*Engineering For Social Change*
*A. Cooper et al. (Eds.)*

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*doi:10.3233/ATDE240842*

# Safe Driving Behavior Model Construction for L2 and L3 Automated Driving

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**Abstract.** The arrival of Level 2 (L2) and Level 3 (L3) of automated driving places new demands on driving behavior, yet drivers who have been accustomed to manual driving do not seem to be adequately prepared. Therefore, to improve driving safety, this study proposes an integrated approach to establishing a safe driving behavior model by combining Hierarchical Task Analysis and Information Decision Action model. Initially, 11 key driving scenarios at the L2 and L3 levels were identified through literature review; Five automated driving experts were invited to grade the importance of the scenarios through the Analytic Hierarchy Process. Additionally, their safety recommendations for each scenario at the L2 and L3 levels were analyzed. Finally, a model of drivers' safe behavior under L2 and L3 conditions was constructed accordingly. The results of this study can not only guide the cultivation of drivers' driving habits, but also provide test scenarios with human-machine co-driving perspectives for the development of automated driving.

**Keywords.** Transdisciplinary engineering, Automated driving, Driving behavior, Transportation safety

## Introduction

Automated driving at the L2 and L3 levels places new demands on the driver's driving habits. The Society of Automotive Engineers (SAE) in their J3016 standard defines L2 and L3 as “Partial Driving Automation” and “Conditional Driving Automation” [1]. L2 and L3 indicate that vehicles have been able to achieve automation in certain functions, but still require human drivers to be involved in driving. L2 and L3 change the human-vehicle interaction patterns by bringing two new operations: monitoring and takeover. During monitoring, the driver needs to flexibly adjust the allocation of attention to ensure effective supervision; For takeover, the driver not only needs to be familiar with the takeover process but also needs to have a high level of emergency response capability to ensure a smooth and safe transition of the vehicle.

Worryingly, drivers seem not to be fully prepared for the arrival of L2 and L3 automated driving. Drivers are often not adequately informed or trained about their roles and responsibilities in such semi-automated vehicles before using them. One study suggests that more than ninety percent of self-driving accidents are related to driver errors [2]. Drivers tend to rely on autopilot systems, leading to a decrease in situational awareness and an increased risk of accidents due to a delayed response in taking back control of the vehicle [3]. Although studies have summarized the driver-related factors that lead to collisions [4][5], there is still a lack of detailed norms for safe driving behavior. Therefore, this study summarized 11 key scenarios of L2 and L3 levels of automated driving and established a drivers' safe driving behavior model, as shown in Fig. 1. On the one hand, this work provides a theoretical basis for subsequent training of drivers' driving habits. On the other hand, the work not only provides a direct reference for the development of test scenarios for self-driving vehicles, but also helps to improve the potential deficiencies of human-computer interaction in current automated driving to reduce the number of collisions caused by conflicting driving habits.

The paper is structured as follows: Section 1 presents the methodological framework of the paper. Section 2 summarizes the key driving scenarios. Section 3 analyses safe driving behaviors. Section 4 constructs the safe driving behaviors model, and section 5 summarizes the contributions, limitations, and future work of this study.

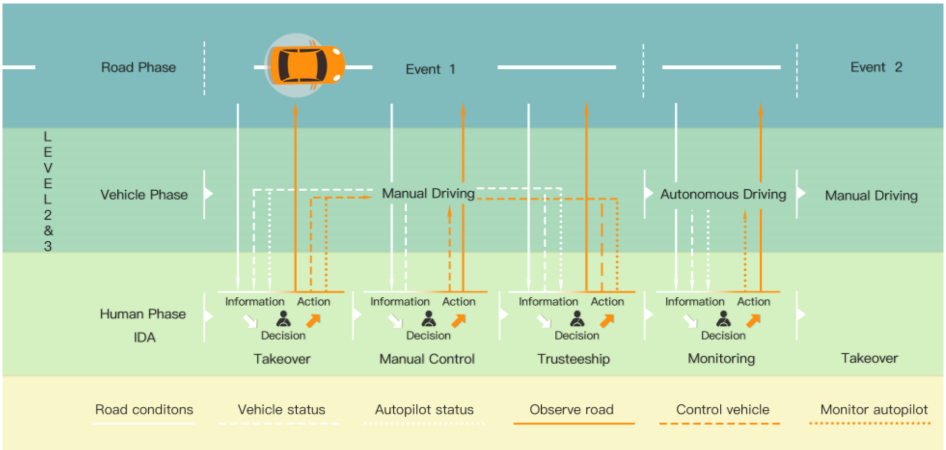



**Figure 1.** A visual summary of the safe driving behavior model for L2 and L3 automated driving.

## 1. Methodology

This section proposes a framework of methodology for the construction of the safe driving behavior model, as shown in Figure 2. The framework consists of three stages, namely key scenario extraction, safe driving behavior analysis, and model integration.

The first is key driving scenario extraction. To extract representative driving scenarios from complex ones, literature research was used to summarize the focused scenarios in previous studies. At the same time, the importance of key scenarios was categorized using the Analytic Hierarchy Process (AHP).

This was followed by a safe driving behavior analysis. Automated driving experts were invited to analyze the safe driving behaviors of the above key scenarios using Hierarchical Task Analysis (HTA). Specifically, the objectives and tasks of the key scenarios were first identified. Afterward, they were decomposed into sub-objectives and sub-tasks using Hierarchical Task Analysis (HTA). The sub-objectives and sub-tasks were further decomposed until they could be expressed through a single action by the driver. Then, hundreds of specific actions of the 11 key scenarios were integrated through semantic analysis to improve the generalization ability of the model.

Finally, based on the IDA (Information, Decision, Action) theory, a safe driving behavior model centered on driver interaction behavior was constructed by analyzing the driver's information input, decision, and action at different driving stages.

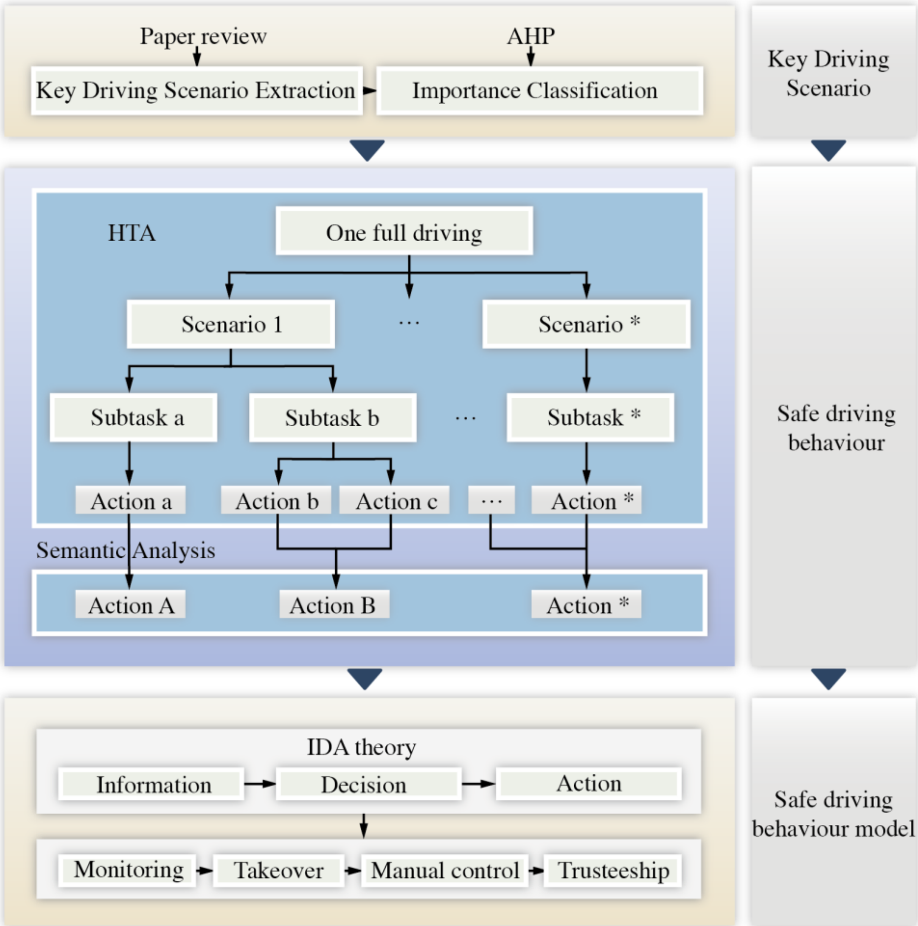



**Figure 2.** The framework of methodology.

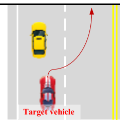
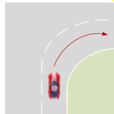
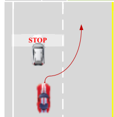
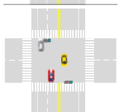
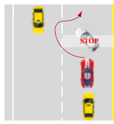
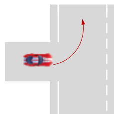
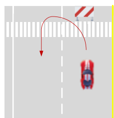
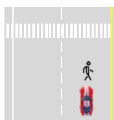
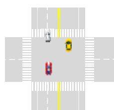
## 2. Key Driving Scenario Extraction and Importance Classification

### *2.1. Key Driving Scenario Extraction*

In L2 and L3 automated driving, various driving scenarios are crucial to ensure safe and efficient operation. These scenarios typically include complex traffic conditions, diverse road environments, and challenging weather conditions. Shladover and Aoki et al. summarized the decision-making process of self-driving vehicles at intersections[6] [7]; Ji et al. focus on merging or lane changing scenarios for self-driving vehicles[8];

Gerónimo et al. investigated traffic modeling to cope with a variety of road users (e.g. pedestrians, cyclists) in a complex urban environment[9]. Castro et al. summarized the impact of inclement weather on driving safety[10]. Such studies involving critical driving scenarios were used as a reference point, and five experts related to automated driving categorized and integrated the above scenarios. Eleven critical driving scenarios were finally extracted, as shown in Table 1.

**Table 1.** 11 Key Driving Scenarios.

| No. | Description | Example |
|---|---|---|
| Scenario 1: | On a two-way four-lane expressway, the subject vehicle goes straight on the leftmost lane, and other cars either follow it or overtake it. The drivers can decide to overtake other cars by cutting into the right lane. |   |
| Scenario 2: | The vehicle drives in a hairpin turn and the driver may have to take over the control. |  |
| Scenario 3: | A car in front of the subject vehicle is suddenly stopped and the driver may have to take over the control. The vehicle is required to cut into the lane on right side. |   |
| Scenario 4: | The subject vehicle passes the junctions with relatively lower traffic and low visibility. |  |
| Scenario 5: | The subject vehicle passes the junctions with relatively higher traffic and low visibility. |  |
| Scenario 6: | A car parks on the street and it blocks half of the drive lane. Hence, the subject vehicle has to stop and wait for the oncoming traffic to overtake it. |   |
| Scenario 7: | Cruising near exits. The subject vehicle is going to merge into the lane with a relatively low speed limit. |  |
| Scenario 8: | A sudden traffic diversion. The subject vehicle has to take a bypass road according to road signs. |  |
| Scenario 9: | A pedestrian suddenly crosses the road. The subject vehicle has to stop. |  |
| Scenario10: | The subject vehicle passes the junctions with no traffic light. |  |

| | | |
|---|---|---|
| scenario 11: | A car does not turn on the lights and suddenly cut in the line of the subject vehicle. The driver may have to take over the control. |  |

## 2.2. Critical Driving Scenarios by Importance

The Analytic Hierarchy Process (AHP) was used to classify the importance of the 11 key driving scenarios mentioned above. Five experts were invited and were asked to use the complexity of the scenario, the hazard factor, and the likelihood that the autopilot would need to take over as measures of importance. The level of importance between the key scenarios was compared using the comparison scale method, and the judgment matrix is shown in Table 2. After that, the geometric mean method was used to calculate the weight vectors, which were normalized to the weight values, and the results are shown in Figure 3. Finally, to ensure the consistency of the results in the Pairwise comparison process, the consistency test was carried out. Checking the table of international average random consistency index RI values, CR = 0.039 < 1.52, the matrix meets the consistency requirements.

**Table 2.** Judgment matrix.

| | **Sce 1** | **Sce 2** | **Sce 3** | **Sce 4** | **Sce 5** | **Sce 6** | **Sce 7** | **Sce 8** | **Sce 9** | **Sce 10** | **Sce 11** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Sce 1** | 1 | 4 | 0.5 | 2.5 | 1 | 0.2 | 3 | 0.667 | 0.333 | 0.4 | 0.286 |
| **Sce 2** | 0.25 | 1 | 0.2 | 0.4 | 0.25 | 0.125 | 0.5 | 0.222 | 0.167 | 0.2 | 0.167 |
| **Sce 3** | 2 | 5 | 1 | 3.5 | 2 | 0.25 | 4 | 1.5 | 4 | 0.667 | 0.4 |
| **Sce 4** | 0.4 | 2.5 | 0.286 | 1 | 0.4 | 0.167 | 1.5 | 0.333 | 0.222 | 0.25 | 0.2 |
| **Sce 5** | 1 | 4 | 0.5 | 2.5 | 1 | 0.2 | 3 | 0.667 | 0.333 | 0.4 | 0.286 |
| **Sce 6** | 1.5 | 8 | 4 | 6.5 | 5 | 1 | 7 | 4.5 | 3 | 3.5 | 2.5 |
| **Sce 7** | 0.333 | 2 | 0.25 | 0.667 | 0.333 | 0.143 | 1 | 0.286 | 0.2 | 0.222 | 0.2 |
| **Sce 8** | 1.5 | 4.5 | 0.667 | 3 | 1.5 | 0.222 | 3.5 | 1 | 0.4 | 0.5 | 0.333 |
| **Sce 9** | 3 | 6 | 0.25 | 4.5 | 3 | 0.333 | 5 | 2.5 | 1 | 1.5 | 0.667 |
| **Sce 10** | 2.5 | 5.5 | 1.5 | 4 | 2.5 | 0.286 | 4.5 | 2 | 0.667 | 1 | 0.5 |
| **Sce 11** | 0.5 | 6.5 | 2.5 | 5 | 7.5 | 0.4 | 5.5 | 3 | 1.5 | 2 | 1 |

The importance of the scenario is related to the complexity of it. The more complex the scenario, the more information the driver needs to pay attention to, and the more difficult it is to take over. In scenario 6, where the driver needs to notice vehicles in front, behind, and left at the same time, the traffic is the most complex and therefore has the highest level of importance at 24.81%. On the contrary, scenarios 2, 4, and 7 are simpler in driving and therefore less important with 1.82%, 3.02%, and 2.49% respectively.

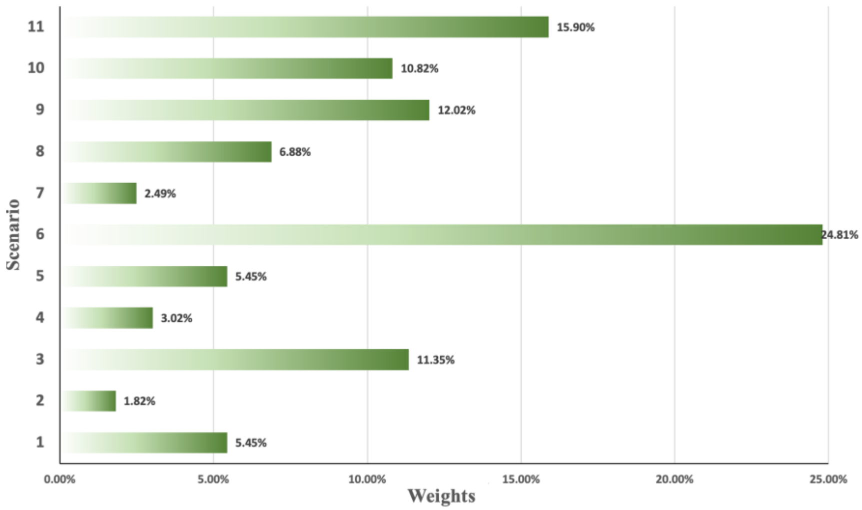



**Figure 3.** Result of AHP.

## 3. Safe Driving Behaviour Analysis

Five experts in automated driving were invited to participate in analyzing the safe driving behavior in L2 and L3. In L2 and L3 automated driving, although the vehicle can take over part of the driving task, the driver is still required to maintain constant attention to the vehicle and its surroundings and to be ready to take over the driving. Therefore, the analysis of safe driving behavior focuses on both supervision and takeover. Hierarchical task analysis (HTA) was used, and the partial results are shown in Table 3. Taking Scenario 6 as an example, a driver's behavior can be divided into three phases based on the progression of the scenario, namely the observation phase, the incident phase, and the recovery phase, whether it is monitoring or takeover. Each phase can be subdivided into multiple subtasks. For example, when monitoring, the subtasks of the overtaking phase (incident phase) are observing the left lane, observing the distance between cars, and observing the right lane. It should be added that the 11 scenarios were all analyzed using the right-hand drive as an example, and we believe that the results are similar for the left-hand drive and can be mirrored.

**Table 3.** HTA of Safe driving behavior.

| No. | Monitoring Scenarios | Takeover Scenarios |
|---|---|---|
| …… | …… | …… |
| 6 | **6.1 Observing phase.**<br>6.1.1 Observe the distance to the car in front of you.<br>6.1.2 Observe the distance to the car behind you.<br>6.1.3 Observe the speed of your vehicle.<br>6.1.4 Observe the status of the vehicle's autopilot system.<br>**6.2 Incident phase.**<br>6.2.1 Observe the condition of the left lane.<br>6.2.2 Observe the distance of the vehicle on the right through the right-side mirror.<br>6.2.3 Observe the right front road condition. | **6.1 Observing phase.**<br>6.1.1 Check the rearview mirror.<br>6.1.2 Slow down.<br>6.1.3 Observe the distance and stopping position of the vehicle in front of you.<br>6.1.4 Check the rearview mirror for vehicles behind you.<br>6.1.5 Stop and wait for the moment.<br>**6.2 Incident phase.**<br>6.2.1 Observe the left-side mirror.<br>6.2.2 Check the rearview mirror for cars behind you to maintain a safe distance. |

| | | |
|---|---|---|
| | **6.3 Recovery phase.**<br>6.3.1 Observe the distance to the overtaken vehicle through the rearview mirror.<br>6.3.2 Observe the status of the vehicle's autopilot system. | 6.2.3 Step on the gas and Steer left.<br>6.2.4 Watch the distance in your right-side mirror.<br>6.2.5 Straighten the steering wheel.<br>6.2.6 Observe the distance between cars in the right-side mirror.<br>6.2.7 Steer right and drive into the original lane.<br>6.2.8 Straighten the steering wheel.<br>**6.3 Recovery phase.**<br>6.3.1 Return to normal speed.<br>6.3.2 Keep driving straight. |
| …… | …… | …… |

Semantic analysis was used for clustering of the above safe driving behaviors to extract features. Initial safe driving behaviors for each scenario were obtained by analyzing the subtasks. However, there are similarities in many of these behaviors. To better generalize the features of drivers' safe driving behaviors, this study identifies similar driving behaviors and merges them through semantic analysis. After clustering, the characteristics of safe driving behaviors for each scenario are shown in Table 4.

**Table 4.** Safe driving behavior of monitoring and takeover.

| **Monitoring** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Observe the autopilot system | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observe the target lane | ✓ | | ✓ | | | ✓ | ✓ | ✓ | | | |
| Observe the distance and speed | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observe the traffic light | | | | ✓ | ✓ | | | | | | |
| Observe the pedestrian/barrier | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observe the （right/left）rearview mirror | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Takeover** | | | | | | | | | | | |
| Decelerate/ Accelerate/Stop | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Steer right / left | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | |
| Use lights | ✓ | | ✓ | | | ✓ | ✓ | ✓ | | | |

The monitoring and takeover phases are sequential, but the safe driving behaviors in the monitoring and takeover phases are juxtaposed. In other words, the driver is either in the monitoring or takeover phase in the scenario and can switch from the monitoring phase to the takeover phase at any time, instead of performing all the monitoring behaviors first and then the takeover behaviors. The L3 has a higher degree of automation versus the L2 and is more capable of coping with complex road conditions and unexpected scenarios. Therefore, compared to L2, L3 automated driving has a higher proportion of driver supervision and a lower proportion of takeover. However, in terms of safe driving behaviors and habits themselves, the requirements of L2 and L3 are the same.

## 4. Modeling Safe Driving Behaviour

The safe driving behavior model was constructed through the IDA model. The IDA model represents “Information”, “Decision”, and “Action”, which are considered to significantly influence the outcome. These three aspects are specified in L2 and L3 automated driving. “Information” refers to the driving environment around the driver, including vehicles, roads, and pedestrians. “Decision” is the driver's judgment of the current driving environment based on personal experience. Action refers to safe driving behaviors taken by the driver in response to a decision.

L2 and L3 automated driving can be divided into four phases based on the driver's interaction behavior in each key driving scenario, which are Supervision, Takeover, and Driving & Trusteeship. To summarise, in the supervision phase, the driver needs to receive information from the road including traffic lights, traffic signs, other vehicles, and pedestrians. At the same time, the driver also needs to receive information about the status of the automated driving system, including takeover alerts and other assisted driving functions. In addition, the driver needs to pay attention to dynamic information about the vehicles, including position, speed, and steering angle, as shown in Figure 4. In the takeover phase, while the driver continues to pay attention to the road conditions and the vehicle status, the driver needs to switch the vehicle from the automatic driving mode to the manual driving mode. The manual driving phase means that the main control of the vehicle is done by the driver, and the trusteeship phase means that the driver confirms the road and vehicle conditions and switches the vehicle from the manual driving mode to the automatic driving mode. These four phases cycle back and forth.

Scenario 6 is used as an example to illustrate the analysis process of the safe driving behavior model. Firstly, the driver maintains manual control of the vehicle. When the automated driving conditions are met, the vehicle will indicate that the automated driving can be turned on, and the driver will decide whether to trust the vehicle after judgment. After trusteeship, the vehicle is in the automatic driving state, and the driver will be in the monitoring state. When a dangerous scenario (Scenario 6) occurs, the driver may switch from monitoring to taking over at any time, and resume manual driving after taking over. The specific behavior of monitoring and takeover has been defined in section 3.

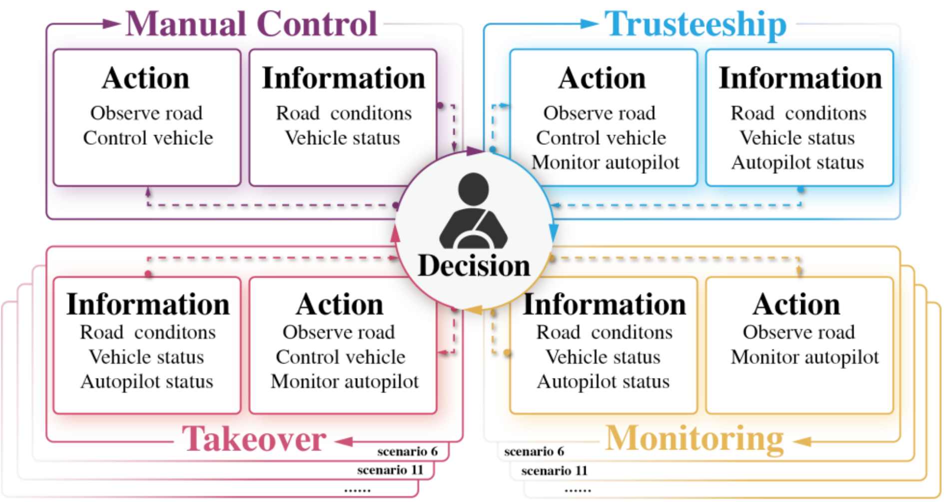



**Figure 4.** Safe driving behavior model.

The complete driving process is created by a random permutation of 11 key driving scenarios. Each key driving scenario consists of four phases: supervision, takeover, driving, and trusteeship. The driver driving behavior model for each phase is constructed through the IDA model, where the detailed safe driving behaviors for the two most important driving phases - Supervision and Takeover - have been defined in Section 3, "Safe Driving Behaviour Analysis". This completes the construction of the safe driving behavior model centered on driver interaction behaviors for L2 and L3 automated driving.

## 5. Conclusion

Automated driving safety is a top priority, and the promotion of automated driving at L2 and L3, while facilitating mobility, poses a new problem for drivers' safe driving behaviors and habits. To reduce the potential risk of automated driving, this study established a model of drivers' safe driving behavior. The results of this study can not only guide the cultivation of drivers' driving habits, but also hope to provide test scenarios for automated driving from the perspective of human-machine co-driving and optimize the automated driving system from a human-centered perspective. This study is mainly carried out from the theoretical level, and we plan to construct an automated driving behavior training platform based on this theory to further validate the effectiveness of the model, and improve the safety of automated driving at the same time.

## Acknowledgment

The study is supported by the Smart Traffic Fund (PSRI/43/2207/PR).

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