured as the time it took for the driver to look at the driving-related AOI for the first time after the takeover request.

Takeover quality was assessed in terms of longitudinal and lateral control of the vehicle using two measures; the standard deviation of velocity (SDV) and the standard deviation of lateral position (SDLP). These measures have been previously used in similar experiments to evaluate takeover quality (145; 146; 88; 147; 148). Even though SDLP varies between individuals, it is a stable and reliable measure within subjects (149; 150), even when conducted on pc-based driving simulators (151). Previous studies show that it can take drivers up to 40 seconds to stabilize vehicle control after taking over (88). So, we calculated SDLP and SDV for the 30 seconds period immediately after the driver switched to manual driving.

NDRT Engagement

In the first and second experiments, we calculated engagement in the NDRT as the number of questions participants attempted to answer and the number of questions participants asked in each automated driving phase. Automated driving phase started when vehicle automation took control of driving and ended when the driver resumed driving. This included the time between the takeover request and the time driver deactivated driving automation.

Data Analysis and Results

For analyzing the data, we used a mixed-effects regression approach where participants were included as a random effect to account for baseline differences among subjects. We used the R package lme4 (152) for the models. R package car (153) was used to assess significance in the form of chi-square tests, and marginal means were estimated using the emmeans package (154).

Experiment 1

We used a mixed-effect logistic regression approach to examine whether the probability of people interleaving during takeovers is related to cognitive demands of texting conversations or takeover time budget. We analyzed the relationship between the takeover strategies (interleaving and suspension) and the takeover performance (SDLP, SDV, ADT, GRT) and engagement in NDRT (number of attempted questions) using mixed-effects linear regression models. We treated the NDRT (types of texting conversations) and time budgets as covariates and included them as fixed effects to control for their effects on dependent variables.

Effects of different texting conversations and takeover time-budget on takeover strategy (RQ1.1)

We found that the probability of drivers adopting an interleaving or suspension takeover strategy is related to the takeover time budget but not to the different cognitive demands of texting conversations (presented in Table 7). Drivers were more likely to interleave between driving and NDRT in the longer takeover time budget condition compared to the shorter time budget condition (shown in Figure 9). However, the probability of interleaving did not vary between assimilation, retrieval, and generation texting conversations.

Table 7 Effects of texting conversations and time budget on the probability of adopting the interleaving strategy; estimates are in logit.

Predictors		Interleaving probability β(SE)	χ^2(p)
	Intercept	-3.82(0.71)	
Tasks	Generation	0.29(0.77)	0.55(0.76)
	Retrieval	0.55(0.75)	
Time budget	30 sec	1.70(0.68)	**6.20(0.01)**
Tasks:Time budget	Generation:30 Sec	-0.24(0.93)	0.18(0.91)
	Retrieval:30 sec	-0.38(0.90)	

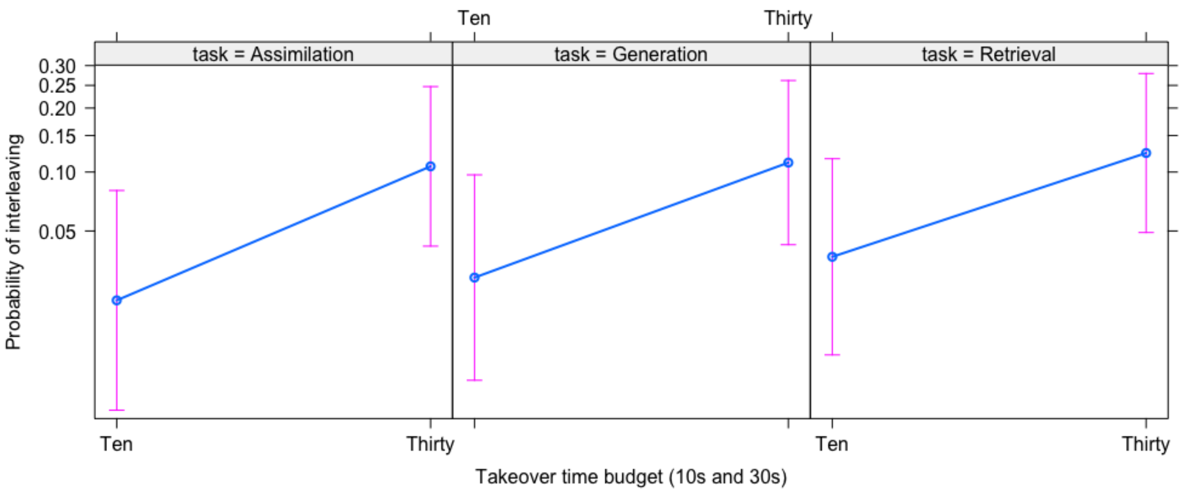

Figure 9 Relationship between takeover time budget and probability of adopting interleaving strategy during takeovers.

Effects of takeover strategy on takeover performance and driver's engagement in different texting conversations (RQ1.2)

We did not find any significant effects of the takeover strategy on takeover quality in terms of lateral and longitudinal control (SDLD, SDV). The control variables (NDRT, time budget) did not have a significant effect either. However, both measures of takeover timing (ADT $\chi^2(1)=22.23$, $p<0.0001$, GRT $\chi^2(1)=46.99$, $p<0.0001$) were influenced by the takeover strategy drivers adopted. Drivers took longer to look at the driving scene in the suspension strategy but were quicker to take over driving after the takeover request compared to when adopting an interleaving strategy (presented in Table 8). For these models, both control variables also had significant effects. We did not find any significant effects of the takeover strategy on NDRT engagement in terms of the number of questions attempted by the participants. The effects of the control variables were significant.

Table 8 Marginal means estimated from the corresponding models. Results are averaged over the three levels of tasks and two levels of takeover time budget.

		Suspension Mean (SE)	Interleaving Mean (SE)	
Takeover quality	SDLP (cm)	20.40(1.40)	19.50(1.74)	t(344)=0.69, p=0.49
	SDV (kmph)	3.27(0.34)	3.92(0.45)	t(347)=-1.92, p=0.06
Takeover timing	ADT (sec)	8.04(0.85)	11.87(1.10)	**t(347)=-4.70, p<0.0001**
	GRT (sec)	7.26(0.77)	1.36(1.07)	**t(350)=6.83, p<0.0001**
NDRT engagement	Questions attempted	3.18(0.18)	3.5(0.28)	t(351)=-1.26, p=0.21

Experiment 2

Using a mixed-effects logistic regression approach, we evaluated whether the probability of adopting a takeover strategy is affected by the priority of driving or NDRT and the takeover time budget. We also evaluated the interaction between priority and time budget to examine whether the effect of priority is moderated by the time budget. We used a mixed-effects linear regression approach to investigate how the takeover strategies are related to takeover performance and engagement in NDRT. Priority and time budgets were treated as covariates and included as fixed effects to control for their effects on dependent variables.

Effects of priority and time budget on takeover strategy (RQ2.1)

The results show that both the priority of the driving or NDRT and the time budget were significant predictors of the probability of drivers interleaving during takeovers (presented in Table 9). Drivers were more likely to adopt the interleaving strategy when the priority was the NDRT or for longer takeover time budget conditions. We also observed significant interaction that suggests that the effect of priority is moderated by the takeover time budget (shown in Figure 10.

Table 9 Effects of priority and time budget on the probability of adopting interleaving strategy; estimates are in logit.

Predictors		Interleaving probability β(SE)	χ^2(p)
	Intercept	-2.99(0.58)	
Priority	NDRT	1.63(0.61)	**7.26(<0.01)**
Time budget	30 sec	2.83(0.61)	**21.18(<0.001)**
Priority:Time budget	NDRT:30 sec	-1.71(0.74)	**5.30(0.02)**

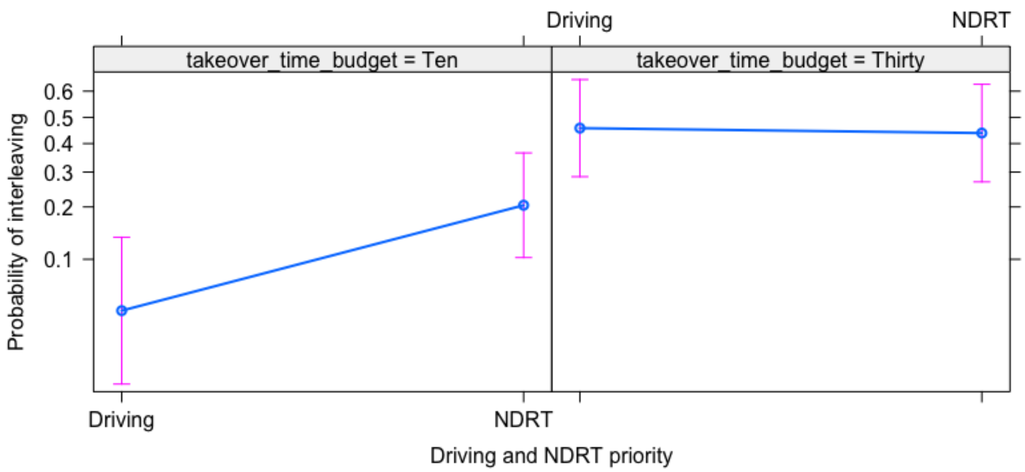

Figure 10 Relationship between priority (driving and NDRT) and probability of adopting interleaving strategy during takeover moderated by takeover time budgets.

Effects of takeover strategies on takeover performance and driver's engagement in multistep texting task (RQ2.2)

Our analysis shows no significant effect of takeover strategy on takeover performance in terms of lateral and longitudinal control (SDLP, SDV). Among the control variables (priority and time budget), only the priority had a significant effect on SDV. The takeover time was related to the takeover strategies people adopted, both in terms of ADT ($\chi^2(1)=4.25$, p=0.04) and GRT ($\chi^2(1)=57.01$, p<0.0001). In the interleaving strategy, drivers took longer to take over driving, but they were much quicker to glance at the driving scene after the takeover request (Table 10).

The control variable time budget was a significant predictor in both models, but priority did not have a significant effect. We did not find any significant effects of the takeover strategy on NDRT engagement, both in terms of the number of questions asked and the number of correct guesses by the participant. For these two models, priority did not have a significant effect, but time budget did.

Table 10 Marginal means estimated from the corresponding models. Results are averaged over the two levels of priorities and two levels of takeover time budget.

		Suspension Mean(SE)	Interleaving Mean(SE)	
Takeover quality	SDLP (cm)	17(1.20)	18(1.40)	t(216)=-0.85, p=0.39
	SDV (kmph)	3.89(0.28)	3.79(0.32)	t(216)=0.35, p=0.73
Takeover timing	ADT (sec)	11.80(0.98)	13.30(1.09)	**t(215)=-2.06, p=0.04**
	GRT (sec)	10.20(0.96)	3.4(1.11)	**t(219)=7.51, p<0.0001**
NDRT engagement	Questions asked	6.55(0.29)	6.53(0.33)	t(241)=0.07, p=0.95
	Correct guess	1.15(0.07)	1.18(0.10)	t(249)=-0.34, p=0.73

Discussion

In this chapter, we presented two experiments where we examined how various NDRT factors affect takeover strategy in terms of interleaving between driving and NDRTs. We also examined how the takeover performance and NDRT engagement are influenced by the takeover strategy driver use.

In the first experiment, we found that different cognitive demands for texting conversations did not have any effect on the takeover strategy. Drivers were equally likely to interleave between driving and texting in assimilation, retrieval, and generation conversation conditions. In the second experiment, we found that the priority of driving or NDRT is a significant predictor of takeover strategy. Drivers were less likely to interleave between driving and NDRT when they were asked to prioritize safe driving over NDRT. From research in other domains, we see people's decision on which task to perform or when to switch to another task is related to the potential reward or priority of the task (118; 117; 119). Our findings suggest that the same principle holds true in the context of task switching in highly automated vehicles. Drivers are more likely to be reluctant to stop NDRT right after the takeover request if they are prioritizing the NDRT.

In both experiments, we found that the takeover time budget influenced how often people follow the interleaving strategy for takeovers. People interleave more frequently between driving and the NDRT if they have a longer time budget for takeovers. This is consistent with our findings from the previous study, where we investigated what strategies people use for takeovers (81). A more interesting finding from the second experiment was that the effect of priority on takeover strategy is moderated by the takeover time budget. As we can see in Figure 10, the probability of drivers interleaving during takeovers increases when they prioritize the NDRT compared to safe driving. But we see this effect only for 10 seconds time budget conditions. When the time budget is 30 seconds, even though the probability of interleaving is higher, we don't see any difference in the probability of interleaving for different priorities.

When evaluating the effects of takeover strategies on takeover performance and NDRT engagement, we found similar results in both the first and second experiments. In both experiments, we see no relationship between takeover strategies and takeover quality in terms of lateral and longitudinal control (SDLP and SDV). However, both experiments show that takeover timing is related to what strategy drivers follow for takeovers. When drivers follow the interleaving strategy, they take longer to stop the NDRT and take back control of the vehicle. But they usually look at the driving scene faster for interleaving strategy. Even though we did not see any effect of the takeover strategy on lateral and longitudinal control of the vehicle, this could change in case of more complicated driving scenarios. The driving scenario we used was quite simple; straight highway road in the daytime with no traffic on the road other than the leading vehicle. Since drivers take longer to take back control of the vehicle for the interleaving strategy, this might create dangerous situations when driving in time-critical traffic scenarios.

For both short and long takeover time budget conditions, we found that the probability of interleaving between driving and NDRT was overall higher for the TQT in the second experiment compared to the texting task in the first experiment. This could be because of the attributes of these two NDRTs we used. The TQT is a multi-step task where people get closer to the goal with every question they ask. So, it might be perceived as a more engaging task compared to the texting conversations in the first experiment.

Findings from these two experiments show that we need to investigate takeover strategies in addition to takeover performance to fully understand the process of transition of control in highly automated vehicles. We found that some attributes of the NDRT may influence the takeover strategy. Even two similar tasks that require texting on a smartphone can affect takeovers differently. So, further research is needed to understand which other factors affect takeover strategy and how takeover strategies impact takeover performance in different driving scenarios.

Chapter 5. Conclusion

The way people work is rapidly changing, often facilitated by continuous technological advancements (155; 156; 157; 158). For conditionally automated vehicles to be considered viable workspace, we have to make sure that the drivers can engage in activities of their choice in the car without compromising safety. Among many facets of this problem, in this thesis, we focused on productivity (designing driver interactions to perform NDRTs) and safety (safely transitioning from automated to manual driving).

Conventional automotive UIs are designed to support only simple non-driving activities like operating the radio, navigation system, or climate control system. People still engage in more demanding tasks like texting while driving, often at the cost of inferior driving performance. So, if the driver of a highly automated vehicle wants to engage in any complex activities, they will likely be interacting with an unconventional UI. When designing interactions for any new UIs, adopting a top-down approach can often neglect how the end users expect to use that interface. So, to explore RQ1, we explored how a participatory design approach can be used for designing interactions for an unconventional automotive user interface (AR Windshield display) based on feedback from the drivers. Our analysis shows that people find it difficult to agree on interactions for interfaces they are not familiar with. So, they rely heavily on their experience of interacting with common interfaces to come up with interactions for new UIs. For example, people often use touchscreen interfaces in their daily life. So, when asked to come up with interactions for AR WSD, they often use the same interactions they would use if the WSD were a touchscreen. Even though the participants did not know whether the WSD was touch-sensitive or whether they could reach it because of the distance between the driver and the windshield, they still used interactions they are familiar with. This legacy bias can be used to design interactions so that drivers can use interactions they are familiar with to operate new UIs that they never used before. We also found that people mostly preferred voice commands compared to gestures for engaging in complex NDRT using AR WSD. Findings from our experiment provide insights into how people would want to interact with WSD in highly automated vehicles and what type of gesture or voice commands they would want to use. This thesis underscores the importance of designing new UIs for automated vehicles, especially for drivers to be able to reclaim some of the driving time and the need for considering end-user feedback for the design process. A similar method can be used to explore other interaction modalities and user interfaces to design interactions using a participatory design approach. Future work should examine whether the findings from such studies hold true in a real driving environment. Different driving conditions, like the presence of passengers in the car and complex traffic scenarios need to be examined to understand how they influence the driver's interaction in the car. Other non-driving related activities also need to be examined to see whether peoples' interactions and preferences for interaction modality are moderated by the types of tasks they are performing.

The other focus of this thesis was to understand the takeover process in conditionally automated vehicles. Even though other studies examined various aspects of the takeover process, they mostly treated it as a single-step process and focused on takeover performance. Based on the interleaving framework proposed by Janssen et al., we were able to analyze the process of transitioning from NDRT to driving in greater detail by dividing the takeover process into multiple stages. To answer the RQ2, in the first driving simulator study, we found empirical evidence for the framework proposed by Janssen et al. We also observed two variations of the sequence of stages in takeovers. In other words, people use different strategies while taking over control of the vehicle, and they often interleave between driving and NDRT. These findings raise the question of the influence of different factors on takeover strategies and the effects of interleaving (different takeover strategies) on takeover performance and safety. To explore RQ3, we then conducted two more driving simulator studies to understand these takeover strategies in more detail. The results show that factors like the driver's priority in terms of driving and NDRT and the allowed time for them to take over can influence their probability of interleaving between driving and the other task. But these effects are not easy to interpret as the effects of one factor can be moderated by other factors. For example, based on our findings, drivers are more likely to interleave when they prioritize NDRT. Even though this is true, this statement does not paint the full picture, as it is only true when the takeover time budget is short. For the long takeover time budget, we don't see any influence of priority on the probability of drivers interleaving. This shows that it is important to examine not only the effects of various factors but also the interactions among those factors to fully understand how they influence takeover strategies. Moreover, other factors like task engagement, the stage of the task, and different support mechanisms for the driver can also influence the takeover strategy. Participants in our three driving simulator studies were students from the University of New Hampshire. The homogeneous nature of the sample population in our studies makes it challenging to generalize some of the findings. So it is important to investigate other factors like drivers' age, gender, and cultural differences as they can also influence how people go through the takeover process. We also found that even if some tasks look similar, like typing different texts on a smartphone, they can have different effects on takeover strategy depending on the nature of the texts. So, the common approach of analyzing the effects of different NDRTs based on the resources needed or the cognitive demand of those tasks may not show the full picture. The effect of the takeover strategy on takeover performance was mixed. Interleaving between driving and NDRT did not have any significant effect on vehicle control after takeovers. However, when interleaving, drivers take longer to resume driving. Even though this longer reaction time did not deteriorate driving performance in the simple driving scenarios of our experiments, they can cause dangerous situations for time-critical driving scenarios.

Based on the above discussion, we pose the following questions that future research needs to address so that we can support drivers to safely perform various non-driving activities in future conditionally automated vehicles:

- How do different aspects of NDRT (e.g., stage of the task, engagement) and individual differences among people (e.g., age, gender, culture) influence takeover strategy when the manual and cognitive demands remain the same?
- How does the interleaving takeover strategy affect takeover performance in time-critical driving situations?
- How does providing support for resuming NDRT affect the takeover strategy?
- How do drivers transition from driving to NDRT in conditionally automated vehicles?

The combined findings in this thesis have implications for designing user interfaces for conditionally automated vehicles that allow drivers to safely and efficiently utilize the time vehicle automation offers. It also provides insights into how to examine which activities may be suitable for performing in the car and when drivers may need support, especially for transitioning from non-driving activities to driving.

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156. *Digital labour platforms and the future of work.* **Janine Berg, Marianne Furrer, Ellie Harmon, Uma Rani, M Six Silberman.** 2018, Towards Decent Work in the Online World. Rapport de l'OIT.

157. *Virtual nature experiences and mindfulness practices while working from home during COVID-19: Effects on stress, focus, and creativity.* **Nabil Al Nahin Ch, Alberta A Ansah, Atefeh Katrahmani, Julia Burmeister, Andrew L Kun, Caitlin Mills, Orit Shaer, John D Lee.** 2023, International Journal of Human-Computer Studies, Vol. 171, p. 102982.

158. *Human-Computer Interaction and the Future of Work.* **CHIWORK Collective, Naveena Karusala, Nabil Al Nahin Ch, Diana Tosca, Alberta A Ansah, Emeline Brule, Nadia Fereydooni, Le-En Huang, Azra Ismail, Pranjal Jain.** 2022. CHI Conference on Human Factors in Computing Systems Extended Abstracts.

Appendix

Approved IRB notice

University of New Hampshire

Research Integrity Services
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Mar 10, 2023 9:40:05 AM EST

Andrew Kun
Dean of CEPS (UDCEPS), Electrical & Computer Eng Dept (UDEE00)

Study Title: Future of Work
IRB #: IRB-FY2022-17
Study Expiration Date: July 17, 2023
Modification: Change to Interleaving Study Duration
Modification Approval Date: March 10, 2023

The Institutional Review Board for the Protection of Human Subjects in Research (IRB) has reviewed and approved your modification to this study, as indicated above. Further changes in your study must be submitted to the IRB via Cayuse IRB/Human Ethics for review and approval prior to implementation.

Researchers who conduct studies involving human subjects have responsibilities as outlined in the document, Responsibilities of Directors of Research Studies Involving Human Subjects.

Note: IRB approval is separate from UNH Purchasing approval of any proposed methods of paying study participants. Before making any payments to study participants, researchers should review the Payment of Incentives/ Compensation to Research Participants guidance to ensure they are complying with institutional requirements. If such institutional requirements are not consistent with the confidentiality or anonymity assurances in the IRB-approved protocol and consent documents, you may need to request a modification from the IRB.

If you have questions or concerns about your study or this approval, please feel free to contact Melissa McGee at 603-862-2005 or melissa.mcgee@unh.edu. Please refer to the IRB # above in all correspondence related to this study.

For the IRB,

Julie F. Simpson
Director