Exploring factors in Human Cognition that affect Human Performance during Takeover in Autonomous Driving

Zijing Liu [1, *], Jiayi Zhang [2]

[1] School of International Education, Guangxi University of Science and Technology, Liuzhou 545006, China

[2] Parsons School of Design, New York City 10011, United States of America

* Corresponding email: z.liu.43@student.scu.edu.au

Abstract. Driver's mental load is an important influence on the design of the human-machine interface (HMI) for self-driving cars. During the autopilot-forced takeover process, aspects of the user's cognition, decision-making, attention, and emotional state affect the takeover performance. Therefore, the cognitive and psychological states of drivers must be considered in the HMI design of self-driving cars. And a good HMI design will reduce the user's mental burden and improve the takeover performance. In this study, a model affecting drivers' takeover performance was designed through human factors. And we refine the analysis from three aspects of cognitive load, emotional load, and environmental load by making subjective likert-style-questionnaires, derive the main influencing factors through the reliability analysis of the data, factor analysis, and other methods. This work finds that the clarity, comprehensiveness, and level of humanization of takeover messages, as well as the driver's arousal level when receiving the message, have the greatest impact on the driver's workload.

Keywords: Autonomous Vehicles, human-machine interface (HMI), Mandatory Transition, exploratory factor analysis (EFA).

1. Introduction

Automated Vehicles (AV), known for their equipped automated system that aim to bring convenience to driving, quickly gained its reputation after the product debuted from various Big-Names in the Automotive and Technology industries, such as Tesla, Waymo, and Zoox. However, due to over 400 cases of AV collisions reported in the 2021-2022 calendar year [1], opinion towards AV has gradually become more critical, which furtherly caused the increased amount of research to target potential risks and to enhance safety levels by various fields of studies including Human Factor, Bio-Engineering and Electronic Engineering. Statistic Reports from 2021 showed nearly 89% of AV collisions were identified to occur during Level 3 Automated Driving – The Conditional Automation mode when the system performs driving tasks while the driver remains available to take over.- and had an inevitable relationship to the driver performance [1]. In this case, working towards reducing the likelihood of human misuse of the Automated system, Human Factors implication on human driver's performance can be considered as an essential topic.

In the past few years, most Human Factors research on the Human-Machine-Interface were focusing on the topic of collision obstacles from cases initiated by the failed cooperation between humans and the automated system. Wu et al. researched the factors that are closely bounded to the quality of driver performance, with results showing a significant number of considerations that need to be taken into human factors, such as driver's understanding, trust, and perception towards the system. Moreover, they classified the danger exposed to Mandatory Transition by the following factors: 1) Human Factors: Driver's attention on driving and current situation, The perception of their ability to control or the automated system, The state of Mental power and cognitive load; 2) Information Distribution: Channels that Transition-indicating signs take to be distributed to the driver; The time when the sign is sent; The tone of the sign (how it appears to the driver) [2]. Throughout their findings, the main idea that safety in Mandatory Transition is related to the responsibility of both the automated system and driver is proposed. And it can be concluded that during the human-automation transition, interaction and coordination, between human and automation is essential to ensure safety. As Wu et al. brought up the Mandatory Transition as the main scene the human driver and the automated system would have the most interactions, which would further draw straightforward clues to driver performance, the research on safety in this scene should be given special attention. In the research on defining Mandatory Transition by categorizing and evaluating all types of transitions, Z Lu et al. found out that in AIDC, also known as the mandatory transition, the most frequent times of interactions between human and the automated system takes place. According to their graphic of the "Classification of different transitions of control", the AIDC (Automation-initiated-driver-controlled) can be categorized to be the only scenario of mandatory transition, referring to the mode of driving that the driving action is initiated by the automated system and then transitioned to the human driver when abnormal road conditions, like an unidentified object, had been detected [3]. The flowchart of the driver performing a forced takeover during autonomous driving was shown in the Figure 1.

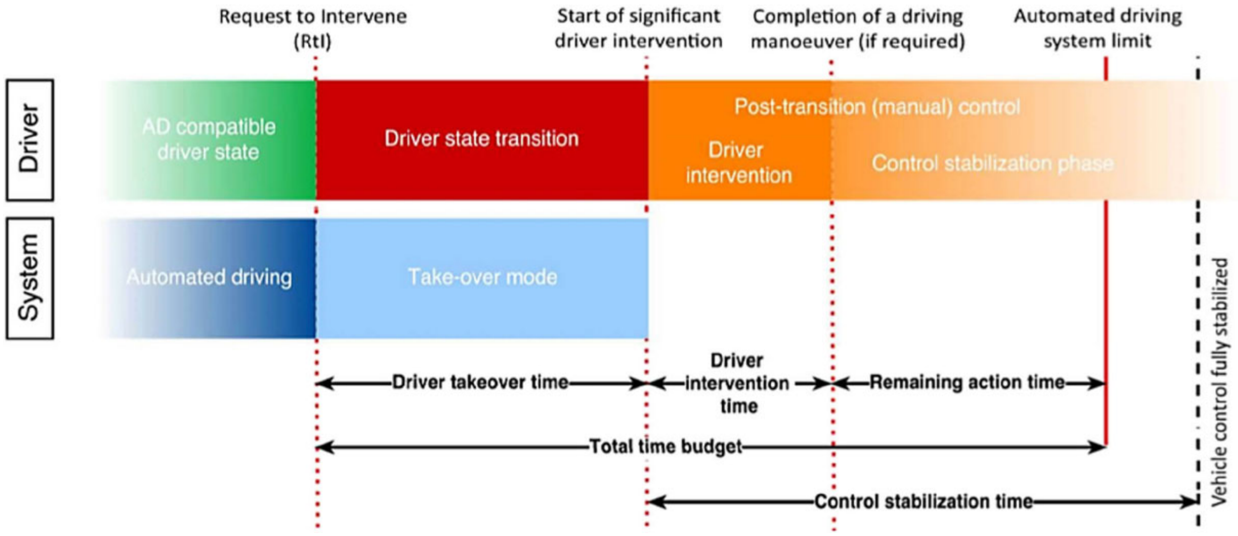

Figure 1. Transition of control (photo credited: original)

To conclude, factors from diverse perspectives, like the human factor and the system's information display, were believed to have close impacts on human driver mental load and further contribute to the remote effects on driver performance, specifically the AIDC scene. However, in the driver-performance-influential-factors from previous research that were found to affect driver performance, limitations have been found: 1. the exact manifestations of the factors, which would ideally correspond to any specific in-car function or any step in the driver-automation transition flow, are still remaining unclear. 2. The importance of each factor, which generates the priority level of the factors, was not yet clarified enough, in a way, would bring difficulties into design practice. 3. The factors are mostly fresh off the research and lacking application to the design in enhancing driver performance. Moreover, a lateral comparison between the design integrating the factors and the original design to testify to the effectiveness and examine the factors is also needed to demonstrate the effectiveness of the factors when contextualizing them into the design of real-life automated driving practice. Therefore, aiming to look for influencing factors that affect driver performance, we decide to look into human factors cross-fields, like Cognitive science, then we will next connect the dots of influencing factors and the exact point in an AIDC transition scene as a way to conceptualization the influential factors and bring into practice. Our study will be of the following two parts:

(1) The preliminary research part that narrows the scope of the factors on human task load that affects human performance in AIDC transition while congregating and filtering the factors into a hypothetical model;

(2) A quantitative research that is aimed to test drivers with Automated driving experiences in a way to form up a priority sorting on all listed factors, connect the factors to all the potentially

influential areas on a driver HMI interface for design, together with a test on Reliability and Validity of our Hypothetical model.

2. Preliminary Research

2.1. Take over action in AIDC

One critical factor in Automated Driving safety is driver performance during Takeovers. Melnicuk et al. explored the effect of cognitive load on drivers' state and task performance during automated driving to manual control transitions. They found that non-optimal levels of workload during automated driving impaired driving performance, especially lateral control of the vehicle, and the magnitude of this impairment varied with increasing cognitive load [4]. The study also introduced a novel method for determining stabilization times following a transition of vehicle control [5]. Furthermore, Maggi et al. investigated how drivers behaved depending on their initial role during transitions between highly automated driving (HAD) and longitudinally assisted driving [5]. They found that whenever drivers initiated the transition, they were more engaged with the driving task and less prone to follow proposed strategies compared to when the automation initiated the transition. In converse, when the transition is initiated by the automation and controlled by drivers, drivers are relatively more cling to follow the instruction from the automation. However, when the driver in AIDC transition is more likely to rely on the automation system than drivers in any other transition, the normal qualities that the driver should possess and self-check, such as perception, decision-making, and control can remain unused when most of the driving works are conducted via the interaction with the vehicle's automation system and the driver would spend most of his/her time monitoring the system. Merat et al refer to this situation in the term called "Out-of-the-loop performance problem", in which scenarios are presented based on the driver's potential loss of skills and situational awareness caused by vigilance and complacency issues that could leave him/her off from automated systems and furtherly make him/her unable to take over in the event of system failure [6].

2.2. SAW and HLIF

In the case of the out-of-the-loop problem, Merat el al identified the main cause of a driver's vigilance and complacency issue to be Situational Awareness and potential loss of skill, which are Human Factors, the major field of study that various research studies have stepped in, in a way to analyze driver's behavior from their cognition and mentality. When mentioning Situation Awareness (SAW), one significant study defined by Mica R. Endsley shows that SAW is "the perception of the elements in the environment within a volume of time and space, the understanding of their meaning, and the projection of their status in the near future" [7]. Alternatively, SAW is seen as the result of High-Level Information Fusion (HLIF), which refers to the driver's internal process of integrating multiple data sources to produce more consistent, accurate, and useful information [8]. Research on HLIF in recent studies have presented the term to be closely intertwined with the ability of human driver to handle the cooperative task with the automated system. Blasch et al introduce the major topics involved in HLIF to be related to the quality of human drivers and also the interactive abilities and the level of informatization of the system by proposing the following related subjects [9]: Data and Knowledge Representation, Situation, Threat, and Impact Assessment, Uncertainty Analysis, Semantics and Ontologies, Systems Design, Evaluation, and Information Management.

2.2.1. SAW model (Process of work load break down)

Breaking down the process of human perceiving any external input to perform any action as output was shown in the Figure 2, as well as suggesting Implicit/ Explicit factors that might affect the process.

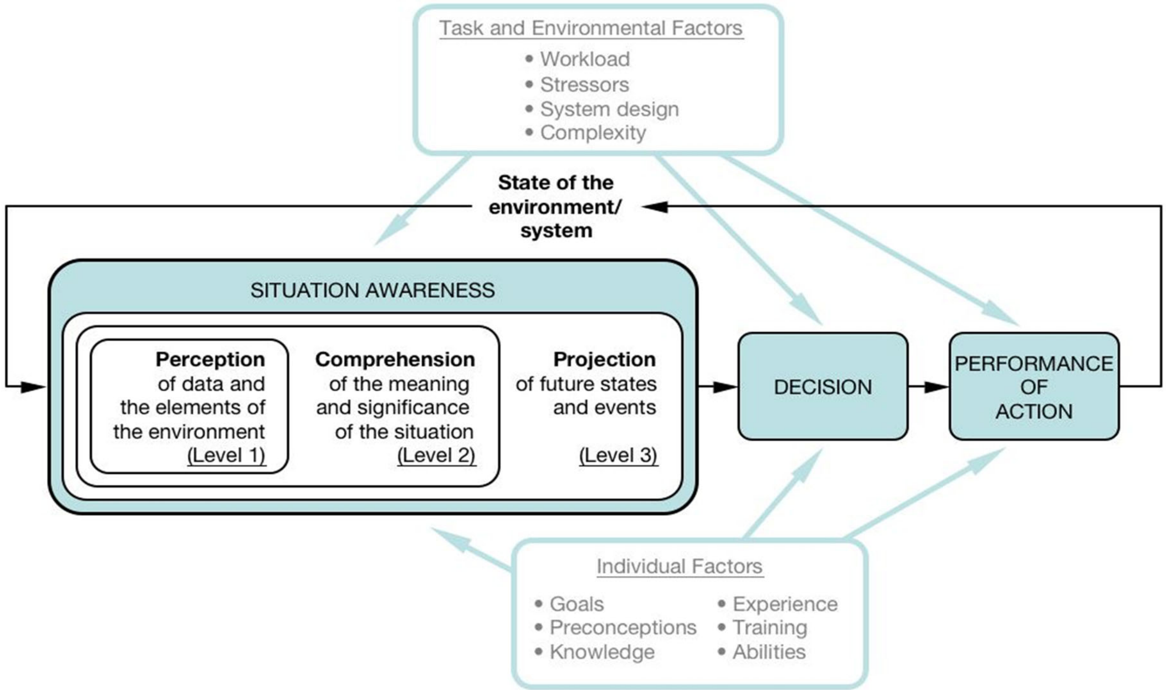

Figure 2. The SAW Model made of Endsley (photo credited: original)

In this model, the cognitive processes and mechanisms through which humans assess situations for the purpose of producing SA, and the task and environmental factors that influence the likelihood of producing SA are presented. The three levels of SA: perception, understanding, and projection are also described in detail.

In a normal Emergency Response scene of any Human-Automation cooperative operation task, the human drivers' reaction can be broken down into the following steps:

Level 1: Perceiving the status, characteristics, and dynamics of relevant elements in the environment; Level 2: Synthesising the disjointed elements of Level 1 SA through the processes of pattern recognition, interpretation, and evaluation; Level 3: The third and highest level is the ability to project future actions of environmental elements [7].

Besides, the model also points to a number of tasks and environmental features that influence SA, such as high workload and stress like Information overload, or conversely, under load (vigilance conditions); The complexity of the systems and situations a person is in which makes it difficult to form accurate mental models for the person; System Transparency with required information being provided, which would be related to the level of cognitive engagement and trust of people to automated systems; And lastly, the ability of the system and user interface to convey important information to the person in a way that is easy to integrate and process.

Implementing the model of Situational awareness into the analysis of automated driving will help to explain the problems caused by attention deficit:

In the situation the automated driving is initiated by the Automation with driving assistance turned on, the driver is carrying out other non-driving-related activities such as watching videos when the car needs the driver to take over in an emergency. The driver in the absence of attention needs to be retrieved back to the current environment in their own car. Alongside this, the surrounding vehicle conditions and a series of factors such as perception, understanding, prediction, and decision-making will be subsequently executed.

Completing the above steps in a very short period of time is likely to cause the driver to experience cognitive overload and end up scrambling, leading to tragedy, which is why assisted driving requires the driver to be in a reasonable situational awareness. In this case, Workload and ability, experience, and training all have a direct impact on performance in situational awareness, decision-making, and execution.

2.2.2. Human Cognition aspect of SA: Analyzed together with the Yerkes–Dodson's Law

In psychology, Yerkes–Dodson's Law is used to describe the relationship between arousal and performance, as shown below. From the research by Broadhurst, P. L., Arousal can reflect a person's current physiological and psychological state, from the physiological point of view arousal from low to high can be described as sleep, fatigue, relaxation, normal, anxiety, stress, and pain, and it is associated with Stress, Attention, Alertness, Cognitive Load, and Workload [10]. In this case, humans' subjective reactions to explicit impulses can be considered as part of the contribution to their workload, specifically their mental workload. There is an optimal region of performance arousal levels was shown in the Figure 3, where too little or too much arousal can adversely affect task performance.

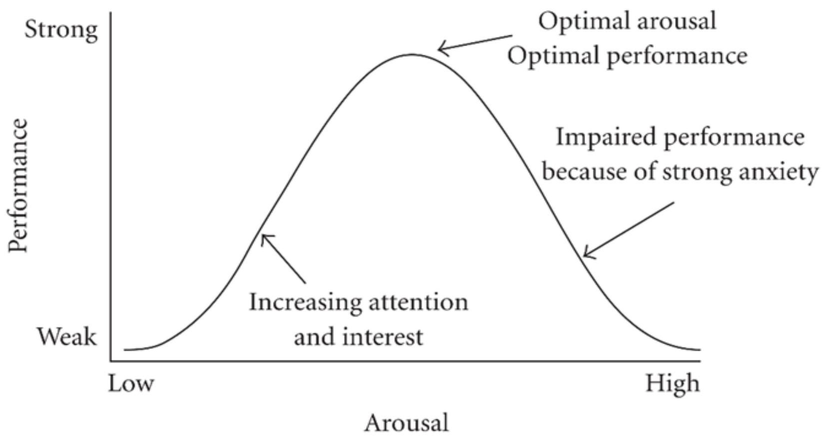

Figure 3. A region of performance arousal levels (photo credited: original)

2.3. Information display and its impact on drivers' performance in Take Over

Besides human drivers' reactions to the information, how the information displayed appeals to the drivers is also an important aspect to investigate into. Cooperative human-machine interfaces are essential for effective interaction between drivers and autonomous systems in self-driving vehicles. Muslim et al. analysed the impact of cooperative human-machine interface designs on drivers' trust in and interaction with automated driving systems during lane changes [11]. Their results indicate improvements in driving performance and system usage under certain cooperative interface designs.

Endsley discusses the automation conundrum, where increased reliability and robustness of autonomous systems result in lower situation awareness and reduced ability for human operators to take over manual control when needed. This article provides an overview of key design interventions for improving human performance in interacting with autonomous systems, including human-automation interface features and central automation interaction paradigms [7].

2.4. Model

2.4.1. Model building and assumptions

Factors that are related to driver Performance on the Take-Over during AIDC Transition was shown in the Figure 4. And it concluded based on Previous Studies (as labeled as footnotes in the graphic). Following the Golestank's Theory of the Cognitive Mechanics Functional Model of Automated Driving [12].

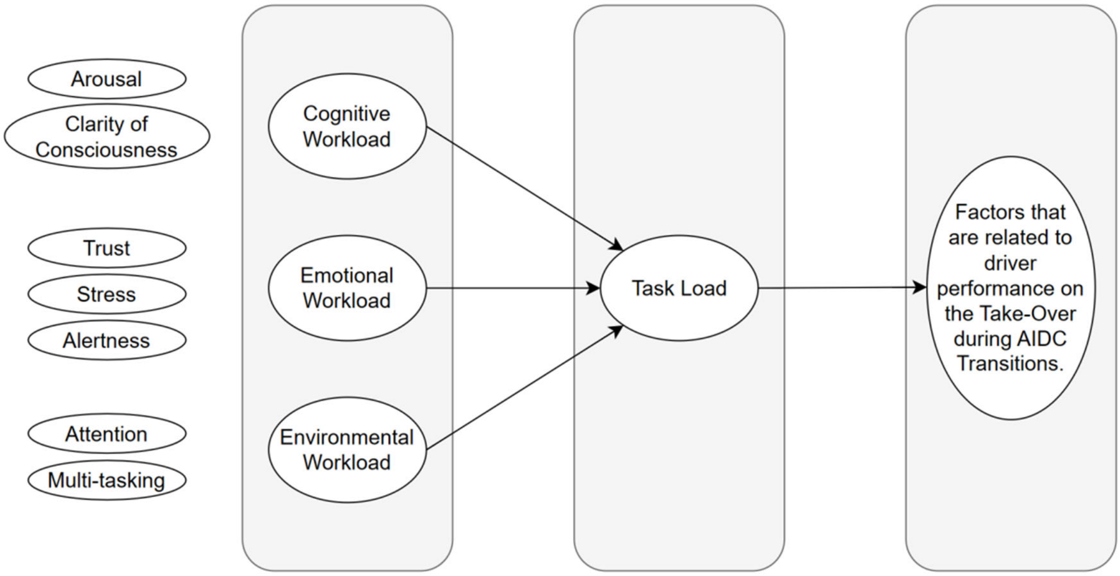

Figure 4. Factors that are related to driver performance on the take-over during AIDC transition (photo credited: original)

The model is built to categorize factors collected in the preliminary research on breaking down the driver's workload when the AIDC transition takes place and the driver takes over the driving control. Based on the preliminary research, the driver's workload can be categorized into:

(1) Cognitive workload (Generates while perceiving the stimuli of the takeover information, and defines the overall capacity of the information that can be perceived);

(2) Emotional workload (Generates while processing the stimuli; affects the drivers' mental state when processing the information, and further impacts the quality of the processing);

(3) Environmental workload (Generates when side-tasks besides processing the information occur, and impacts the quality of the processing).

Within the three main types of workloads, each type is affiliated with hypothetical subordinate factors:

(4) Driver's arouseness and clarity of consciousness are hypothesized to be the two contributing factors to a driver's cognitive workload;

(5) Driver's trust in the system, stress level, and alertness are hypothesized to impact their emotional workload;

(6) Driver's attention distribution and participation in multi-tasking are hypothesized to impact on their environmental workload.

3. Method

3.1. Survey on examining the hypothetical affiliated factors of driver's workload during the takeover

During the AIDC Transition when the takeover information is displayed. The impact of subordinate factors on various parts of the driver's operational process was shown in the Figure 5.

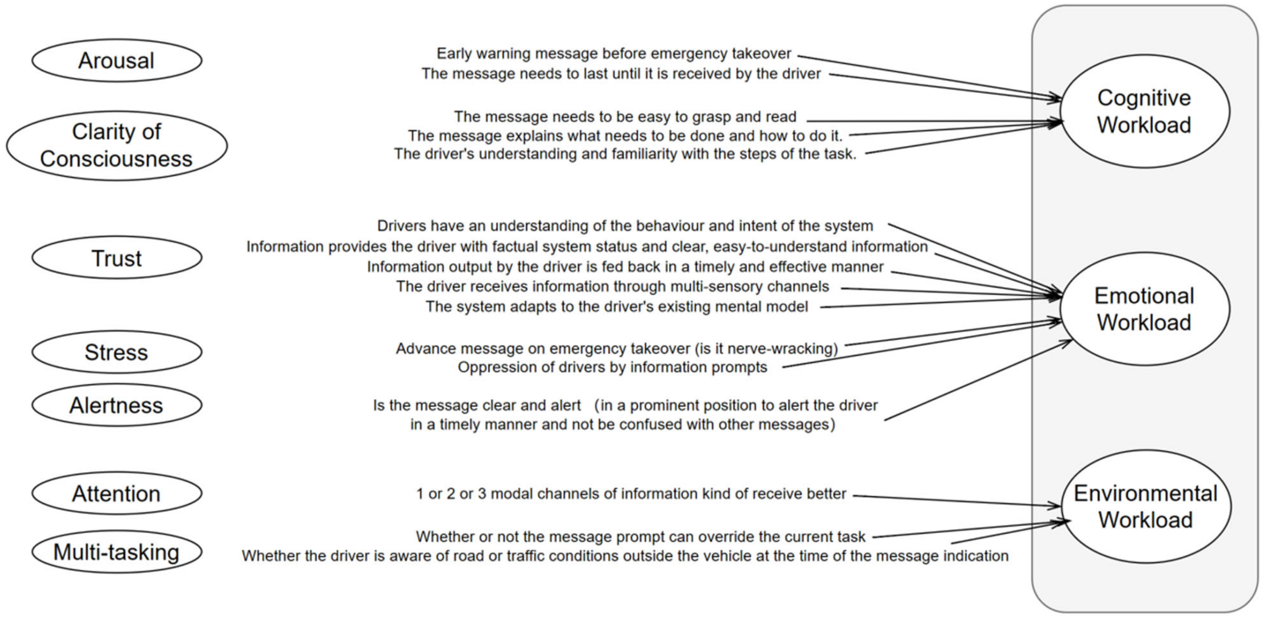

Figure 5. Combination of slave factors and driver take-over operations (photo credited: original)

Questionnaire questions was shown in the Figure 6, and in designing the survey: Verbalizing the subordinate factors to make it easier to be understood by survey takers.

Stage	Independent Variable	Related Indicators	Intermediary Variable	Title
Access to information - reception process Level 1-Perception This level involves simply recognizing and detecting elements in the environment.	Alerting stage - Alerting in advance before emergency takeover.	information flux	Cognitive Workload	When there is a takeover task that needs to be completed by me, which is more likely to grab My attention?
	Duration of message alert - needs to last until it is received by the driver.		Cognitive Workload	When the system's message gives a cue, it lasts long enough to be noticed by my eyes, rather than a brief cue.
	Message reception phase - the driver receives the message through multi-sensory channels.	Multiple message channels	Environmental Workload	When the system communicates takeover information to me by using multiple sensory channels such as vision, hearing, and touch, it interferes with My perception of the environment outside the vehicle.
	Alerting phase - is the alert before the emergency takeover stressful?	Information prompt form	Mental Workload	I do not feel nervous or panicked when there are cues (e.g., visual, auditory, and tactile cues) to take over the task
	Message Cueing Phase - Is the message clear and alert (in a prominent position, alerts the driver in time, not confused with other messages)		Mental Workload	I do not feel frightened when there are informational cues (e.g., visual, auditory, and tactile cues) to take over the task I can easily recognise when I am prompted with a takeover message (e.g. a visual, auditory or tactile prompt) that this prompt is different from others
	Channel of message alert - which of the 1 or 2 or 3 modes is better received?	Multiple message channels	Environmental Workload	When the system delivers a takeover message, a single-channel (visual, auditory, or tactile only)cue is more likely to get my attention than a multi-channel (visual-auditory, combined visual-tactile, etc.) cue.
	Handover cues - do the cue channels cover the task at hand?	Information prompt form	Environmental Workload	When I am engaged in other non-driving activities (e.g. listening to a song, observing the road outside the car), I can recognise the presence of a cue to take over the task if the task is suddenly taken over. I don't have a problem with a task taking over while I'm doing other non-driving activities (e.g. listening to a song, observing the road outside the car) if the takeover message suddenly interrupts and overrides my current activity.
Understanding Scenarios - Processes Level2-Comprehension At this level, the person not only perceives the elements but also understands their significance and how they relate to each other.	Information prompting phase - the system should be adapted to the user's existing mental models and preferences, customised anthropomorphism.	Information carrier presentation	Cognitive Workload	When system prompts are conveyed through sounds that add tone, etc., it helps me understand the state of the system when it takes over, the level of trust, or the response to an emergency. I feel stressed and overwhelmed when I read messages from the system to take over tasks.
	Information reception phase - cues are oppressive to the driver.	Multiple information channels	Mental Workload	I feel stressed and overwhelmed when I am reading a message from a system takeover.
	Message complexity - need to be easily grasped and readable.	Information load, Information hierarchy	Cognitive Workload	When I read a message from a system takeover, it is difficult for me to understand the content of the message.
	Message cueing phase - the driver should be aware of the system's behaviours and intent of the system.	Predictable system state	Cognitive Workload	I understand the system better when I am clear about the responsibilities of the human and machine in each situation.
	Information Cueing Phase - Provide the driver with real-time system status and clear, easy-to-understand information to the driver.	Predictable system state	Cognitive Workload	The system provides me with detailed information about the current traffic environment and road conditions in real time, which helps me to understand the system's decisions.
	Awareness of the path outside the vehicle at the time of the message cue or traffic conditions.		Environmental Workload	I can understand what's going on outside the car when I read the information from the system about taking over tasks.
output behaviour Level 3-Projection: The highest level of situation awareness involves the ability to anticipate future events based onthe current situation.	Information output stage - the driver correctly and accurately anticipates hazards based on the information.	Information Security	Cognitive Workload	When I read the takeover message from the system, I can accurately take immediate action based on the situation outside the car.
	The driver knows exactly what tasks need to be done and how to do them.	Information Orientation	Cognitive Workload	When I read a takeover message and am ready to take action, I know exactly what needs to be done.
	Information-based execution phase - the driver's knowledge and familiarity with the steps of the task.		Cognitive Workload	When I read the takeover message and am ready to take action, I know exactly what to do.
	Information output phase - the driver's output is fed back in a timely and effective manner.	Information Feedback	Environmental Workload	When the system provides timely feedback to the user, it helps the user to understand the information in the system.

Figure 6. Questionnaire questions design (photo credited: original)

From the model that classifies the driver's workload during the AIDC transition, a questionnaire was designed. The questionnaire includes the latent variable information on the observed variables. Observational variables included seven latent variables and 16 observational variables: ranging from information content, information carriers, information access, system transparency and trust in human-computer interaction (HCI) of AVs, which could potentially impact on driver's workload, as shown in Figure 5.

In the survey design, the sixteen variables were methodically converted into a set of questions to guarantee a lucid and thorough technique. The questions were primarily formulated for self-administration and incorporated first-person narratives to capture the crux of the driver's encounter in takeover scenarios, associated with sixteen variables in particular. Within the sixteen variable-derived questions, five questions were related to the measurement of the Cognitive workload of the driver during the takeover, eight questions were related to the measurement of the emotional workload of the driver during the takeover, and three questions were related to the measurement of the environmental workload during the takeover. To gauge the responses accurately, we employed a five-point Likert scale. Participants assessed their level of agreement on a scale from "1 = strongly disagree" to "5 = strongly agree." Additionally, we strategically incorporated an attention checker into the survey. This question was inserted in the middle of the survey to assess participants' fundamental comprehension of initiating the takeover mode. For example, the survey requested details on instances where respondents were required to take over control from the automated system. Meticulous attention was given to the survey methodology to ensure data collection was diligent and trustworthy. The questionnaire focused on variables and formed the central part of the study. The questionnaires were accompanied by an introductory section that provided information on the purpose and terms of the questionnaire. Additionally, a concluding segment gathered demographic details and information about the prior driving experiences of participants.

The data were collected via an online survey platform in Chinese. The Chinese questionnaire design and publication platform “Wen Juan Wang”, or “The Survey Net”, was used as an administrative tool to display the questionnaire and collect participants’ questionnaires. By distributing the questionnaires into the user groups of self-driving vehicles with automated driving systems equivalent to or beyond the SAE Level-3, an overall number of 849 participants were reached and 849 questionnaires were collected in full data. After subtracting. Invalid questionnaires that failed the attention checker question, a total of 374 answer sheets were further selected for analyzable results.

4. Results

4.1. Demographic Information of participants

Our survey comprised 823 participants between the ages of 18 and 45, all of whom held valid driving licenses. Notably, our participants possessed a diverse range of driving experiences, with 28.3% holding licenses for more than five years, 61.4% holding two to five years of experience, and 10.3% holding less than two years of experience. In relation to self-driving experiences, 39.5% of respondents reported utilizing level-3 autonomous systems more than five times per week. A further 22% used these systems between one to five times weekly, while 32.4% stated using them between one to three times per week. The remaining 10% used self-driving mode less than once weekly. These figures offer an extensive account of our participants' profile and the extent of their interaction with self-driving technology. Such insights are vital to the understanding of their viewpoints and encounters.

4.2. Questionnaire reliability and validity analysis

In the KMO and Bartlett’s test, as shown in table 1, the value of the KMO test is 0.946, which is greater than the threshold value of 0.9. In the results of the Bartlett’s test of spherical, the corresponding P value is 0.000, which is less than 0.05. And there is a correlation between the individual variables. This indicates that the questionnaire has good structural validity and is very suitable for exploratory factor analysis (see Figure 7).

Table 1. Results of the KMO and Bartlett’s test.

KMO and Bartlett’s Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.946
Bartlett’s Test of Sphericity	Approx. Chi-Square	5343.635
	df	136
	Siq.	.000

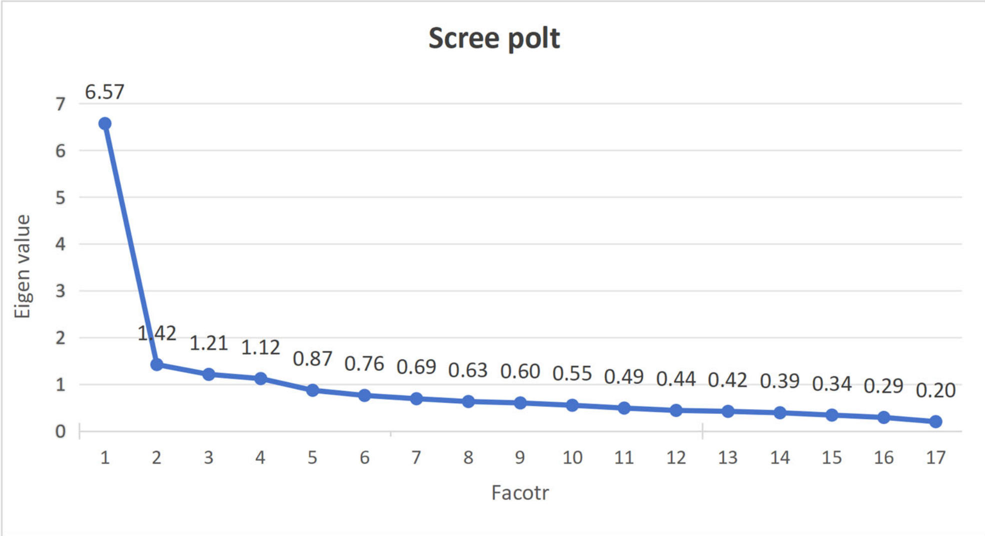

Figure 7. Scree plot (photo credited: original)

4.3. Exploratory Factor Analysis (EFA) for validity

Table 2. Total variance explained

Total Variance Explained									
Factor	Eigen values			% of Variance (Initial)			% of Variance (Rotated)		
	Eigen	% of Variance	Curn. % of Variance	Eigen	% of Variance	Curn. % of Variance	Eigen	% of Variance	Curn. % of Variance
1	6.573	38.665	38.665	6.573	38.665	38.665	3.863	22.722	22.722
2	1.422	8.363	47.028	1.422	8.363	47.028	3.544	20.845	43.567
3	1.213	7.134	54.161	1.213	7.134	54.161	1.663	9.782	53.349
4	1.123	6.603	60.765	-	-	-	-	-	-
5	0.870	5.120	65.885	-	-	-	-	-	-
6	0.765	4.500	70.385	-	-	-	-	-	-
7	0.691	4.067	74.452	-	-	-	-	-	-
8	0.627	3.690	78.142	-	-	-	-	-	-
9	0.595	3.502	81.645	-	-	-	-	-	-
10	0.547	3.217	84.862	-	-	-	-	-	-
11	0.494	2.906	87.767	-	-	-	-	-	-
12	0.443	2.604	90.371	-	-	-	-	-	-
13	0.417	2.451	92.822	-	-	-	-	-	-
14	0.389	2.288	95.110	-	-	-	-	-	-
15	0.345	2.029	97.139	-	-	-	-	-	-
16	0.289	1.697	98.936	-	-	-	-	-	-
17	0.198	1.164	100.000	-	-	-	-	-	-

We decided to conduct an Exploratory Factor Analysis to extract factors that could be bounded together (see Table 2). In our result, three factors had eigenvalues greater than 1.2, as shown in the scree plot in Figure 7 (Previous page). The initial 17-item structure explained 53% of the variance in the pattern of relationships among the items. The percentages explained by each factor were representatively 38.665% (group 1), 8.363% (group 2), and 7.134% (group 3).

4.3.1. Rotated Component matrix (table)

Table 3. explaining the different groupings of factors generated by the matrix

Factor Loading (Rotated)				
Items	Factor Loading			Communalities
	Factor 1	Factor 2	Factor 3	
Q7_ When the system delivers takeover information, a single-channel (visual, auditory, or tactile only) cue gets my attention more than a multi-channel (visual-auditory, combined visual-tactile, etc.) cue	0.146	0.696	-0.085	0.513
Q8_ When the system delivers takeover information to me by using multiple sensory channels such as vision, hearing and touch, it interferes with my perception of the current environment outside the vehicle	0.145	0.697	-0.116	0.521
Q9_ I don't have a problem with a takeover task suddenly interrupting and overriding my current activity when I'm doing other non-driving activities (e.g. listening to a song, observing the road outside the car) if the takeover task's alert message suddenly interrupts and overrides my current activity	0.395	0.096	0.262	0.234
Q10_ When I am doing other non-driving activities (e.g. listening to a song, observing the road outside the car), if there is a sudden takeover task, I can recognise the appearance of the takeover task's alert message	0.535	0.171	-0.033	0.316
Q11_ When system prompts are communicated through sound, adding emotion/tone to the voice prompts helps me understand the state of the system when it takes over, and the emergency situation to which it is responding, as opposed to normal voice prompts.	-0.195	0.900	0.148	0.870
Q13_ When a message from the system alerts me, it lasts as long as I notice it before disappearing, rather than briefly alerting me and then disappearing immediately.	-0.123	0.881	-0.133	0.809
Q14_ When an information cue for a takeover task (e.g. visual, auditory and tactile cues) is given, I can easily recognise it as a takeover cue and not other types of information (e.g. speed, power related information)	0.093	0.649	0.132	0.448
Q15_ When taking over the task with informational cues (e.g., visual, auditory, and tactile cues), it was easy for me to adjust from a relaxed state to a takeover state	0.680	0.099	-0.076	0.477
Q16_ I don't feel nervous and panicky when information about the takeover task is cued in advance (e.g. visual, auditory and tactile cues) during the pre-takeover phase	0.588	0.172	-0.073	0.381
Q17_ I don't get nervous or flustered when I'm reading takeover task messages from the system (e.g. voice alarm alerts, steering wheel vibration alerts, etc.)	0.284	0.447	0.187	0.315
Q18_ When I'm reading a message from the system taking over a task, I may ignore road or traffic conditions outside the car	-0.270	0.207	0.856	0.849
Q19_ When I was reading the message that took over, understanding what was in the message (e.g., the text of the operational information provided by the display) was very difficult	0.159	-0.252	0.830	0.777
Q20_ When I am ready to take action after reading the information about the takeover task, I know exactly which actions need to be completed	0.647	0.002	-0.007	0.418
Q21_ When I read the message from the system to take over the mission, I can accurately take action on the spot based on what's going on outside the car.	0.637	0.028	-0.132	0.423
Q22_ When I am in the take-over phase of the operation, the system provides me with detailed information in real time about the status of the car and the current traffic environment and road conditions, which helps me to understand the system's decisions	0.623	-0.090	0.173	0.426
Q23_ I will know more about the system when my actions are performed accurately in unexpected circumstances	0.965	-0.263	-0.025	1.001
Q24_ During the takeover process, the system can give me timely feedback when I make a takeover operation	0.432	0.321	-0.010	0.290

The Exploratory Factor analysis resulted in three significant factors with significant eigenvalues. Our results show that each of the 17 questions corresponds to one of these factors. As shown in the results, there are 17 factors, with 8 factors in group 1 corresponding to the evaluation of Cognitive Workload, 6 factors in group 2 corresponding to the evaluation of Emotional Workload, and 2 factors in group 3 corresponding to the evaluation of Environmental Workload.

The percentages explained by each group were 38.665%, 8.363%, and 7.134%, respectively, based on their percentage of variance. Additionally, a single rotation was performed to obtain a more accurate percentage of variance for each group resulting from the exploratory factor analysis process. The three groups had representative percentages of variance of 22.722%, 20.845%, and 9.782%.

4.3.2. Groupings of the variables and interpretations

Analysis of the participants' ratings of the question revealed a tendency to divide into three groups based on the numerical value of the factor loading. The study identified three groups of related factors that correlated with specific questions (factor with values under 0.5 are neglected). The first group included factors related to questions 10, 15, 16, 20, 21, 22, and 23. The second group included factors related to questions 7, 8, 11, 13, and 14. The third group included factors related to questions 18 and 19. Question 9 was excluded from the groups as it was determined as qualitative question that did not generate a numerical rating.

From the groupings, it can be inferred that grouping 1 has the most impact on the following factors: Q10. Identifiable takeover message among all other ongoing tasks, Q15. Takeover message's ability to awake the driver for the takeover, Q16. Gradual exposure of the takeover message, Q22. Transparency of system regarding detailed information in real time about the status of the car and the current traffic environment and road conditions, Q23. Feedback about accuracy on driver's performance upon completion of the takeover process, Q20. Driver's confirmation of the exact action required to take over, and Q21. Driver's ability to decide his/her action based on external information outside the car. While grouping 2 has the most impact on Q7. Multi-modal way of delivering takeover message, Q8. Multi-modal takeover message's interference on driver's perception of the current environment outside the vehicle, Q11. Anthropomorphic style in takeover messaging, Q13. Lasting takeover messaging until driver's notice, and Q14. Preference on takeover messaging being front of the priority and distinctive. And grouping 3 has the most impact on Q18. Takeover message that requires excess attention on reading and comprehension which may lead to neglection on road or traffic conditions outside the car and Q19. Takeover message that is textually hard to comprehend.

Within the groupings, Implicit variables in each principal groupings could be detectable by extracting the commonalities among factors: Grouping 1 can be defined as the the ability of system to transmit takeover message that arouse drivers and facilitate their recognition on both in-car and off-car environment; While Grouping 2 as the designated features of takeover message for being more comprehensive, clearly instructional and humanized; And Grouping 3 as flexibility on perception on off-car environment that takeover message offers.

5. Conclusion

Based on the previous acceptable model of AVs, a model of factors related to takeover during AIDC transition was constructed by classifying the workload of drivers at takeover with 3 groups of factors: Cognitive workload, Emotional workload, and Environmental workload. Mathematical analyses were conducted using the exploratory factor analysis model, and the results showed that all three factors significantly affected the workload of drivers when taking over during the transition period of AIDC.

The problems that may arise during driver operation were analysed from the perspective of 7 subordinate factors. It was further verified that the multitasking of the takeover prompt message, the arousal of the message to the driver, and the clarity of the driver's awareness when receiving the message all had an impact on the driver's workload during the takeover. It was found that the arousal level of the takeover message and the clarity of the driver's awareness when receiving the message had the greatest impact on the driver's workload. To some extent, this suggests that during the transition period of AIDC, people's workload at the time of takeover is more influenced by the manifestation of the Cognitive workload factor.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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