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Modeling takeover behavior in level 3 automated driving via a structural equation model: Considering the mediating role of trust

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ABSTRACT

The takeover process in level 3 automated driving determines the controllability of the functions of automated vehicles and thereby traffic safety. In this study, we attempted to explain drivers' takeover performance variation in a level 3 automated vehicle in consideration of the effects of trust, system characteristics, environmental characteristics, and driver characteristics with a structural equation model. The model was built by incorporating drivers' takeover time and quality as endogenous variables. A theoretical framework of the model was hypothesized on the basis of the ACT-R cognitive architecture and relevant research results. The validity of the model was confirmed using data collected from 136 driving simulator samples under the condition of voluntary non-driving-related tasks. Results revealed that takeover time budget was the most critical factor in promoting the safety and stability of takeover process, which, together with traffic density, drivers' age and manual driving experience, determined drivers' takeover quality directly. In addition, the pre-existing experience with an automated system or a similar technology and self-confidence of the driver, as well as takeover time budget, strongly influenced the takeover time directly. Apart from the direct effects mentioned above, trust, as an intermediary variable, explained a major portion of the variance in takeover time. Theoretically, these findings suggest that takeover behavior could be comprehensively evaluated from the two dimensions of takeover time and quality through the combination of trust, driver characteristics, environmental characteristics, and vehicle characteristics. The influence mechanism of the above factors is complex and multidimensional. In addition to the form of direct influence, trust, as an intermediary variable, could reflect the internal mechanism of the takeover behavior variation. Practically, the findings emphasize the crucial role of trust in the change in takeover behavior through the dimensions of subjective trust level and monitoring strategy, which may provide new insights into the function design of takeover process.

1. Introduction

Automated vehicles, considered an effective measure to improve road safety and traffic efficiency, have attracted increasing attention and have been under active development by many companies in recent years (Fagnant and Kockelman, 2015). Driving automation systems are categorized into five levels in accordance with the standard SAE J3016 (2018). The limitations of technologies and the ethics of traffic safety require a long time to realize full automation (L5), while the conditional automation (L3) is expected to enter the mass production stage in the next few years (Dokic et al., 2015). Level 3 automation allows the driver to engage in non-driving tasks, provided they are available to takeover vehicle control in a certain amount of time again should the system detects a system limit and request it. As a result, the driver commonly engages in non-driving tasks, and this situation promotes an orientation of attention away from the driving environment. The distraction promotes a loss of situation awareness, leading to the extension of takeover time and the deterioration of takeover quality (Merat et al., 2012a,b; Zeeb et al., 2016; Naujoks et al., 2019) and even to a key accident causation (Favarò et al., 2017). Takeover process is a fundamental element in considering various design aspects of human–machine interfaces and automated driving systems (Avery and Knight, 2017). It determines the controllability of automated vehicle functions and thereby traffic safety. The takeover performance in conditional

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automated driving systems, especially when drivers are distracted, should be evaluated.

Various studies have been conducted within the past years, providing insights into the factors influencing drivers' behavior in takeover situations. As a party providing assistance to drivers in the process of human–machine interaction, the performance of an automated driving system plays a leading role in determining the readiness, decision making, action execution, and evaluation during takeover. The performance includes takeover time budget (Gold et al., 2017), takeover request modality (Petermeijer et al., 2017), automation level (Gold et al., 2013a,b), and system reliability (Schwarz et al., 2019). In addition to the system characteristics, driving environment (e.g., traffic conditions (Gold et al., 2017), road elements (Louw et al., 2017), and weather conditions (Louw et al., 2015a)) was proven to determine drivers' performance by affecting takeover task complexity. Individuals exhibit a wide variability in their takeover reaction and performance. Age (Clark and Feng, 2017), personality (Chen et al., 2020b), trust (Körber et al., 2018a,b), driver fatigue and drowsiness (Feldhütter et al., 2017), alcohol (Wiedemann et al., 2018), manual driving experience (Chen et al., 2020a), and pre-existing experience with an automated system or a similar technology (Zeeb et al., 2016) are related factors.

Among the influential factors mentioned above, trust is a special variable. In a certain experiment or period, other factors are often fixed attributes or variables that can be set in advance in accordance with the experimental requirements; by contrast, trust, as dynamic cognitive performance, is time varying and difficult to manipulate. Wide ranges of factors affect trust. Such factors include age (Gold et al., 2015), gender (Chalmers, 2001), personality (Lee and See, 2004), manual driving experience (Chen et al., 2020a), pre-existing experience with an automated system or a similar technology (Gold et al., 2015), takeover time budget (Lee and See, 2004), system reliability (Sanchez, 2006), and traffic density (Cramer et al., 2008). Most of the key factors influencing takeover behavior have certain effects on the change in trust level. Accordingly, trust plays a mediating role, that is, the key factors may not only directly affect takeover performance but also indirectly affect the change in takeover process through influencing the trust level. The majority of relevant research has focused on the relationship between trust and takeover behavior (Körber et al., 2018a,b) or the joint effect of other factors on trust and takeover behavior (Payre et al., 2016), but profound experiment and exploration for the above complex relationship is lacking.

In addition, the abovementioned insights are derived from controlled experiments reported in previous research. Such experiments considered only one or two independent variables at a time, while other factors were kept constant. However, the environment of an automated driving vehicle is often a complex traffic system, which covers all factors of people, vehicles, and roads. Therefore, the aforementioned research on individual influencing factors has certain limitations in practical application. Other studies have considered various factors when quantifying takeover performance. For example, Gold et al. (2017) established a regression model on key takeover performance variables through a series of experimental data. When combining key factors, such as takeover time budget, traffic flow density, secondary tasks, current lane, driver's age, and number of experiments, the models for takeover time, time to collision, and crash probability provide detailed insights into the coherence and influencing factors when considering takeover performance. Nevertheless, such a study mainly used a combination of multiple experimental data rather than a single experiment and did not include trust as an important intermediary variable in the analysis.

From the literature above, research did not consider multiple dependent variables at a time through a single experiment to quantify the takeover performance in accordance with the changes in multiple key indicators from several dimensions. In addition, the complex relationship between factors and takeover performance has not been widely quantified and explored; the direction of causality is unclear; the extent and ways of influences of the factors on takeover performance are uncertain. Trust, as time-varying cognitive performance, which determines the human–machine interaction and the willingness to use an automated technology, was not fully considered by past studies, particularly about the complex role it plays in the formation and evolution of takeover.

This paper proposes a quantitative approach to modeling the takeover performance of level 3 conditional automation in multiple dimensions. Combined with various key factors, such as trust, system characteristics, environmental characteristics, and driver characteristics, a driving simulator experiment is conducted. A structural equation model is presented to capture multiple key takeover performance measures at a time and evaluate the differential contribution of the above factors to takeover behavior and their influencing mechanism.

2. Theoretical framework of the structural equation model for quantitative analysis of takeover performance

The construction of a reasonable theoretical framework of the relationship between the key influential factors and takeover performance is the premise for the subsequent structural equation modeling and analysis. Based on the ACT-R cognitive architecture and research results, reasonable assumptions on the relationship between factors and takeover performance, especially the specific role of trust, which is time-varying cognitive performance playing as a mediator, should be established.

2.1. ACT-R cognitive architecture

From the perspective of cognition, this study combs the logic of the formation of cognition (e.g., trust) and takeover behavior to find a reasonable solution to the above problems. ACT-R is a cognitive architecture (Fig. 1a), which was developed by Anderson (1976). The theory posits a fixed set of mechanisms that use task knowledge to perform a task, thereby predicting and explaining the steps of cognition that form human behavior. It also predicts the activation of brain regions used to generate behavior by using mechanisms that utilize procedural (how to do a task) and declarative (facts about the world) knowledge and working memory for activation to perform tasks (Ritter et al., 2019).

People receive external information through the perception module (vocal, aural, and visual), which works together with the declarative memory module in the central production system to form the cognition of the current state (including attitude, thought, and imagination). Finally, behavior is produced using the manual module under the joint action of the above modules (Anderson, 2007; Anderson et al., 2004a,b).

Not only external information, but also a declarative module for retrieving information from memory affects the formation of cognition and behavior. The declarative memory architecture in ACT-R is designed to mimic human memory. Evidence that declarative memory can be divided into two systems (episodic and semantic memory) comes from many sources (Nyberg et al., 2003; Nyberg, 1994; Jöreskog and Sörbom, 1989). Episodic memory is a neurocognitive memory system that enables people to remember specific past happenings that they have encountered (Tulving, 1993). That is, episodic memory is mainly related to specific things and events, and the corresponding influencing factors are attributes related to specific experiences or feelings. As for semantic memory, it is a mental thesaurus, organized knowledge a person possesses about words and other verbal symbols, their meaning and referents, the relations among them, and their rules and formulas (Tulving, 1972). In the same way, we can deduce that the factors affecting semantic memory are the basic attributes of people, unrelated to special events, experiences, or feelings.

In summary, the ACT-R cognitive system provides not only a cognitive explanation for the generation of takeover behavior but also a reasonable hypothesis for the relationship among different influential factors in this study. In accordance with the cognitive system, external information (including system and environmental characteristics) and

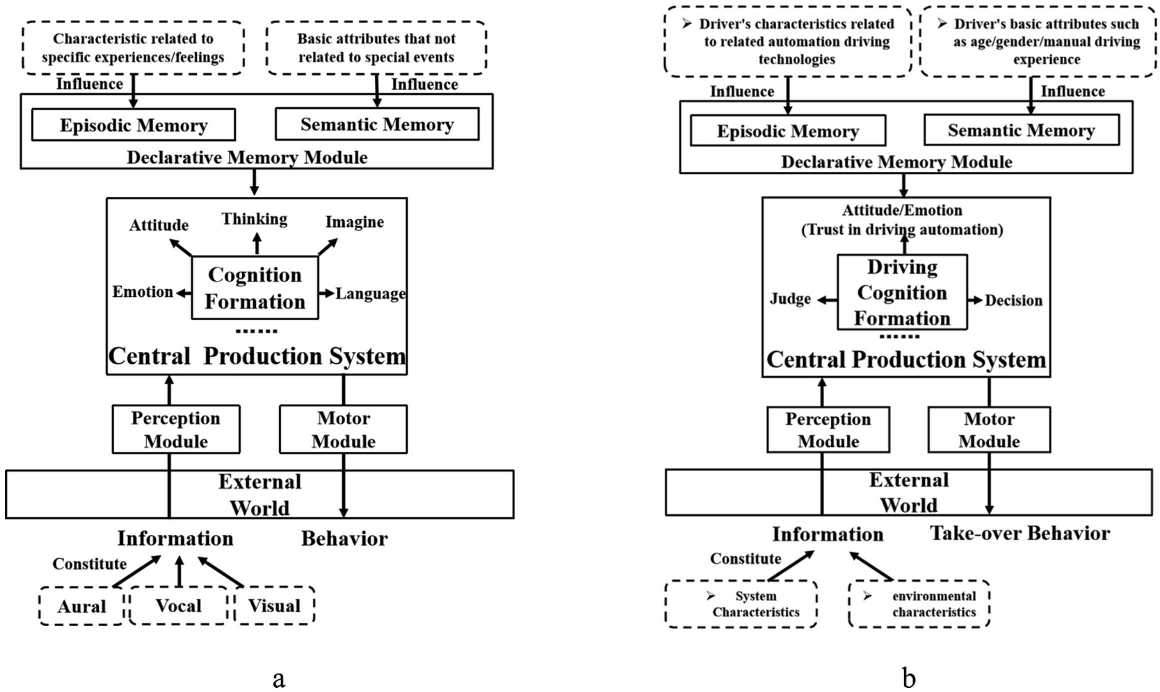

Fig. 1. The simplified structure of ACT-R cognitive system (Figure by authors based on and extending Anderson, 2007 and Anderson et al., 2004a,b, and comments from Ritter, Tulving, Nyberg et al.). *Note*: a. Simplified schematic diagram of ACT-R cognitive architecture; b. The cognitive framework of automated driving with key variables of the model.

internal memory module (affected by the driver's characteristics) act on the central production system of the human brain, forming cognitions, such as attitude (trust) to the current state. Combined with the driver's judgment, evaluation, and decision making, the takeover behavior is finally generated (Fig. 1b). Causality exists not only between factors and takeover performance but also among different influential factors. Among them, trust, as a form of cognition, plays a mediating role.

2.2. Assumptions on the relationship between factors and takeover performance

From the above *ACT-R Cognitive Architecture*, we sorted out the logic of takeover behavior from the perspective of cognition and then preliminarily determined the positioning and function of different factors in the model. Among them, trust, as a form of cognition, plays a mediating role. Next, combined with the empirical results of peer-reviewed experiments and relevant research, theoretical support for the above relationship was sought, and reasonable assumptions ***H1–H7*** were established to construct the theoretical framework of the model.

2.2.1. System characteristics and takeover performance

The system behavior (e.g., takeover time budget (Gold et al., 2017), takeover request modality (Petermeijer, Bazilinskyy, et al., 2017), automation level (Gold et al., 2013a,b), and presence of takeover request (Strand et al., 2014)) directly reflects the function, boundary, and reliability of the automated vehicle. These automation effects influence the drivers' physical, visual, and cognitive components of the takeover process (Zeeb et al., 2015). Among them, the takeover time budget is a crucial feature (McDonald et al., 2019). On the one hand, it determines whether time is available for the driver to acquire situation awareness and regain complete control of the driving task (Lu et al., 2017; Samuel et al., 2016). On the other hand, it provides an effective reference for establishing a reasonable system boundary by combining sensor range and reliability (Gold et al., 2015). Previous research has demonstrated that takeover time budget has substantial associations with takeover time. A long takeover time budget generally leads to a long takeover time (Zhang et al., 2019a,b; Payre et al., 2016), and this phenomenon is evident in emergency and nonemergency scenarios (Payre et al., 2016). In a meta-analysis, Gold et al. (2017) attributed a 0.33 s increase in takeover time per 1 s increase in time budget to time budgets between 5 and 7.8 s. Zhang et al. (2019a,b) found a similar relationship between time budget and takeover time. In addition, several studies determined that short takeover time budgets deteriorate post-takeover control. These deteriorations are associated with short minimum time to collision (TTC), great maximum lateral and longitudinal accelerations (Wan and Wu, 2018), high crash rates (van den Beukel and van der Voort, 2013), and great Standard Deviation of Lane Position (SDLP; Mok et al., 2015a). On the basis of the above evidence, we proposed that

H1. System characteristics, such as takeover time budget, have considerable effects on takeover behavior.

2.2.2. Driving environment and takeover performance

In addition to system characteristics, the driving environment also affects the performance of the driver during the takeover process. For example, few alternative escape routes (Zhang et al., 2018), harsh weather conditions, and poor driving environment on expressways (Li et al., 2018) increase the takeover time of drivers and lead to decreased takeover quality. Scholars have extensively focused on surrounding traffic state, which is the most common environmental impact variable. Traffic density refers to the number of vehicles in a lane or a direction in a unit length (usually 1 km) section, which is used to express the density of vehicles on a lane (McDonald et al., 2019). An increase in traffic density means that various environmental objects need to be perceived by drivers, and the complexity of takeover scenarios and tasks increases (Körber et al., 2016), which causes additional challenges to drivers. The findings on traffic density are inconsistent. Several studies have suggested that a high traffic density leads to a long takeover time and decreased takeover stability and urges drivers to adopt a brake avoidance strategy instead of steering (Körber et al., 2016; Radlmayr et al., 2014; Eriksson et al., 2018). However, Gold et al. (2017) found that 15.7 vehicles/km was a quadratic centered with lower or higher values, leading to decreased takeover time. They hypothesized that 15.7 vehicles/km represents a dilemma zone where it is unclear if changing lanes is a viable alternative; by contrast, with low or high traffic densities, drivers may immediately recognize a lane change, or braking is the optimal evasive maneuver. From the above evidence, we proposed that

H2. Traffic density and other environmental characteristics affect the takeover behavior to a certain extent, although the specific impact mechanism has not been unified.

2.2.3. Driver factors and takeover performance

As the main behavior part, the influences of drivers on their relevant performance in the takeover process are worthy of in-depth analysis. Several scholars have emphasized the importance of "exploring the relationship between driver characteristic and behavior in automated driving" (Gold et al., 2017; McDonald et al., 2019), and some relevant characteristics have been included in studies. Among them, age, as the most commonly used demographic variable, has been widely examined in studies of takeover performance (Clark and Feng, 2017; Gold et al., 2017; Körber et al., 2016). Gold et al. (2017) found significant differences in the takeover time of drivers in diverse age groups after classifying the age by 46 years old. Li et al. (2018) identified similar results in young (20–35 years) and old (60–81 years) drivers, that is, older drivers have a significantly slower takeover response, a longer takeover time, and worse takeover quality. The training before the experiment (Hergeth et al., 2017) and prior experience with automated takeovers (Banks and Stanton, 2015; Seppelt and Victor, 2016) or an automated driving technology, such as adaptive cruise control (Zeeb et al., 2017), also affect the visual reaction time and adjust the learning effect during the takeover process. Several scholars have conducted experimental studies on the relationship between driver's personal characteristics and takeover behavior. For instance, Chen et al. (2020b) investigated the effect of driving style on takeover performance in level 3 automation. The results indicated that the experience of aggressive drivers in manual emergency driving makes their emergency evasive maneuvers considerably stable in automated takeover. As for manual driving experience, Chen et al. (2020a) found that manual driving experience significantly affects the maximum resultant acceleration during the takeover process. From the above evidence, we proposed that

H3. Personal characteristics, such as age, personality, manual driving experience, and prior experience of related technologies, have certain effects on the driver's takeover behavior.

2.2.4. Trust in the automated driving system and takeover performance

In addition to the abovementioned characteristics, the attitude and emotion of the driver during the interaction process are closely related to the takeover performance (Lee and See, 2004). Among them, trust is a key dimension in the relationship between the driver and the automated driving system. Similar to its role in interpersonal relationships, trust in technology plays a leading role in determining the willingness of humans to rely on automated systems in situations characterized by uncertainty (Zeeb et al., 2017). In addition, it directly affects the public's acceptance and use of relevant technologies (Panagiotopoulos and Dimitrakopoulos, 2018; Kaur and Rampersad, 2018; Liu et al., 2019; Zhang et al., 2019b) and then directly determines the real implementation and popularization of the automated driving technology (IEEE, 2014; Liu et al., 2019). Some preliminary attempts have been made to understand the relationship between trust in the automated driving system and takeover behavior, measuring the trust subjectively (e.g., questionnaires (Gold, Körber, et al., 2015)) and objectively (e.g., eye-tracking parameters (Körber et al., 2018a,b)). An increase in subjectively measured trust in the automation leads to an increase in takeover time (Körber et al., 2018a,b; Payre et al., 2016) and a decrease in post-takeover control performance, measured by maximum lane deviation (Shen and Neyens, 2014) and short minimum TTC (Körber et al., 2018a,b). Few studies have found a strong relationship between the subjective measurement and objective indicators of trust (Körber et al., 2018a,b). Nonetheless, Hergeth (2016) and Korber et al. (2018) reported a negative correlation between self-report trust in driving automation and the gaze behavior during a mandatory engagement in a non-driving-related task (NDRT). On the basis of the above evidence, we proposed that

H4. Trust in the automated driving system has a certain effect on the driver's takeover behavior.

2.2.5. System characteristics and trust in the automated driving system

Many scholars have shown that system characteristics, such as takeover time budget, can significantly affect the driver's trust in the automated system. Lee and See (2004) believed that timely and accurate takeover requests would promote driver's trust in driving automation. In addition, takeover time budget has been widely used as an experimental variable to reflect system reliability, and system reliability has been proven to affect the trust of participants significantly (Bailey and Scerbo, 2007; Rovira et al., 2007; Sanchez, 2006). From the above evidence, we proposed that

H5. Takeover time budget and other system characteristics affect the driver's trust in automated driving.

2.2.6. Driving environment and trust in the automated driving system

A broad range of driving environments have been examined in studies of trust in the automated driving system. Bjørner (2019) found that trust is affected not only by the process of human–computer interaction but also by environmental factors, such as road, traffic, and weather. Research by Cramer et al. (2008) showed that in the case of high traffic density, various environmental objects need to be perceived by drivers, and the complexity of takeover scenarios and tasks increases. This condition leads to a decrease in drivers' sense of security in using the system and then affects the trust in the system. From the above evidence, we proposed that

H6. Traffic density and other environmental characteristics affect the driver's trust in automated driving.

2.2.7. Drivers' personal characteristics and trust in the automated driving system

Exploring the relationship between personal characteristics and trust is common in the entire automation field. For example, researchers have shown that the age difference of users have a significant effect on trust (Schwarz and Brown, 2016; van Driel and van Arem, 2005; Gold et al., 2015), and users of different age levels adopt different strategies when analyzing system credibility (Ezer et al., 2007, 2008; McBride et al., 2010). In the field of artificial intelligence, scholars have found that personality is a stable factor affecting automation trust. Szelma and Taylor (2011) demonstrated that when users are outgoing and confident, they are likely to accept the help provided by the system and thus likely to trust or rely on the system. Apart from the above factors, prior knowledge and experience of related technologies also affect users' trust level. Khastgir et al. (2018) discovered that a prior notification to the driver about the true safety boundary and function of the system will make the driver's trust in the system improve. Similarly, Körber et al. (2018) found that the previous experience of familiarity and contact with the system is conducive to promoting the driver's recognition and dependence on the system. Moreover, manual driving experience may have a certain effect on trust. Jin et al. (2020) found that experienced drivers were likely to trust the system but still paid more attention to the road or instrument cluster rather than phone, whereas novice drivers with lower trust were in the out-of-the-loop state more frequently. On the basis of the above evidence, we proposed that

H7. Personal characteristics, such as age, manual driving experience, self-confidence, and prior experience in related technologies, affect drivers' trust in automated driving.

2.3. *Theoretical framework of the structural equation model*

Based on the *ACT*-R cognitive architecture and research results, reasonable assumptions on the relationship between factors and take-over performance were established. We could not consider all the aforementioned factors in one experiment due to the limited time and cost of the experiment. Therefore, in accordance with the research status and practical application scenarios of relevant factors and considering their controllability and testability in the experiment, the researchers selected the following factors as the experimental variables of this study: *takeover time budget*, *traffic density*, *trust*, *age*, *manual driving experience*, *self-confidence*, and *prior experience in using related technologies.*

To sum up, a reasonable construction of the final theoretical framework of the structural equation model is shown in Fig. 2.

3. Methods

3.1. *Participants*

Thirty-four participants (i.e., 14 females and 20 males, mean age = 30.441 years, SD = 7.856 years) were recruited through networks in Beijing, China. All recruited participants had valid driving licenses and normal or corrected-to-normal visions. Sixteen participants had preexisting experience with an automated system or a similar technology, and 18 participants had not yet. Among these participants, 3 (8.82 %) had junior high school degree, 9 (26.47 %) had senior high school degree, 17 (50 %) had bachelor's degree, and 5 (14.71 %) had master's degree or above. For occupation, 10 (29.41 %) were professional drivers, 13 (38.24 %) were office workers and 11 (32.35 %) were college students.

In addition, the researchers also made some statistics and analysis on the driving information of the participants, such as driving age, accumulated mileage (so far), annual driving mileage and driving frequency. On average, they owned a driver's license for 7.735 years (S.D = 6.006 years). For the accumulated mileage which is the total number of driving mileage by the date of statistics, twelve participants were classified as novices, whose accumulated mileage were less than 3000 km. 11 drivers were classified as medium experienced drivers, whose accumulated mileage were between 3000 km and 100,000 km. 11 drivers were classified as experienced drivers, whose accumulated mileage were more than 100,000 km. Moreover, about driving frequency, 10 (29.41 %) participants were professional drivers who drove for a long time every day, 4 (11.76 %) participants needed to drive several times a day (commuting), 2 (5.88 %) participants drove several times a week, 8 (23.53 %) participants drove several times a month, and 9 (26.47 %) participants drove several times a year (Table 1).

It is worth mentioning that, at present, the classification standard of

Table 1
Demographic and socioeconomic characteristics of the participants.

Characteristics	Description	Data type	Simple Statistics Mean (S.D)
Age	Age	Continuous variable	30.441 (7.856)
Preexisting experience	Preexisting experience with a driving automated system or similar technology	16 participants had, 18 participants had not yet	/
Education	Education	3 had junior high school degree, 9 had senior high school degree, 17 had bachelor's degree, 5 had master's degree or above	/
Occupation	Occupation	10 were professional drivers, 13 were office workers, 11 were college students	/
Driving age	The total number of years since the time of getting the driver's license	Continuous variable	7.735 (6.006)
Accumulated mileage	The total number of driving mileage by the date of statistics	12 were less than 3000 km (novices), 11 were between 3000 km and 100,000 km (medium experienced drivers), 11 were more than 100,000 km (experienced drivers)	/
Driving frequency	Driving frequency	10 were professional drivers who drove for a long time every day, 4 needed to drive several times a day (commuting), 2 drove several times a week, 8 drove several times a month, 9 drove several times a year.	/

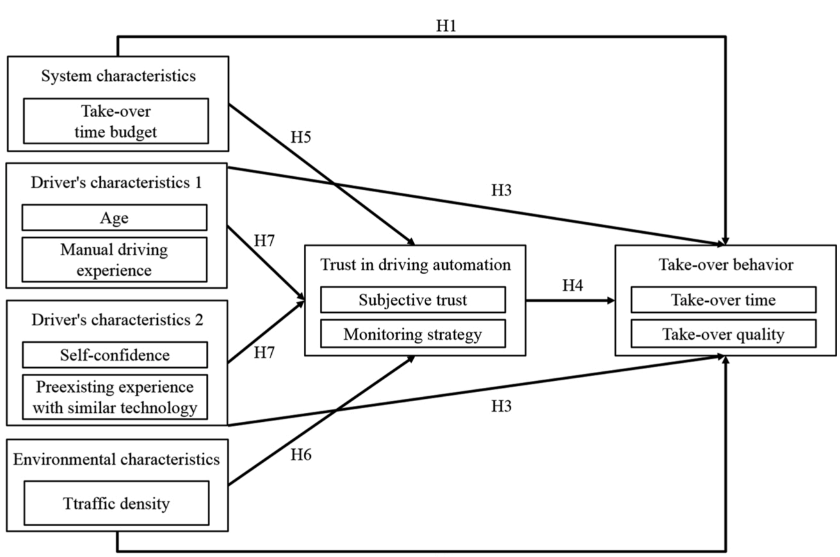

Fig. 2. The final theoretical framework of the model.

driving experience is unclear, and most studies are based on driving age. Nonetheless, there is a special case in China where some people have held legal driving licenses for many years but have never driven a car. Accordingly, we used accumulated mileage to distinguish the driving experience of participants in this study by reference to two studies from China (Lyu et al., 2018; Wang et al., 2010).

The definition, introduction, coding, and descriptive statistical results of the participants' personal characteristics are indicated in Table 2. The sample size of the structural equation model should not be excessively small or large because the number of observation variables in the model and the change range of the covariance matrix have great influences on the analysis results of the model (Zhao et al., 2019). Zhang, Huang, Yin, and Gong (2015) recommended the use of at least 30 cases when examining more than eight latent variables. Accordingly, 136 valid samples were used to examine six latent variables in the structural equation model.

3.2. Apparatus

The study was conducted with a fixed-based driving simulator (Fig. 3), UC-Win/Road 3D virtual reality software, and a SmartEye eye tracker (Fig. 4). The hardware of the driving simulator includes a Logitech G29 steering wheel, an accelerator pedal, a brake pedal, two high-performance computers, three displays, and a control terminal display. The central display screen directly faced the driver and displayed images by simulating the front windshield and the inside rear-view mirror of the vehicle. The two bilateral displays covered an angle of 135 degrees to simulate the scene of left and right field of vision during driving. The left and right rear-view mirrors also appeared in them respectively to monitor the driving behavior of the vehicle behind. In addition, the simulator consisted of a set of driver's seat and audio equipment. The driver could increase comfort by adjusting the front and rear position of the simulator seat and the back angle. The simulator used manual control of automated transmission, so the driver did not need to shift when driving manually, just need to operate the accelerator pedal, brake pedal and steering wheel.

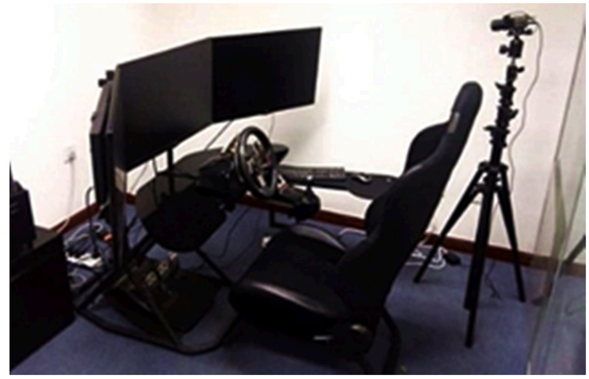

Fig. 3. Driving simulator.

The driving simulator is an automated gear vehicle in manual mode. Thus, the drivers only needed to operate the accelerator pedal, brake pedal, and steering wheel when driving manually. As for UC-Win/Road, it can realize complex road structures, vehicle installation, and traffic control. The researchers could also obtain experimental data from the ego vehicle and surrounding objects in real time at a frequency of 25 Hz, including 3D space position coordinates and driving operation data, in addition to those from the above hardware and software tools. The eye tracker recorded the specific indicators of the driver's monitoring strategy (gaze behavior) at a frequency of 60 Hz.

3.3. Experimental environment

The experiment was designed in a real section of the Beijing–Tibet Expressway from the Qinghe Toll Station to the North Fourth Ring Road. It was a two-way six-lane expressway provided with central separation belt, all of which were interchange without signal light. Both sides of the road were equipped with roadside trees, speed limit signs, street lamps, and other road accessories. Surrounding 3D models, such as various

Table 2
Definitions of variable, their codes and statistics.

Latent variable	Observed variables		Description and coding of input value	Simple Statistics Mean (S.D)
	Name	Description		
Driver's personal characteristics 1	Age	Age	Continuous variable	30.441(7.856)
	Manual driving experience	The total number of manual driving mileage on the actual road from the time of getting the driver's license to the day of statistics.	0→(0, 3000 km] ; 1→(3000 km, 100,000 km] ; 2→(100,000 km, ∞] ;	/
Driver's personal characteristics 2	Preexisting experience with an automated system or a similar technology	Prior to the experiment, the driver's preexisting experience with an automated system or a similar technology.	0→ No experience ; 1→Have experience ;	/
	Self-confidence	The degree of confidence that drivers have in their ability to ensure the safety and stability of simulated vehicles.	Continuous variable [0,5]	4.368(0.644)
Subjective trust	Questionnaire	Five subscales: Reliability/Competence, Familiarity, Trust, Understanding, and Intention of Developers.	Continuous variable [0,5]	3.797(0.431)
Monitoring strategy	Monitoring ratio	The percentage of time that glances are within monitoring $\sum \frac{(t_{gaze1}, t_{gaze2}, \ldots, t_{gazen})}{t_{\text{non-driving-related task}}}$	Continuous variable	0.461(0.240)
	Monitoring frequency	The number of glances per unit of time on monitoring $\sum \frac{n_{\text{monitoring gazes}}}{t_{\text{non-driving-related task}}}$	Continuous variable	0.508(0.239)
System characteristics	Takeover time budget	The time to collision (TTC) at the moment of takeover request (TOR).	0→7s ; 1→10s ;	/
Environmental characteristics	Traffic density	The number of vehicles in a lane or a direction in a unit length (usually 1 km) section.	0→10 vehicles/km ; 1→30 vehicles/km ;	/
Takeover time	Takeover time	The time between the TOR and the first conscious reaction by the driver.	Continuous variable	2.878(0.748)
Takeover quality	Maximum lateral acceleration	To evaluate the longitudinal and lateral stability of the evasive maneuver in the process of takeover after the TOR.	Continuous variable	1.193(0.708)
	Maximum longitudinal deceleration		Continuous variable	4.291(1.516)
	Standard deviation of lane position		Continuous variable	0.469(0.125)

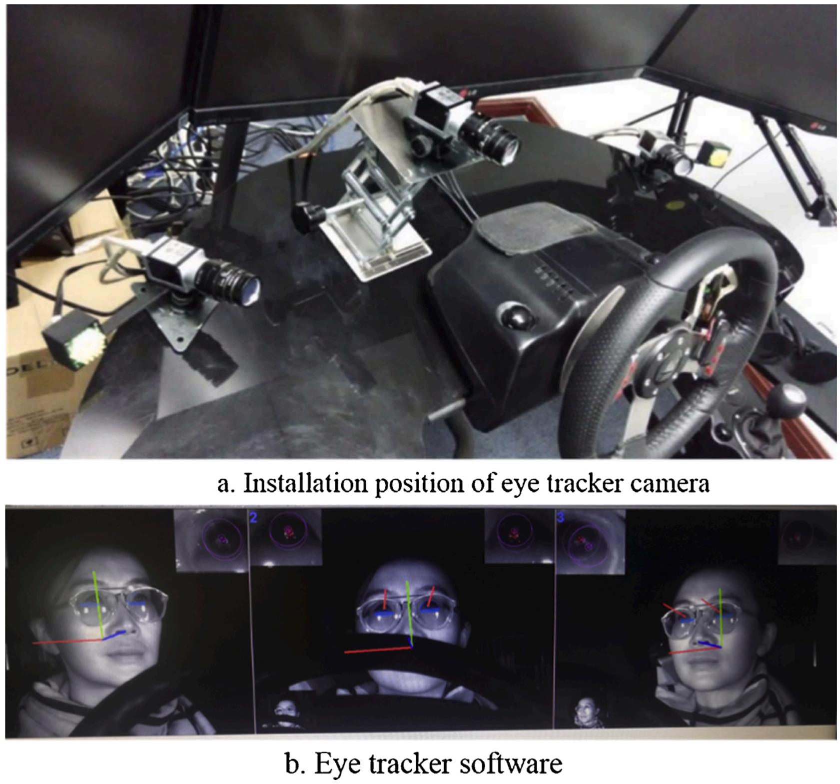

Fig. 4. SmartEye eye tracker.

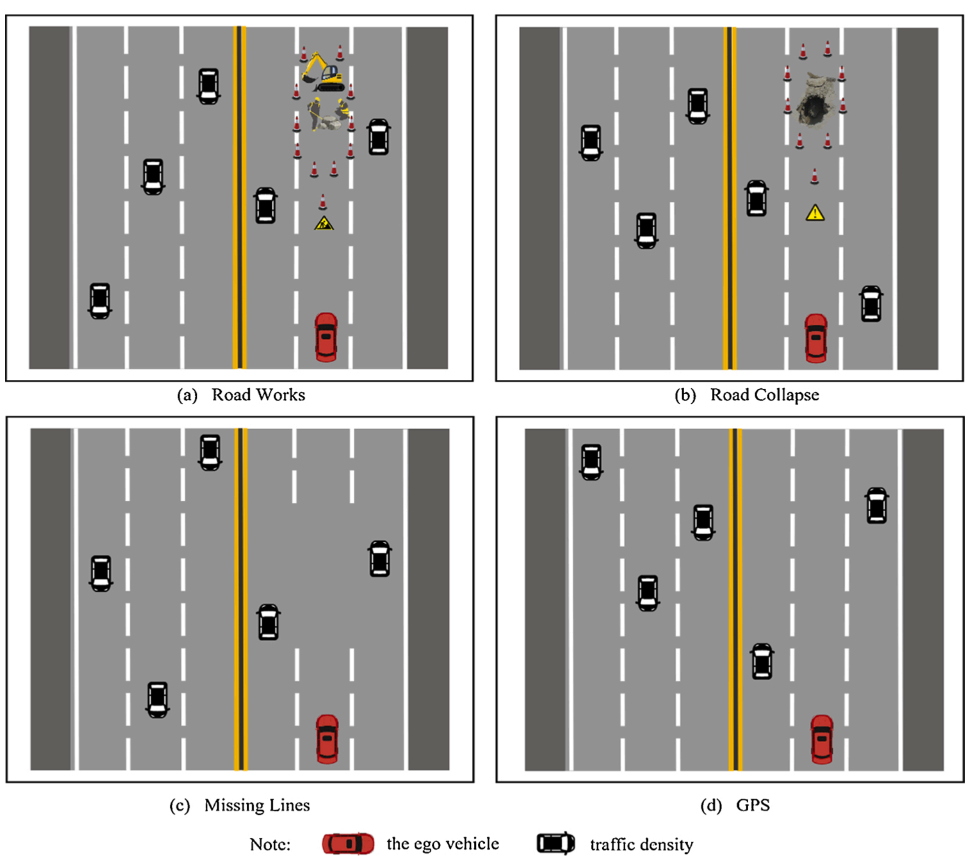

Fig. 5. Schema of takeover scene.

vegetation and continuous buildings, were added around the road to simulate the urban landscape and enhance the reality.

As shown in Fig. 5, the takeover scenarios were chosen to correspond to realistic takeover situations in automated driving (Aeberhard et al., 2015). The scenarios *Road works* (Fig. 5a) and *Road collapse* (Fig. 5b) represented road works or sudden accidents on the participant's lane, which required bypassing on an alternative lane. The scenario *Missing lines* (Fig. 5c) represented a highway section where the right lane markings were missing, and the scenario *GPS* (Fig. 5d) represented a takeover request (TOR) caused by missing GPS data. With reference to the experimental design of Gold et al. (2013), a leading vehicle drove on the middle lane at a constant speed to ensure that a random glance at the scenery does not lead to a premature detection of the system boundary. While TOR was prompted, the leading vehicle suddenly swerved to the side lane and uncovered the takeover scenarios.

When the automated system was disabled, it sent a strong and rapid beep. While playing the audio, the relevant explanation about the system failure appeared at the screen bottom to increase the perceived understanding of the system (Körber et al., 2018a,b), which lasted for approximately 10 s after TOR. The participants could drive the vehicle manually again by turning the steering wheel or pressing the brake pedal.

3.4. Experimental design

As visualized in Fig. 6, the experiment adopted a 2 × 2 within-subject design with traffic density and takeover time budget as the within-subject factors. With reference to the study of Körber et al. (2016) and the simulator characteristics, traffic density was set to 10 or 30 vehicles/km and was manipulated by the number of other vehicles and their constant and equal distance to the ego vehicle. The takeover time budget was set to 7 or 10 s in accordance with the study of Gold et al. (2013) and Melcher et al. (2015). Therefore, each participant went through four takeover processes in the experiment, and the sequence of the scenes followed a 4 × 4 Latin square design. A situation without takeover process was included in the experiment to prevent the participants from learning effects and the influences of fixed and continuous takeover scenarios on the takeover behavior. The two situations were designed counterbalance.

The takeover request modality of this experiment used an auditory alert, which was widely used in previous studies (Gold, 2016; Clark and Feng, 2017). When the automated driving system was deactivated, it made a strong and rapid beeping sound. After receiving the takeover request from the automated driving system, the participants were required to take over the vehicle in time and return to the middle lane to continue driving.

3.5. Non-driving-related task (NDRT)

Most of the simulator experiments related to automated driving use mandatory tasks to simulate the driver's distracted state when the automated driving function is turned on (Körber et al., 2016; Gold, 2016). While mandatory engagement in secondary activities allows an accurate control of the tasks in which drivers are involved in, it is different from how drivers would typically engage in non-driving-related activities in daily life. A driver would determine when to engage, what activity, and how much involvement on the basis of his or her assessment of the driving situation under natural driving (Clark and Feng, 2017). In addition, mandatory tasks usually result in drivers' lack of freedom to decide under high workloads. Therefore, reliance behavior and monitoring strategy are minimally affected by trust, and the variability of the relationship between these variables is limited (Hergeth, 2016). The effect of a voluntary rather than mandatory engagement in NDRTs on driver status and takeover behavior should be studied (a similar proposal was noted in Hoff and Bashir (2015)).

Thus, participants in this experiment were required to behave naturally in accordance with their usual driving habits as much as possible, and they could use mobile phones to engage in non-driving-related activities at any time provided they considered the current driving state and environment safe and stable. Before the formal experiment, the researchers emphasized that "once a vehicle collision occurs, the participants need to take main responsibility, and the final remuneration will be deducted to a certain extent" to prevent participants from being excessively casual about the experiment.

3.6. Experimental dependent variable

The indicators for evaluating the takeover performance include the *takeover time, maximum longitudinal deceleration, maximum lateral acceleration,* and *SDLP*. These indicators were also widely used in previous studies (Gold et al., 2013a; Körber et al., 2016; Wiedemann et al., 2018). *Takeover time*, introduced by Gold et al. (2013) as "the time between TOR and the first conscious reaction by the driver," is a widely used measure of takeover performance. *Maximum longitudinal deceleration, maximum lateral acceleration, and SDLP*, which occurred after TOR, were

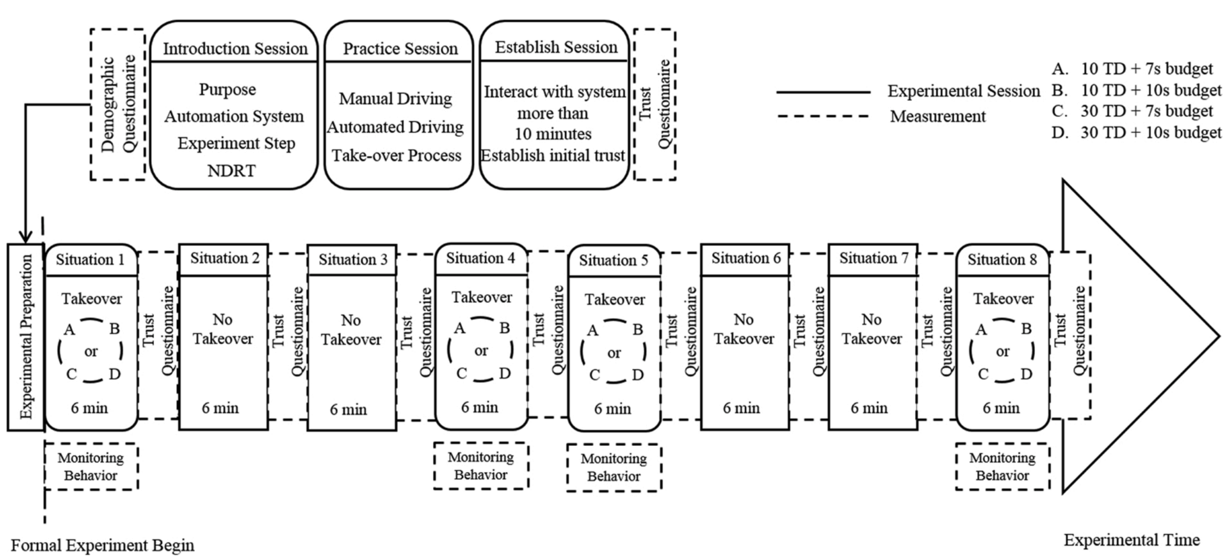

Fig. 6. Example of the experimental process.

used to evaluate the safety and stability of evasive maneuver in the takeover process separately. They were also called post-takeover control (McDonald et al., 2019).

As for automation trust, the researchers used the questionnaire *Trust in Automation* developed by Körber (2015) to assess the trust in automation directly, which has been proven valid in previous studies (Körber et al., 2018a,b). The questionnaire was structured into 5 subscales (Reliability/Competence, Familiarity, Trust, Understanding, and Intention of Developers) and contained 19 items on a Likert-type rating scale. It could evaluate the subjective trust level in detail in multiple dimensions.

Monitoring behavior was also regarded as a dependent variable reflecting the trust level, considering that the subjective method was incapable of capturing temporary changes in the trust in automation. The monitoring strategy of drivers on vehicles and roads has been widely associated with trust in the field of automated driving. For instance, Hergeth (2016) and Korber et al. (2018) reported a negative correlation between self-report trust in driving automation and the gaze behavior during a mandatory engagement in an NDRT. Therefore, the participants' eye movement was tracked to judge the monitoring behavior. The measures were *monitoring ratio* (the percentage of time that glances are within monitoring) and *monitoring frequency* (the number of glances per unit of time in monitoring), which are widely used to quantify monitoring strategy.

3.7. Procedure

Before the formal experiments, each participant was required to sign an informed consent and complete a demographic questionnaire. They were provided with information about the experimental process and automated system, followed by a practice session of driving to gain familiarity with the simulated driving environment and vehicle control. At the end of the above process, the participants experienced automated driving for 10 min to establish initial trust in the system, during which neither system failure nor the situation of reaching the boundary occurred. Then, the participants were asked to fill in a trust questionnaire to obtain their initial trust level before the formal experiment. After the practice session, the participants started the formal experiments (four with takeovers/four without takeovers). The participants filled in the trust questionnaire immediately after each session to obtain their current trust level. At the end of the experiments, each participant received a compensation of 150 yuan.

3.8. Data analysis

In this study, the analysis of moment structures (AMOS) module of IBM SPSS was used to establish the structural equation model. AMOS can exchange data files efficiently within the framework of SPSS. In addition, it has an intuitive drag-and-drop drawing tool to draw the path map rapidly, customize the model without programming, and test the influence mechanism and the reason among variables (Wu, 2009).

4. Results

4.1. Definitions of variables, their codes, and related statistics

Thirty-four drivers (20 males and 14 females) who met the requirements of the experiment participated in the experiment. Each participant experienced four different sessions of takeover in the formal experiment and the data from these four sessions were analyzed, that is to say, one participant created four different experimental samples. Therefore, a total of 136 experimental samples were provided by 34 participants for subsequent analysis and modeling.

Table 2 shows the name, definition, model input code value, and descriptive statistical result of relevant variables in this study. Among them, exogenous variables (model input) include the driver's personal characteristics, environmental characteristics, and system characteristics; the corresponding indicators are *takeover time budget*, *traffic density*, and the driver's *age, manual driving experience, self-confidence, and pre-existing experience with an automated system or a similar technology.* The mediating variables are *subjective trust* and *monitoring strategy*; the indicators are *questionnaire*, *monitoring ratio*, and *monitoring frequency*. Correspondingly, the output of the model in the endogenous variables is takeover performance, including *takeover time* and *takeover quality*. The indicators include the *takeover time*, *maximum longitudinal deceleration*, *maximum lateral acceleration*, and *SDLP*.

4.2. Structural equation model

The structural equation model consists of three parts: 1. measurement model of endogenous variables (Y measurement model); 2. measurement model of exogenous variables (X measurement model); 3. structural model of causality or correlation between exogenous and endogenous variables (Kim et al., 2011). The structural equations used in this study are shown in Eqs. (1) and (2).

Measurement model:

$$X_{\rm i} = \delta_i F_{Xi} + \theta_i. \\ Y_{\rm i} = \lambda_i F_{Yi} + \mu_i. \tag{1}$$

where X_i, Y_i are vectors of observed variables; F_{Xi}, F_{Yi} are vectors of latent constructs; δ_i, λ_i are vectors of parameters; and θ_i, μ_i are vectors of measurement errors.

Structural model:

$$F_{\rm Yi}^{**} = \eta_i F_{\rm i}^{*} + \Gamma_i F_{\rm Xi} + o_{\rm i}. \tag{2}$$

where the endogenous variable F_{Yi}^{**} is a function of the endogenous effect of the mediating variable F_i^{*} and the effect of the exogenous variable F_{Xi} plus residual terms O_i. η_i and Γ_i are parameter vectors.

The results of the model and standard path parameters are shown in Fig. 7 and Table 3, which present the relationship and specific influence mechanism among variables.

In Fig. 7, the rectangle represents the measured variable (observation variable), the ellipse represents the latent variable that cannot be directly measured, the arrow pointing from the latent variable to the observed variable represents the regression path. In addition, two latent variables connected by a curved double-headed arrow indicate that a common change exists between them. The SEM model consists of 6 latent variables and 13 observational variables.

4.2.1. Measurement model

The standardized load factor (represented by δ_i, λ_i in Eq. (1)) and the relevant test parameters in the measurement model are shown in Fig. 7 and Table 3. From the above chart results, we can compare and analyze the effect of each observation variable on potential variables. For the measurement model X_i of exogenous latent variables, *manual driving experience*, *age*, *self-confidence*, and *pre-existing experience with an automated system or a similar technology* are important indicators of the driver's personal characteristics. Among them, *manual driving experience* is the most significant factor that positively affects *driver's personal characteristics 1* (factor loading = 0.9). In addition, *pre-existing experience with an automated system or a similar technology* is the main factor that affects *driver's personal characteristics 2*, which is related to current specific things (factor loading = 0.58). In accordance with the measurement model Y_i for endogenous latent variables, *monitoring ratio* is the best indicator to reflect the monitoring strategy (factor loading = 0.93). Takeover stability is mainly reflected in the *maximum lateral acceleration, maximum longitudinal deceleration,* and *SDLP* during the takeover process. Among them, the *maximum lateral acceleration* is a relatively appropriate indicator to describe (reflect) the stability of takeover (factor loading = 0.79).

The results of relevant goodness-of-fit indexes in the confirmatory

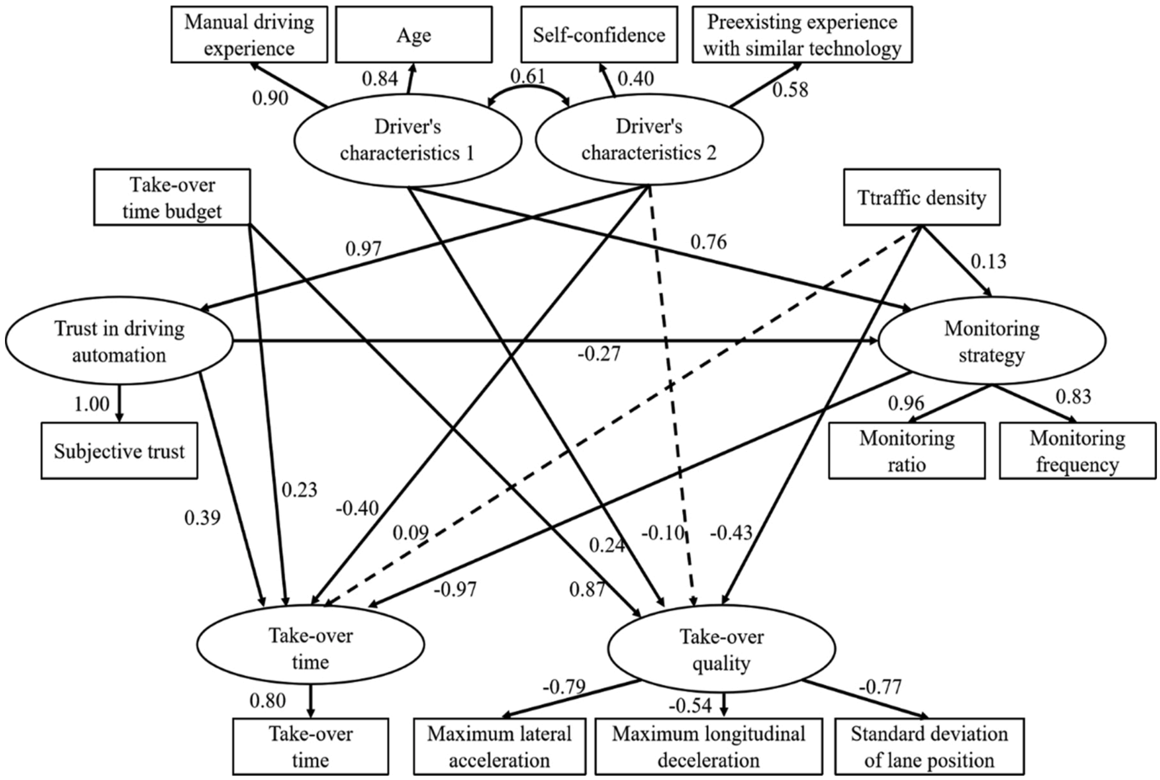

Fig. 7. The final SEM and standardized path coefficients. (Rejected hypothesis is shown in broken lines, $p \geq 0.05$).

Table 3
Results of the SEM estimation.

SEM Variables	Standardized Path coefficients	p
Driver's characteristics 1→Age	0.84	***
Driver's characteristics 1→Manual driving experience	0.90	***
Driver's characteristics 1→Monitoring strategy	0.76	***
Driver's characteristics 1→Takeover quality	0.24	***
Driver's characteristics 2→Preexisting experience with an automated system or a similar technology	0.58	***
Driver's characteristics 2→Self-confidence	0.40	***
Driver's characteristics 2→Subjective trust	0.97	***
Driver's characteristics 2→Takeover time	−0.40	***
Driver's characteristics 2→Takeover quality	−0.11	0.117
Subjective trust→Monitoring strategy	−0.27	0.036
Subjective trust→Takeover time	0.39	***
Monitoring strategy→Monitoring ratio	0.96	***
Monitoring strategy→Monitoring frequency	0.83	***
Monitoring strategy→Takeover time	−0.97	***
Takeover time budget→Takeover time	0.23	***
Takeover time budget→Takeover quality	0.87	***
Traffic density→Monitoring strategy	0.13	0.070
Traffic density→Takeover time	0.09	0.210
Traffic density→Takeover quality	−0.43	***
Takeover time→Takeover time	0.80	***
Takeover quality→Maximum lateral acceleration	−0.79	***
Takeover quality→Maximum longitudinal deceleration	−0.54	***
Takeover quality→Standard deviation of lane position	−0.77	***

factor analysis (CFA) test (Table 4) imply that the measurement model provides a reasonable fit for the experimental data. All the observed variables have high load values (factor load coefficient $> 0.5, p < 0.001$) on the corresponding latent variables (e.g., driver's personal characteristics, driver's status, and takeover performance), indicating that all

Table 4
Fit statistics for structural equation models.

Fit index	Criteria of acceptable fit	SEM models
χ^2/d.f.	1−3	1.684
GFI	≥0.9	0.901
AGFI	≥0.8	0.847
CFI	≥0.9	0.948
NFI	≥0.9	0.984
IFI	≥0.9	0.949
TLI	≥0.9	0.931
RMESA	≤0.08	0.071

the latent variables analyzed are reliably evaluated and convergent validity is established.

4.2.2. *Structural model*

The relationship among exogenous latent variables (represented by F_{Xi} in Equation (2)), endogenous latent variables (represented by F_{Yi}^{**} in Equation (2)), and intermediate latent variables (represented by F_i^{*} in Equation (2)) is shown in Fig. 7. The normalized path coefficients ($p < 0.05$) of significant structural relationships among variables are shown in the corresponding arrows in Fig. 7. In terms of *takeover time*, the *monitoring strategy* of drivers on vehicles and roads in the process of automated driving is the most important factor (standardized path coefficient = 0.97, $p < 0.001$), followed by *driver's personal characteristics 2* (standardized path coefficient = −0.40, $p < 0.001$) and *trust* (standardized path coefficient = 0.39, $p < 0.001$). By contrast, the effect of *traffic density* is insignificant (normalized path coefficient = 0.09, $p =$ 0.210). The main factor that affects *takeover quality* is the *takeover time budget* (standardized path coefficient = 0.87, $p < 0.001$), followed by *traffic density* (standardized path coefficient = −0.43, $p < 0.001$) and *driver's personal characteristics 1* (standardized path coefficient = 0.24, p < 0.001).

Table 5 summarizes the direct, indirect, and total effects of each

Table 5
Statistics of direct, indirect and total impact mechanisms on take-over performance.

Model output	Impact path	Impact mechanism		
		Direct	Indirect	Total
Takeover time	Takeover time budget→Takeover time	0.229	0	0.229
	Traffic density→Takeover time	0.088	−0.124	−0.035
	Driver's characteristics 1→Takeover time	0	−0.731	−0.731
	Driver's characteristics 2→Takeover time	−0.404	0.535	0.131
	Subjective trust→Takeover time	0.391	0.261	0.652
	Monitoring strategy→Takeover time	−0.966	0	−0.966
Takeover quality	Takeover time budget→Takeover quality	0.873	0	0.873
	Traffic density→Takeover quality	−0.431	0	−0.431
	Driver's characteristics 1→Takeover quality	0.242	0	0.242
	Driver's characteristics 2→Takeover quality	−0.105	0	−0.105
	Subjective trust→Takeover quality	0	0	0
	Monitoring strategy→Takeover quality	0	0	0

factor on takeover performance. For takeover time, the total effect of the driver's monitoring strategy is the largest. It is followed by the effects of the driver's personal characteristics and trust in automated driving and, finally, the effects of takeover time budget and the number of experiments. For takeover quality, the overall effect of takeover time budget is the largest, followed by that of traffic density and, finally, that of the driver's personal characteristics.

5. Discussion

Structural equation modeling (SEM) was utilized to develop models capturing takeover performance. The roles of trust, system characteristics, environmental characteristics, and driver characteristics in the prediction of takeover behavior variation were examined by considering takeover time and quality in this study.

The SEM results demonstrated that the data fitted well with our theoretical model. Significant paths showed the predictive power of driver's *subjective trust*, *monitoring strategy*, system characteristics (i.e., *takeover time budget*), environmental characteristics (i.e., *traffic density)*, and driver characteristics (i.e., *age, manual driving experience, self-confidence,* and *pre-existing experience with an automated system or a similar technology*) on real-time takeover behavior variation. The complex relationship and influence mechanism of these factors demonstrated in our SEM could be detailed as follows.

5.1. Effect of takeover time budget

The results showed that the *takeover time budget* of the automated system had an extremely important direct effect on the driver's takeover performance, especially the *takeover quality*. Compared with the 7 s takeover time budget, the 10 s budget resulted in larger *maximum lateral acceleration* and *maximum longitudinal deceleration* during the takeover process while reducing the driver's *takeover time*. That is, aside from accelerating the decision-making process, the shortening of warning time also deteriorates post-takeover control, which will lead to traffic accidents. It is similar to the conclusions of related studies (Wan and Wu, 2018; Mok et al., 2015a, b). On the one hand, the *takeover time budget* determines whether the driver has sufficient time to recover from situational awareness and make an effective judgment on the current system failure causes and driving environment (McDonald et al., 2019). On the other hand, the above environmental perception and judgment affect drivers' preference of evasive maneuver (Lee et al., 2007), consequently determining the stability of takeover behavior. Accordingly, *takeover time budget*, as the factor that directly decides the time of decision and execution in the takeover process, had the most essential influence on *takeover quality* compared with other factors.

In addition, *takeover time budget* was positively related to *takeover time* in accordance with SEM, and the internal relationship was direct and significant. Similar to that reported by Gold et al. (2017); Payre et al. (2016), and Zhang et al. (2019a), long takeover time budgets generally lead to long takeover time.

5.2. Effect of traffic density

Traffic density had a significant direct effect on *takeover quality,* as the second most important factor. With an increase in *traffic density*, the *maximum lateral acceleration* and *maximum longitudinal deceleration* of the vehicle manually controlled by the driver also increased during the takeover process. At the same time, the driving track of the vehicle was unstable, and the *SDLP* increased. That is, the increase in *traffic density* means that various environmental objects need to be perceived by drivers, and the complexity of takeover scenarios and tasks increases (Körber et al., 2016); this condition causes additional challenges to drivers' workload and operation. These conclusions, similar to those of previous studies (Körber et al., 2016; Gold, 2016; Eriksson et al., 2018), show that our research is reasonable.

The findings also revealed that the direct effect of *traffic density* on *takeover time* was insignificant, which is inconsistent with the previous research conclusions of several scholars (Körber et al., 2016; Radlmayr et al., 2014). This inconsistency could be attributed to the setting of traffic density in the experiment to some extent. Gold et al. (2017) found in their meta-analysis that 15.7 vehicles/km represents a dilemma zone where it is unclear if changing lanes is a viable alternative; by contrast, with lower or higher traffic densities, drivers may immediately recognize a lane change, or braking is the optimal evasive maneuver. Accordingly, the two traffic densities of 10 and 30 vehicles/km set in this research are on both sides of the extreme points of the quadratic curve, and the drivers are not in a dilemma; hence, they can make the decision of changing lanes or braking rapidly. Consequently, after the takeover request was received, the *traffic density* in the environment did not affect the process of action selection, and the possible significant direct impact was not reflected in this model.

From Table 5 and Fig. 7, *traffic density* had an indirect effect on *takeover time* by influencing the driver's *monitoring strategy*. With an increase in surrounding vehicles, drivers' attention to their own cars and roads increased, which affected their physical, visual, and cognitive components of the takeover process (Sub-subsection *5.5*).

5.3. Effects of driver's personal characteristics

Compared with the abovementioned system and environmental characteristics, the specific effect mechanism of *driver's personal characteristics* (especially *manual driving experience*) on takeover behavior has not been widely demonstrated, although many scholars have emphasized the importance of exploring the effects of driver heterogeneity and state on takeover behavior (Gold et al., 2017; McDonald et al., 2019).

The results of the SEM model shown in Fig. 7 indicated that *driver's personal characteristics* had a complicated and major effect on takeover behavior.

5.3.1. Driver's personal characteristics 1

As for *age* and *manual driving experience* (*driver's personal characteristics 1*), these basic attributes of drivers (independent of specific scenarios/events) were positively related to *takeover quality*, leading to certain changes directly.

In accordance with SEM, older drivers experienced less *maximum* *lateral acceleration*, less *maximum longitudinal deceleration*, and a more stable driving trajectory when taking over an automated vehicle than others. This finding is inconsistent with that of some existing research. This inconsistency could be attributed to two reasons, that is, concerning the range setting of *age* in this experiment and the close relationship between *age* and *manual driving experience*. First, the average age of the participants in this study was 30.441 years old (min = 21 years old, max = 47 years old); drivers older than 60 (applied by Körber et al., 2016; Wright et al., 2016; Gold et al., 2017; Clark and Feng, 2017) were excluded in the analysis. Therefore, the deterioration of takeover quality caused by the age of the elderly drivers was not reflected in this model. Second, the connection between *manual driving experience* and *age* in the experiment is difficult to avoid due to the strong correlation between them in real life (Körber et al., 2016; Lenné et al., 2010). As a result, experienced older drivers visually identified more hazards with a smaller time budget and took over the vehicle more safely and smoothly than inexperienced younger drivers did, as stated by Wright et al. (2016).

From SEM, experienced drivers were proven to take more stable evasive maneuvers than novice drivers did. It is consistent with the previous studies, which argued that manual driving experience significantly affected takeover behavior. According to Lee (2007), Klauer et al. (2014), and Wright et al. (2016), novice drivers generally had worse vehicle control skills during manual driving and took a longer time to regain their situational awareness than experienced drivers did in driving automation. In addition, Chen et al. (2020a) found that manual driving experience significantly affects the maximum resultant acceleration during the takeover process. In this study, experienced drivers adapted to the driving automation system more rapidly and were less affected by the tension or discomfort of the takeover process. Their accumulated experience in manual driving could be well used in the automated driving system, and the action execution became stable and safe. Consequently, the results of similarity with most of the existing studies further confirm the reliability of this study.

Except for the direct effect on *takeover quality*, *age* and *manual driving experience* also had indirect effects on *takeover time* by influencing the driver's *monitoring strategy*. With an increase in *age* and *manual driving experience*, drivers' attention to their own cars and roads increased, which affected their physical, visual, and cognitive components of the takeover process, resulting in minimal *takeover time* (Sub-subsection *5.5*).

5.3.2. Driver's personal characteristics 2

As for *pre-existing experience with an automated system or a similar technology* and *self-confidence* (*driver's personal characteristics 2*), these special personal characteristics of drivers (closely related to specific scenarios/events) were negatively related to *takeover time* (the secondary factors) and *takeover quality*, leading to certain changes directly.

From SEM, pre-existing experience or knowledge of an automated system or a similar technology accelerated the physical, visual, and cognitive components of the takeover process, decreasing takeover time. In line with the findings from emergencies in manual driving (Aust et al., 2013; Lee et al., 2002), repeated exposure, similar to related experience, showed a substantial effect on takeover time. Prior real-world experience with automated vehicle technologies, such as adaptive cruise control, has also been shown to affect visual reaction time and mediate the learning effect (Zeeb et al., 2017).

Aside from the direct effect, these special driver characteristics also indirectly affected *takeover time* by affecting *trust*. With an increase in the *pre-existing experience* and *self-confidence* of drivers, they had an enhanced level of trust in automated systems, leading to increased *takeover time*. On the basis of the studies of Szalma et al. (2017), *self-confidence* is a stable factor affecting automation trust. When users are highly confident, they are likely to trust or rely on the system. Körber et al. (2018) stated that *pre-existing experience* of familiarity and contact with the system is conducive to promoting the driver's recognition and dependence on the system. Therefore, the change in drivers' *self--confidence* and *pre-existing experience* would be indirectly transmitted to *takeover time* through the change in their trust in the system, causing corresponding changes (Sub-subsection *5.4*).

5.4. Effect of driver's subjective trust in level 3 automated vehicles

As previously assumed, trust, as a dynamic intermediary variable, played a complex and critical role between other influencing factors and takeover behavior. Several studies have investigated the effect of subjectively measured trust on takeover performance (Körber et al., 2018a, b; Payre et al., 2016; Shen and Neyens, 2014). A voluntary NDRT instead of a mandatory NDRT was adopted in this study to make the distraction simulation close to reality; relatively, it provided a higher degree of decision-making freedom for drivers. Under the above premise, the correlation between driver's psychology and behavior (or the reflection of driver's psychological changes in behavior) is clear.

In addition to the *driver's personal characteristics*, *subjective trust* also had critical implications for *takeover time* rather than *takeover quality* and the mechanism for influence included direct and indirect effects.

When drivers' *subjective trust* in the automated vehicle increased, their response and judgment to the takeover request slowed down, leading to a long *takeover time*. This condition could be attributed to two reasons concerning the role of reliance and monitoring strategy. First, when the subjective trust level of drivers on the system increased, their recognition of the system reliability also enhanced gradually, then they were more dependent on the system than they were before (Körber et al., 2018a,b; Payre et al., 2016). That is, participants' willingness to rely on the conditional automated driving system translated to actual reliance. Summala (2000) argued that a distinction exists between drivers' ability to intervene rapidly and their motivation to intervene and explained that "it is not always necessary to react as soon as possible." If sufficient time exists, drivers do not take over as rapidly as they can but first assess the situation (e.g., by checking the mirrors and system reliability) (Gold, Damböck et al., 2013) before taking over. Therefore, the drivers who approve of the system reliability and the sufficiency of takeover time budget would hold a high trust level. They believe that the judgment, decision making, and operation time reserved by the system are adequate when the takeover request is issued and do not take over as rapidly as they can. Consequently, the *takeover time* was directly affected by *subjective trust*.

Second, participants with high *subjective trust* scanned the environment minimally (Gold, Körber et al., 2015; Körber et al., 2018a,b; Bagheri and Jamieson, 2004; Brown and Noy, 2004; Hergeth, 2016). On the basis of the SEM in this study, *subjective trust* was negatively related to *monitoring strategy* and had an indirect positive effect on *takeover time*. To a certain extent, automation trust, as an attitude, could be inferred from the gaze behavior during conditional automated driving. When drivers had a high level of *subjective trust* in the system, their attention to vehicle and road conditions declined to a certain extent (the corresponding *monitoring ratio* and *monitoring frequency*); this variation in gaze behavior was a critical factor affecting drivers' situational awareness (Gawron, 2019; Paletta et al., 2017). As stated by Vlakveld et al. (2018), drivers need time to develop situation awareness when they have to resume driving. After having been out of the loop, drivers have to construct a mental representation of the traffic situation before they can recognize latent hazards and perform the takeover behavior. Consequently, the increase in *subjective trust* affected the *monitoring strategy* and situational awareness of drivers to a certain extent, which indirectly led to slow judgment and reaction in the takeover process. The takeover time extended finally.

5.5. Effect of driver's monitoring strategy in level 3 automated vehicles

As we have mentioned above, the relationship between automation trust and related behavior (e.g., takeover behavior) decreases under a high workload because people sometimes have a minimal choice but to rely on a system to deal with the high workload (Hoff and Bashir, 2015); this situation is different from how drivers would typically engage in non-driving-related activities (Clark and Feng, 2017). In addition, implicit and intuitive processes that are not captured by self-report measures might have mediated the relationship between *subjective trust* and *monitoring strategy* (Hergeth, 2016). Hence, this paper extends the scene of NDRT to the form of voluntary, encouraging drivers to behave naturally in accordance with their usual driving habits as much as possible and judge freely whether to engage in NDRT on the basis of the status themselves.

Under the above experimental conditions, which were close to daily life, the researchers found a strong direct relationship between *monitoring strategy* and *takeover time*. When drivers minimal less attention to the current driving status, they needed a long time to reconstruct situational awareness and to judge and make decisions when the takeover request was issued, which directly led to the extension of takeover time.

In accordance with SEM, the largest part of the variation in takeover time was explained by *monitoring strategy*. When drivers paid more attention to NDRT and paid less attention to the state of vehicles and their surroundings, their response, judgment, and decision-making speed in response to takeover request were limited, which led to the extension of takeover time. Some evidence points to a detrimental effect of such engagement in NDRT on driving performance with conditional automation (Louw et al., 2015b; Merat et al., 2012a,b; Zeeb et al., 2016; Körber et al., 2018a,b; Schwarz et al., 2019). For example, Körber et al. (2018) and Schwarz et al. (2019) came to a similar conclusion in their research, which is that the gaze behavior of drivers had a certain correlation with automated driving trust and takeover performance in the case of mandatory NDRT. In line with this conclusion, Merat et al. (2012a,b) used a verbal task to simulate phone conversations during highly automated driving. The researchers found the degradation of responding to a critical event while the drivers were being engaged in a verbal task.

In addition, the changes in the above *monitoring strategy* were actually caused by the combined effect of many factors, including the age of the driver, manual driving experience, self-confidence, preexisting experience, traffic density and the subjective trust. Among them, the driver's manual driving experience and subjective trust were the most important factors. On the one hand, the increase of manual driving experience made drivers pay more attention to the driving scene even when the automated driving function is enabled; on the other hand, the improvement of subjective trust level would make drivers more dependent on the system and reduce their supervision. Under the comprehensive effect of the above factors, the driver's monitoring behavior showed a complex evolution, and the above effects are reflected in the takeover behavior.

5.6. The relationship between driver's subjective trust and monitoring strategy

According to the relevant literature (Hergeth, 2016; Korber et al., 2018), we assumed that drivers' subjective trust in the system would affect their objective performance, such as the monitoring behavior of driving scenes and the corresponding distraction behavior. When drivers trusted the system more, it was not only reflected in the subjective trust rating of the questionnaire, but also reflected in the more frequent distracted behaviors of drivers (or the higher degree of attention to non-driving-related task).

The model showed that there was a significant negative correlation between driver's subjective trust and monitoring strategy, that is, drivers' subjective trust in the system would directly affect their monitoring strategy during the automated driving. When drivers recognized the function of the system or were familiar with the system, they would have more frequent distractions and pay less attention to the situation of the vehicle and the surrounding environment. The above results verified the consistency of the two different types of trust measurement methods, and further demonstrated the relationship between them, which was consistent with the trend of most existing research conclusions (Hergeth, 2016; Gold et al., 2015; Körber et al., 2018a,b), although they use mandatory tasks to simulate the distracted state.

However, it was worth noting that from the influence path coefficient of the model, we could find that the subjective trust was not the most critical factor affecting monitoring behavior (or distraction behavior). On the contrary, the age and manual driving experience of drivers were the most important characteristics determining their monitoring strategy. That is to say, with the increase of drivers' subjective trust in the system, their monitoring frequency and attention to driving scenes would decrease to a certain extent; however, the direct positive effect of age and manual driving experience was more dominant, and the older drivers and experienced drivers showed more conservative monitoring strategies. They may be less involved in NDRT or distractions. This is in fact consistent with the relevant phenomenon of manual driving scene (Klauer et al., 2014).

The above phenomenon can be explained by the following two aspects. First, through the interviews with the participants after the experiment, most of the experienced drivers showed that they had witnessed or experienced serious traffic accidents, and their awe of life was greater than that of novice drivers, so they could not easily move their eyes away from the road to do something unrelated to driving, and this highly concentrated habit does not change significantly due to short contact with the automated system. Second, the above phenomenon can also be explained from the perspective of the different attractiveness of NDRT to different participants. Some scholars have shown that compared with young drivers, mobile devices such as mobile phones are not attractive to old drivers (Clark and Feng, 2017).

5.7. Limitation

The first limitation could be attributed to the driving simulator. The fixed-based driving simulator, as well as the dynamic motion system and visual displays used in this study, was different from real vehicles and might have caused some errors. Among the influencing factors related to driver characteristics, driving state, such as drinking and fatigue driving, can be added to measure the influence of driver heterogeneity on takeover behavior comprehensively. The age range of participants in this study ranged from 21 years old to 47 years old, and the elderly drivers were excluded in the relevant analysis. Therefore, the relevant conclusions might not be applicable to the elderly drivers (older than 60 years), which should be supplemented later. For the evaluation index of takeover behavior, we could consider the visual reaction time to distinguish the specific time of driver's eye movement and the specific time of decision-making operation in the takeover time to refine the influencing factors of driver's behavior in different stages during the takeover process. Lastly, regarding the differences in takeover scenarios, although previous studies have proven that they did not significantly affect trust and takeover behavior, we should also consider relevant experiments and explorations under the premise of voluntary NDRT.

6. Conclusion

In this study, we attempted to explain drivers' takeover performance variation in a level 3 automated vehicle in consideration of the effects of trust, system characteristics, environmental characteristics, and driver characteristics by using a structural equation model. The model was built by incorporating drivers' takeover time and quality as endogenous variables. A theoretical framework of the model was hypothesized on the basis of the ACT-R cognitive architecture and relevant research results. The validity of the model was confirmed in accordance with the data collected from 136 driving simulator samples under the condition of voluntary NDRT. The results revealed that takeover time budget was the most critical factor in promoting the safety and stability of the takeover process, which, together with traffic density and driver characteristics, determined drivers' takeover quality directly. Driver characteristics and takeover time budget also strongly influenced takeover time directly. Apart from the direct effects mentioned above, trust, as an intermediary variable, explained a major portion of the variance in takeover time. Theoretically, these findings suggested that takeover behavior could be comprehensively evaluated from the two dimensions of takeover time and quality through the combination of trust, driver characteristics, environmental characteristics, and vehicle characteristics. The influence mechanism of the above factors is complex and multidimensional. In addition to the form of direct influence, trust, as an intermediary variable, could reflect the internal mechanism of the takeover behavior variation. Practically, the findings emphasized the crucial role of trust in the change in takeover behavior through the dimensions of subjective trust level and monitoring strategy, which might provide new insights into the function design of takeover process.

Contribution

Experimental design: Mengxia Jin, Guangquan Lu, Facheng Chen;
Data collection: Mengxia Jin, Xi Shi, Haitian Tan;
Data processing: Mengxia Jin, Facheng Chen, Haitian Tan;
Data analysis: Mengxia Jin, Guangquan Lu, Facheng Chen;
Paper writing: Mengxia Jin, Guangquan Lu, Facheng Chen;
Paper revising: Mengxia Jin, Guangquan Lu, Facheng Chen, Junda Zhai.

Declaration of Competing Interest

The authors report no declarations of interest.

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